EXTRAPOLATIVE BELIEFS AND THE VALUE PREMIUM

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To my parents, my husband, my mentor, and also myself, who has never stopped seeking her true self and deep passion for this world.

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ABSTRACT

In models of stock returns where investors with extrapolative beliefs on future stocks (e.g., Barberis and Shleifer (2003)[1]), price momentum and the value premium both arise naturally. The key insight from these models is that, the strength and timing of these cross-sectional return anomalies will be conditional on the degree of extrapolative bias. More specifically, higher (lower) degree of over-extrapolation leading to stronger value premium (momentum).

Using the time-series variation in the degree of over-extrapolation documented in Cassella and Gulen (2018)[2], I first directly test the hypothesis that both value and momentum stem from over-extrapolation in financial markets. I find that the average momentum return is 1.00% (0.10%) per month when the degree of over-extrapolation is low (high), whereas the average value premium is 0.51% (1.29%) per month following low (high) levels of over-extrapolation.

Furthermore, I extend the model in Barberis and Shleifer (2003)[1] by having both within-equity extrapolators and across asset-class extrapolator. The extension is based on the idea that when extrapolators move capital in and out of the equity market, they disproportionately buy growth stocks in good times and sell value stocks in bad times. The model predicts that the cross-sectional value premium should be stronger following states of large market-wide over- or undervaluation due to additional extrapolative demand to buy or sell. This prediction is tested empirically and I find strong support for it. The value premium is 3.42% per month following market-wide undervaluation and 1.70% per month following market overvaluation. In the remainder 60% to 80% of the sample, when the market is neither significantly over or under-valued, there is no significant value premium in a monthly horizon and the value premium is only 0.54% per month in an annual horizon. I provide some suggestive evidence regarding portfolio return dynamics, investor expectation errors and fund flows that supports the extrapolative demand channel. Overall, this work examines more closely at the effect of extrapolative beliefs on the cross-section of asset prices and offers some support for extrapolation-based asset-pricing theories.

1. INTRODUCTION

There is extensive literature documenting that the price-scaled variables (B/M, E/P, and etc.) have significant predictive power in future stock market returns.[1] Recent theory and empirical work in behavioral finance tie such return predictability to the presence of investors with extrapolative beliefs (i.e. extrapolators) in the market (e.g., Barberis, Greenwood, Jin, and Shleifer (2015)[9], Cassella and Gulen (2018)[2]). Return extrapolation is the tendency to believe that future stock returns will continue to be higher after observing good performance, and that future returns will continue to be lower after recent poor stock performance.[2] At the aggregate level, extrapolators move capital into (out of) the stock market based on the recent equity market performance, prices go above (below) its fundamental value as a result of the aggregate extrapolative flow. The mispricing is eventually corrected, thus generating patterns of aggregate return predictability.

Within the equity market, return extrapolation can also drive the time-series variation in the profitability of some cross-sectional anomalies. In markets with investors whose expectation on future return exhibits extrapolative bias, momentum and the value premium arise naturally, since extrapolators are drawn to stocks that have recently done well, and shy away from stocks that have done poorly. Through such positive feedback trading, extrapolators can generate a pattern of price momentum in the cross section. Moreover, extrapolators' additional demand for certain stocks causes prices to deviate from their fundamental values. Eventually, extrapolators' over-reaction to past returns leads to a value effect, whereby stocks with high (low) valuation ratios, such as B/M, experience higher (lower) returns in the future. Given a growing body of empirical work based on surveys (e.g., Greenwood and Shleifer (2014)[20]), laboratory experiments (e.g., Landier, Ma, and Thesmar (2020)[21]),

[1] ↑For evidence on dividend-to-price ratio (D/P), see Fama and French (1988)[3], Campbell and Shiller (1988)[4], Cochrane (1992[5], 2008[6], 2011[7]), for book-to-market ratio (B/M) see Lewellen (2004)[8], and for earnings-to-price ratio (E/P) see Campbell and Shiller (1988)[4]

[2] ↑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)[10], Frankel and Froot (1990)[11], De Long, Shleifer, Summers, and Waldmann (1990)[12], Hong and Stein (1999)[13], and Barberis and Shleifer (2003)[1]. More recent studies on the topic include Barberis, Greenwood, Jin, and Shleifer (2015[9], 2018[14]), Glaeser and Nathanson (2017)[15], Cassella and Gulen (2019)[16], DeFusco, Nathanson, and Zwick (2018)[17], Jin and Sui (2018)[18], and Lou and Polk (2019)[19].

and field evidence (e.g. Da, Huang, and Jin (2021)[22]), which has offered some convincing evidence of the pervasiveness of extrapolative bias among investors, return extrapolation is considered to be an intuitive and plausible explanation for momentum and value premium in the equity market.

Different degrees of extrapolative bias can be interpreted from the following two aspect: (i) given the certain population of extrapolators in the market, extrapolative bias can be measured by how much extrapolators depend on the most recent observed performance when forming their expectation on future returns. This aspect can be linked to the parameter θ in extrapolators' expectation function in the Barberis and Shleifer (2003)[1] framework. (ii) given the certain dependence on the most recent observed performance, higher degree of extrapolative bias can also be measured by an increase in the actual extrapolative demand on certain stocks. The additional extrapolative demand not only can come from an increase in trading by current extrapolators, but also can be due to an increase in total population of extrapolators in the market. Though the effects of these two aspects can be tested within the theory frameworks, it is difficult to fully isolate these two aspects empirically.

In Chapter 2, I test the role of the first aspect of return extrapolation for the time-series patterns of momentum and the value premium. I choose my empirical design to closely follow the conceptual framework established in Barberis and Shleifer (2003)[1], who propose a model of financial markets with style chasers who have extrapolative expectations on stock returns. One of many implications generated by their style-investing model is that the strength and timing of momentum and the value premium in the equity market are a function of extrapolators' degree of over-extrapolation (DOX). This structural parameter of extrapolative expectations determines how much style chasers depend on the most recent returns to determine their expectation on future returns and how persistent style chasers' demand flows are, hence has implications on how quickly the arbitrageurs correct the mispricing caused by style chasers' over-extrapolation. In the model, arbitrageurs trade differently when faced with high versus low DOX, suggesting that variation in DOX has implications for the profitability and timing of momentum and value strategies in equilibrium. More specifically, a high level of DOX implies that style chasers' demand flows are more concentrated on stocks' most recent performance and less persistent, which entices arbitrageurs into correcting mispricing in the cross-section more quickly, leading stocks with high price-to-fundamental ratios (growth stocks) to underperform in the subsequent periods over stocks with low price-to-fundamental ratios (value stocks), i.e., generating a positive value premium. On the contrary, low levels of DOX imply persistent extrapolative beliefs, which dissuade arbitrageurs from correcting the mispricing, and hence lead high (low) returns to be followed by even higher (lower) prices in the future, i.e., a momentum effect.

In Chapter 3, I investigate the role of extrapolative demand from both outside and within the equity market on the time-series pattern of the value premium. This chapter first documents the time-series variability of the value premium and the asymmetry in the returns generated by the long and short legs of the value strategy. While the time-series variability can be partially attributed to the time-varying overextrapolation discussed in Chapter 2, this asymmetry can be difficult to reconcile with within-equity theories of extrapolation. It can arise naturally in a richer theoretical framework where there are extrapolators who move capital in/out of equity and bring additional extrapolative demand on certain stocks. To more formally investigate the implications of aggregate extrapolative demand for equities for cross-sectional return predictability, I extend the original model of financial markets with return extrapolators in Barberis and Shleifer(2003)[1]. In the model, extrapolative demand for equities increases following good recent market returns. The flow of extrapolators' capital into the stock market has two consequences on prices. At the aggregate level, and akin to the result in Barberis, Greenwood, Jin, and Shleifer(2015)[9], extrapolators cause overvaluation of the market. In the cross section, extrapolators' aggregate inflows are disproportionately allocated to growth stocks. This differential extrapolative demand for better performing growth stocks causes such stocks to become relatively more overvalued. A similar story holds for periods in which the market experiences negative returns, when extrapolators reduce their exposure to the overall equity market and disproportionately sell value stocks. To empirically test the model implication, in this chapter I propose two measures of market-wide misvaluation RMV and RMV^{mwz}, both of which are calculated by comparing the recent cross-sectional distribution of firm-level B/M ratios to its historical benchmark distribution. To this end, the long-run historical distribution of the average firm-level B/M ratio is used as the valuation benchmark. This is based on the idea that the long-run B/M average represents the mean value to which 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 these measures, in Chapter 3, I show that, over the sample period from 1968 to 2018, the strength of the value premium is *conditional* on the degree of market-wide misvaluation. Furthermore, following a period of extreme market-wide under (over) valuation, the increase in profitability of the value strategy mainly stems from the good (poor) performance of value (growth) stocks.

2. TIME-VARYING OVEREXTRAPOLATION, PRICE MOMENTUM AND THE VALUE PREMIUM

2.1 Introduction

Price momentum and the predictability of stock returns by price-scaled valuation ratios, i.e., the value premium, are two of the most studied asset pricing anomalies in theoretical and empirical finance. More than thirty thousand papers have been written as a direct result of the seminal work of Fama and French (1992)[23] and Jegadeesh and Titman (1993)[24], who offered systematic evidence of momentum and value effects in the cross-section of US equities.[1] This vast amount of follow-up work has either investigated the pervasiveness of momentum and value premium across geographies and asset classes,[2] or has offered theoretical explanations for why momentum and value can arise in equilibrium.[3] On the theoretical side, Barberis and Thaler (2005)[38] and Barberis (2018)[39] argue that perhaps the most natural explanation for momentum and value effects in stock returns is return extrapolation.[4]

In this chapter, I mainly investigate the role played by the degree of extrapolation in investors' beliefs in explaining some time-series properties of momentum and the value premium. Return extrapolation is the tendency to believe that future stock returns will continue to be higher after the good performance of a stock, and that future returns will continue to be lower after poor stock performance. In markets with investors whose expectation on future returns exhibit extrapolative bias, momentum and the value premium arise naturally since extrapolators are drawn to stocks that have done well recently (past winners), and shy away from stocks that have done poorly (past losers). Through such positive feedback trading,

[1]↑Early work on the predictability of stock returns by price-scaled ratios is Stattman (1980)[25], Basu (1983)[26] and Rosenberg, Reid, and Lanstein (1985)[27]. Early evidence of momentum effects include Shleifer and Summers (1990)[28], who document momentum in the pricing of currencies, and Asness (1994)[29].

[2]↑See for instance Moskovitz and Grinblatt (1999)[30], Liew and Vassalou (2000)[31], Erb and Harvey (2006)[32], Gorton, Hayashi and Rouwenhorst (2013)[33], and Asness, Moskowitz, and Pedersen (2013)[34].

[3]↑As I briefly review later in the introduction of this chapter, several theory models have been proposed that explain momentum and value-related reversal by means of: (i) information frictions (Hong and Stein (1999)[13]); (ii)institutional considerations (Vayanos and Wooley (2013)[35]); the presence of behavioral investors (Barberis, Shleifer, and Vishny (1998)[36], Daniel, Hirshleifer, and Subrahmanyam (1998)[37], Barberis and Shleifer (2003)[1], and Barberis, Greenwood, Jin, and Shleifer (2018)[14].

[4]↑Literature has found little evidence on investors overly extrapolating stock fundamental news, such as earnings.

extrapolators generate a pattern of return momentum in the cross section. Moreover, given the weak relation between past and future returns that is observed empirically, extrapolators' demand for certain stocks causes prices to deviate from their fundamental values. Eventually, extrapolators' over-reaction to past returns leads to a value effect, whereby stocks with high (low) valuation ratios, such as M/B, experience lower (higher) returns in the future, when extrapolators' beliefs subside in light of incoming information. Return extrapolation is not only an intuitive explanation for momentum and value premium, but also a plausible one, given a growing body of empirical work based on surveys (e.g., Greenwood and Shleifer (2014)[20]), laboratory experiments (e.g., Landier, Ma, and Thesmar (2020)[21]), and field evidence (e.g. Da, Huang, and Jin (2021)[22]), that has by now offered convincing evidence of how pervasive return extrapolation is among investors.

Whereas extrapolative expectation has been for decades at the center of many theoretical and qualitative explanations of the behavior of asset prices (e.g., Cutler, Poterba, and Summers (1990)[10], De Long, Shleifer, Summers, and Waldmann (1990)[12], Frankel and Froot (1990)[11]), a formal test of extrapolation-based theories of cross-sectional momentum and value premium is still lacking. In this paper, I test the role of return overextrapolation for momentum and value premium directly. I choose my empirical design to closely follow the implications that theory work on extrapolation in the cross-section has for momentum and value premium. In this respect, Barberis and Shleifer (2003)[1] propose a model of financial markets with style chasers who have extrapolative expectations on stock returns, where the strength and timing of momentum and value premium in the cross-section of stocks are a function of extrapolators' degree of over-extrapolation (DOX). This structural parameter of extrapolative expectations determines how persistent style chasers' demand flows are, hence has implications on how quickly the arbitrageurs correct the mispricing caused by style chasers' over-extrapolation. In the model, arbitrageurs trade differently when faced with high versus low DOX, suggesting that variation in DOX has implications for the profitability and timing of momentum and value strategies in equilibrium. More specifically, a high level of DOX implies that style chasers' demand flows are more concentrated on stocks' most recent performance and less persistent, which entices arbitrageurs into correcting mispricing in the cross-section more quickly, leading stocks with high price-to-fundamental ratios (growth stocks) to underperform in the subsequent periods over stocks with low price-to-fundamental ratios (value stocks), i.e., generating a positive value premium. On the contrary, low levels of DOX imply persistent extrapolative beliefs, which dissuade arbitrageurs from correcting the mispricing, and hence lead high (low) returns to be followed by even higher (lower) prices in the future, i.e., a momentum effect.

To more formally investigate the implications of the degree of over-extrapolation for cross-sectional return predictability, I run simulations on changes in DOX and its effect on the profitability of momentum and value premium within the framework of Barberis and Shleifer (2003)[1]. In the original style investing model, DOX is set as a fixed parameter 0.05, whereas the simulation in this paper employs a range of DOX from 0.05 to 0.95 and examine the corresponding price patterns in the cross section in more detail. First, both momentum and value strategies can generate positive returns in the given range of DOX, suggesting that the presence of extrapolative expectations can generate both momentum and value premium. Furthermore, holding everything else constant, different degree of overextrapolation can generate different price patterns in the cross section, hence the magnitude and timing of the momentum and value profitability changes with respect to different levels of DOX. Second, the degree of overextrapolation plays a role in affecting the speed of price reversal. In a market with higher (lower) DOX, prices reverts more quickly (slowly). For higher values of DOX, the style chasers' flows are more dependent on the most recent return performance, so in the short-run momentum works and prices are more likely to deviate more from their fundamental value. However, higher value of DOX also implies less persistency in style chasers' demand flows. Therefore, it makes more sense for arbitrageurs to bet against them and correct the prices more quickly. Thus in the long term, in a market with higher DOX, the profitability of momentum strategy diminishes more quickly, whereas the profitability of investing in value strategy is generated in shorter time horizon and lasts longer. Third, consistent with the previous discussion, for a given portfolio holding period, the momentum strategy is more profitable in a market with lower DOX, whereas the value strategy generates higher returns with higher DOX. Furthermore, the changes in DOX have effect on both long and short legs of momentum and value strategies. Fourth, the model proposes a superior strategy that takes advantage of the time-series variation in momentum and value profitability and combining these two strategies by applying different weights according to the degree of overextrapolation. These model implications unify the potential explanation of momentum and value premium in the cross section.

To test these theoretical insights empirically, a measure of investors' extrapolative beliefs is needed. I rely on the findings in Cassella and Gulen (2018)[2], who use survey data of US investors' return expectations to measure time-series variation in extrapolators' degree of extrapolative weighting in investors' beliefs (DOX). More specifically, DOX measures the relative weight that investors place on most recent returns compared to those in distant past. DOX is recursively estimated and varies considerably over time.[5] Using the time-series variation in DOX, I am able to document four distinct pieces of evidence that are in direct support of extrapolation theories of momentum and value premium in the cross-section. First, the profitability of momentum and value premium is conditional on the degree of overextrapolation. More specifically, I find that following *Low DOX* periods, the average monthly momentum portfolio return is 1.00% over the 12-month post-formation period, whereas it is on average only 0.10% per month following *High DOX* periods. On the other hand, following high levels of DOX, the value premium is on average 1.29% per month over the 12 months after portfolio formation, whereas it is on average only 0.51% per month following *Low DOX* months. I also examine the effect of DOX on the Jensen's alphas of these two anomalies. I find that the alpha of momentum is 0.89% lower following high DOX than low DOX. On the other hand, the average alpha of value premium following high DOX is 0.75% per month higher than that following low DOX. In addition, the results are robust for value premium constructed using E/P and C/P ratios. I also conduct regression analysis and find that the predictive power of DOX on future momentum and value returns is robust after including other macro control variables.

Second, DOX has "amplification" effects on both long and short legs of momentum and value strategies. The higher momentum (value premium) following low (high) DOX

[5]↑The measure DOX proposed in Cassella and Gulen (2018)[2] is at the level of aggregate stock market. Even though this paper is investigating the effect of overextrapolation in the cross-section, the stock-level degree of overextrapolation is not necessary at the moment. In the model, the parameter DOX is universal for all stocks, whereas in reality it is possible for investors to have different degree of overextrapolation for different stocks. It is not easy to measure investors' degree of overextrapolation at the stock level. This paper focuses on the effect of the general market-level DOX, rather than stock-level DOX.

come from both the better performance of Winner (Value) and the worse performance of Loser (Growth). For momentum, the effect of DOX on the long and short legs are similar, whereas the effect of DOX on value premium is stronger on the long leg of the strategy (i.e., value stocks). More specifically, the Winner portfolio generates on average 1.34% following low DOX versus 0.94% per month following high DOX periods, whereas the loser portfolio generates on average 0.34% per month following low DOX versus 0.82% following high DOX periods, indicating that lower DOX amplifies the better performance of Winners, as well as worsens the performance of Losers. For value strategies, the B/M value portfolios generate an average monthly return of 1.70% and 1.20% following periods of high DOX and low DOX, respectively. On the other hand, the growth portfolio generates an average monthly return of 0.41% and 0.68% following periods of high DOX and low DOX, respectively. These results suggest that the higher value premium following higher DOX come from both the better returns of value stocks and worse returns of growth stocks. These findings are also consistent with the model implication.

Third, inspired by the extended style investing model proposed by Cassella, Chen, Gulen, and Petkova (2021)[40], the extrapolative demand for each style also depends on the aggregate market performance, hence the degree of overextrapolation has different impact on the long and short legs of the strategies based on different aggregate market conditions. Intuitively, if the aggregate market is observed to be performing well, there will be additional extrapolative demand coming into the stock market from other asset classes, such as cash or bonds, which is more likely to be disproportionately invested in the relatively better performing stocks, such as the "Winners" or the "Growth" stocks. Thus, when the aggregate market returns are high, given the same degree of overextrapolation, the momentum return is more generated from the continuation of the good returns from the "Winners", whereas the value premium is mostly coming from the future underperformance of the growth stocks. On the contrary, if the aggregate market returns are low, there will be some extrapolative flows out of the stock market, and the outflows are more likely from selling the "Losers" or value stocks, which causes the "Losers" and value stocks to be severely underpriced. Hence, in this scenario, the profitability of momentum is more likely to be generated by the worse returns of "Losers", and the value premium is mostly generated by the future good returns of value stocks. More specifically, I find that conditional on *"Low DOX, High Market"*, the corresponding alpha of momentum is 0.76% per month, with the "Winners" ("Losers") generating 1.05% (0.29%) per month. However, following *"Low DOX, Low Market"*, the corresponding monthly alpha of "Winners" ("Losers") is on average 0.56% (-0.49%). On the other hand, different from the findings in momentum, the monthly alpha of value premium following *"High DOX, Low Market"* is on average 2.01%, of which the long leg generates 2.85% and the short leg only generates 0.83% per month. Following *"High DOX, High Market"*, the corresponding monthly alpha of "Value" ("Growth") is on average 0.18% (-1.24%), indicating that the value premium is mostly generated by the underperformance of growth stocks. These results provide additional support on the effect of extrapolative demand on momentum and value premium.

Fourth, the original style investing model proposes a potential superior strategy, which combines momentum and value strategy by applying different weights, corresponding to different degrees of overextrapolation. Intuitively, the combining strategy is implemented through putting relatively more weight on momentum when DOX is observed to be low, and putting relatively more weight on value strategy when DOX is perceived to be high. Empirically, I test the performance of different combining strategies by applying different weighting schemes. The first combining strategy proposed is only investing in momentum when degree of overextrapolation is low, only investing in value strategy when degree of overextrapolation is high, and investing equally in both momentum and value for the remaining periods. The second combining strategy is more closely related to the optimal strategy proposed in the original style investing model, which sets the weight on momentum as 1 and the relative weight on value strategy as ϕDOX, where ϕ is a fixed parameter from Barberis and Shleifer (2003)[1]. Overall, consistent with the theoretical implication, by combining momentum and value in different ways under different DOX, the combining strategies lower the return volatility and provide higher Sharpe ratios than simply implementing either momentum or value strategy.

This chapter contributes to two main strands of literature. First, the paper contributes to the literature that seeks to determine the primitive mechanisms behind cross-sectional return predictability. In this respect, two main views exist. The first view proposes that predictability in the cross-section must be the consequence of differences in the risk of some stocks over others (Fama and French (1992[23], 1993[41]), Davis, Fama, and French (2000)[42], Cochrane (2011)[7]). The second view argues that predictability is the result of inefficiencies in how investors react to information, and how such information is incorporated into prices (DeBondt and Thaler (1985)[43], Lakonishok, Shleifer, and Vishny (1994)[44]; Daniel and Titman (1997)[45]; Daniel, Titman, and Wei (2001)[46], Cooper, Gulen, and Schill (2008)[47], Cooper, Gulen, and Ion (2020)[48].) My paper adds to this literature, since I provide direct theory-driven evidence on the link between an underlying psychological mechanism, namely, return extrapolation, and the most prominent cross-sectional anomalies, namely, momentum and value. In this respect, my paper offers one answer to Barberis (2018)[39] call for tests of behavioral theories that do not stop at documenting predictability, but also draw a clear link between predictability and its underlying causes.

The second literature this chapter contributes to is the one concerning the timing of cross-sectional anomalies. Whereas much is known about the predictability of aggregate market returns (e.g., Cochrane (2008)[6], Van Binsbergen and Koijen (2008)[49], Cassella and Gulen (2018)[2]), there is a much less evidence concerning predictable variation in anomaly returns in the cross-section. In this respect, my paper joins Cooper, Gutierrez, and Hameed (2004)[50], Wang and Xu (2015)[51], Avramov, Cheng, and Hameed (2016)[52], who study predictability of momentum returns, and Cohen, Polk, and Vuolteenaho (2003)[53], Zhang (2005)[54], and Cassella, Chen, Gulen, and Petkova (2021)[40], who focus on the predictability of value the value premium. This paper adds substantially to this literature, since it shows that both momentum and value in the cross-section can be explained by a unifying behavioral factor, namely, return extrapolation.

2.2 Conceptual Framework in Barberis and Shleifer (2003)

2.2.1 Momentum and Value in Style Investing Model

Following the style investing model in Barberis and Shleifer (2003)[1], the economy has T periods and 2 asset classes, $2n$ risky assets in fixed supply Q and risk-free asset with net return normalized to zero. Each risky asset i is a claim to a liquidating dividend $D_{\mathrm{i},T}$

to be paid at the final date T. There are two kinds of investors in the economy, "style chasers" and "arbitrageurs". The style chasers have extrapolative expectations, and classify the risky assets into two styles X and Y. They buy the styles that have better returns in the past, and sell the styles that have been underperforming the other styles previously. The other investor type is arbitrageurs, who try to prevent the price of risky assets from deviating too far away from their fundamental value. The arbitrageurs in this model are aware of the existence and potential impact of the investment behavior of style chasers, and taking them into consideration when "correcting" the prices. Different from style chasers, arbitrageurs do not categorize risky assets into different styles, and their expectation on risky asset returns do not depend on past performance. The arbitrageurs' investment decision is made through maximizing their expected utility. The focus of this paper is to investigate the profitability of asset-level momentum and value strategy in this economy with different degrees of extrapolation, which is captured by the parameter θ.

More specifically, the asset-level momentum strategy is implemented through

$$N_{\mathrm{i},t}^{MOM} = \frac{1}{2n}[\Delta P_{\mathrm{i},t} - \Delta P_{M,t}], \ \mathrm{i} = 1, ..., 2n, \tag{2.1}$$

where all assets are ranked on their previous returns, and investors buy the assets that did better than the average, and sell those that did worse. An asset-level value strategy is to buys (sells) the assets that are traded below (above) their fundamental value, which is implemented as

$$N_{\mathrm{i},t}^{VAL} = \frac{1}{2n}[D_{\mathrm{i},t} - P_{\mathrm{i},t}], \mathrm{i} = 1, ..., 2n, \tag{2.2}$$

where $D_{\mathrm{i},t}$ is the fundamental value of asset i at time t, and the price of asset i of Style X at time t, obtained by maximizing the arbitrageurs' expected utility, is

$$P_{\mathrm{i},t} = D_{\mathrm{i},t} + \frac{1}{\phi}\sum_{k=1}^{t-1} \theta^{k-1}(\frac{\Delta P_{X,t-k} - \Delta P_{Y,t-k}}{2}), \tag{2.3}$$

where

$$\phi = \frac{n}{\gamma\sigma^2(1 - \rho_1 + n(\rho 1 - \rho 2))}, \tag{2.4}$$

and the parameter θ determines how far back the style chasers look when comparing the past performance across styles. Higher θ shows higher persistence of the style chasers' flows.

2.2.2 Simulation

Following Barberis and Shleifer (2003)[1], the parameters are set as follows, $\psi_M = 0.25$, $\psi_S = 0.5$, $\theta = 0.95$, $\gamma = 0.093$, and $\sigma_\epsilon = 3$. Suppose the return (i.e. price changes) covariance matrix has the same structure as the cash-flow covariance matrix Σ_D. I set $T = 100$, $Q = 0$ and $n = 50$, so that there are 100 risky assets in a zero net supply, of which the first 50 belong to style X and the last 50 belong to style Y. At $t = 0$, the initial price of risky assets $D_{\mathrm{i},0}$ is 50.

The equilibria studied in this paper are obtained from simulation in the following way. The initial value of V is set to be Σ_D. Then for a given randomly generated shock, I use Eq.(2.3) to calculate the prices for risky assets, which will be used to calculate a new price covariance matrix $\hat{V}$. Then I use $\hat{V}$ to calculate a new set of prices for risky assets. This process is repeated till $\hat{V}$ converges. Such equilibria exist for a wide range of parameter choices.[6]

In order to link the following simulation results more closely to the empirical findings in later sections, the discussion will be presented with respect to investors' degree of extrapolative weighting (DOX), rather than θ. In terms of the intuition of the parameter θ, I plot the speed of decaying in weights on lagged terms with respect to different values of in Figure 2.1. From left to right, θ is increasing from 0.05, 0.5, to 0.95. In each figure, the bars shows the relative weight on each lagged terms. In the figure on the left with $theta = 0.05$, the weight on lagged 1 term is around 95%. Compared to the figure on the right with $\theta = 0.95$, the weight is more evenly distributed from lagged 1 to lagged 20 terms. In order to be more intuitive and also better matching with the later empirical analysis, here I introduce the degree of overextrapolation, which is defined as $1 - \theta$. In this way, higher DOX means that extrapolators focus more on the most recent stock performance to form their expectations.

[6]↑Results are comparable with Barberis and Shleifer (2003)[1]. For these parameter values, the style returns in the original model have a standard deviation 1.30 times the standard deviation of the cash-flow shocks. In my simulation, the style returns have a standard deviation 1.21 times the standard deviation of the cash-flow shocks.

In Cassella and Gulen(2018)[2], they use survey data on expectations of future stock returns and empirically estimate DOX, which is essentially $1-\theta$. The estimation of DOX will be discussed in details in Section 2.3.

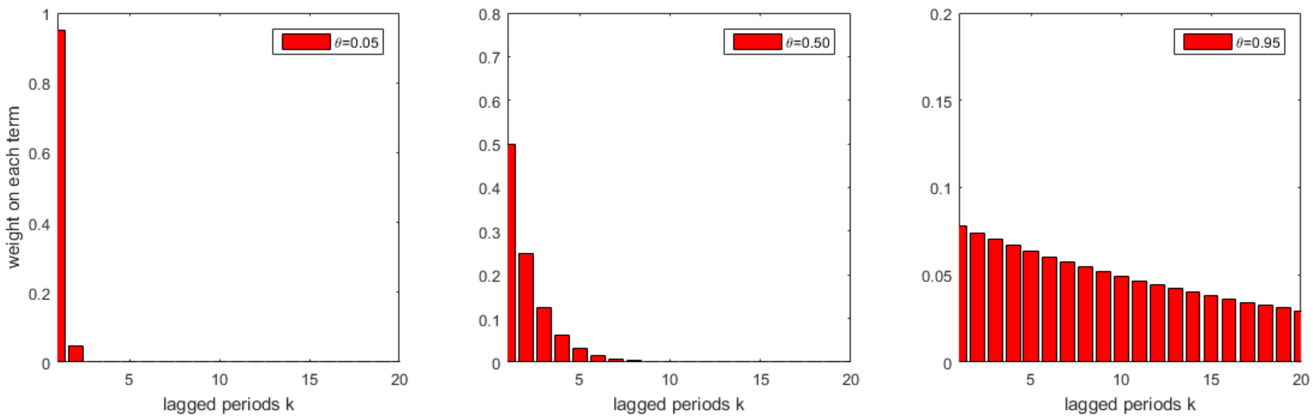

Figure 2.1. Different Speed of Decaying in Weights with Different θ
From left to right, θ is increasing from 0.05, 0.5, to 0.95. In each figure, the bars shows the relative weight on each lagged terms. In the figure on the left, when θ is only 0.05, the weight on lagged 1 term is around 95%. Compared to the figure on the right, where θ is 0.95, the weight is more evenly distributed from lagged 1 to lagged 20 terms.

Speed of Price Reversal

Model Implication 1: *In a market with higher DOX (or lower θ), prices revert to fundamental value more quickly.*

For higher DOX, the style chasers' flows are more concentrated on the most recent performance and are less persistent, so it makes more sense for arbitrageurs to bet against them. Hence the prices revert to fundamental value more quickly. In Figure 2.2, I plot the cumulative wealth of a \$1 initial investment on the asset-level momentum and value strategy under different values of DOX. The left figure of Figure 2.2 shows the cumulative wealth gains of investing \$1 in the momentum strategy. All three lines show an increase in wealth during the first time increment, indicating that in the presence of extrapolative expectations, the momentum strategy is profitable in the short-term. Compared to the blue solid line (low

DOX), the red solid line (high DOX) shows that initial wealth gain is lower and diminishes more quickly. These results show that the profit of momentum strategy is more short-lived with higher values of DOX, and overall, the momentum strategy is not profitable if the portfolios are held for sufficiently long time.

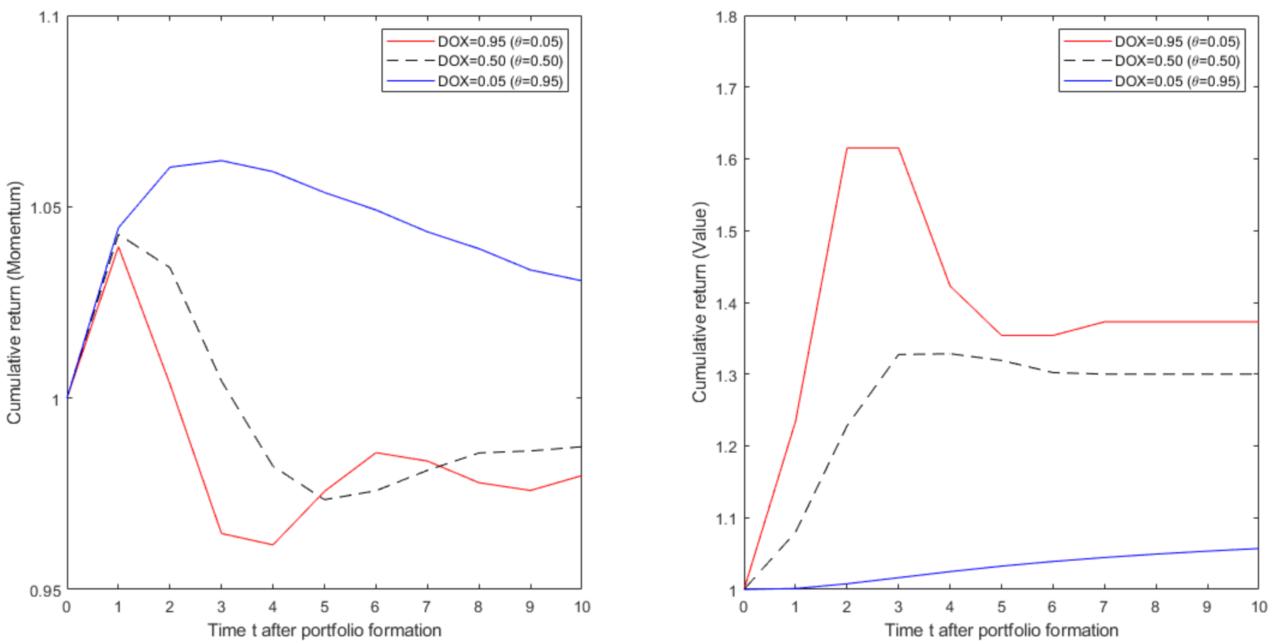

Figure 2.2. Extrapolation and Cumulative Returns of Momentum and Value Strategy

This figure plots the simulated cumulative wealth of investing in $1 in momentum and value strategies. The x-axis is the time increment after the portfolio formation, which is at $t = 0$. The left figure plots the cumulative wealth of asset-level momentum, and the right figure plots the cumulative wealth of asset-level value strategy. The detailed definition and construction are described in Section 2.2. In each figure, the blue solid line represents low DOX of 0.05, whereas the red solid line represents high DOX of 0.95. The black dotted line shows the cumulative wealth when $DOX = 0.50$.

Since the profitability of the value strategy comes from the price reverting back to fundamental value, the results for value strategy are different from momentum. In the right figure of Figure 2.2, the red solid line (high DOX) show that investing in value strategy generates faster initial wealth gains, which is consistent with the hypothesis that higher DOX corresponds to faster mispricing "correction". Furthermore, it is interesting to note that the red line first increases then decreases before reaching a steady level, whereas the blue line is steadily increasing. This finding indicates that with very high DOX, the price might be overly "corrected" in the short-run, which in turn decreases to "correct" the previous overcorrection. On the other hand, with lower DOX, the overcorrection is less likely to happen, thus the price reversion path is smoother.

Profitability of Momentum and Value

Model Implication 2: *The profitability of momentum strategy decreases (increases) with DOX (θ), whereas the profitability of value strategy increases (decreases) with DOX (θ).*

In the proof of Proposition 6 in Barberis and Shleifer (2003)[1], they have the unconditional one-period expected returns of asset-level momentum strategy as

$$R^{MOM} = E(\sum_{\mathrm{i}=1}^{2n} N_{\mathrm{i},t} \Delta P_{\mathrm{i},t+1}) = \frac{k_1(1+\theta)}{(\phi-1)(1+\theta+2/\phi)}, \tag{2.5}$$

and the expected one-period return of asset-level value strategy as

$$R^{VAL} = E(\sum_{\mathrm{i}=1}^{2n} N_{\mathrm{i},t} \Delta P_{\mathrm{i},t+1}) = \frac{k_2}{(\phi-1)(1+\theta+2/\phi)}, \tag{2.6}$$

where k_1 and k_2 are positive constants, and ϕ is an increasing function of θ[7].

The denominator in Eq.(2.6) can be rearranged as $(\phi-1)(1+\theta)+2-2/\phi$, which is increasing in θ, given $\frac{\partial\phi}{\partial\theta} > 0$. Therefore,

$$\frac{\partial R^{VAL}}{\partial\theta} < 0, \tag{2.7}$$

indicating that the profitability of value strategy is higher with higher DOX.

The effect of θ on the profitability of the asset-level momentum strategy is not clear at the moment since ϕ, as a function of θ, doesn't have an explicit form. In order to get some implication numerically, I use the previously set parameters to run simulation on different values of θ and examine their impact on the profitability of momentum and value strategies.

[7]↑This result is computed through simulation. According to both my own simulation and the results from Barberis and Shleifer (2003)[1], $\phi > 1$.

In Figure 2.3, I plot the one-period returns and Sharpe ratios of momentum and value strategies under different values of DOX. The one-period return is the one-period change in wealth from implementing the strategy. The Sharpe ratio is computed as the average one period change in wealth divided by the standard deviation of the one-period wealth change from implementing the strategy. In the left part of Figure 2.3, both returns and Sharpe ratios of momentum strategy are decreasing in DOX[8]. Consistent with the derivative results deducted from Eq.(2.6), the right part of Figure 2.3 shows that the returns and Sharpe ratios of value strategy increase in DOX, indicating that the value strategy is more profitable in a market with higher DOX (or lower θ) than lower DOX (or higher θ). These results are also shown in Table 2.1.

To examine the effect of extrapolation on the returns of momentum and value strategies in more details, I plot the cumulative returns of the long and short legs of both strategies under high versus low DOX in Figure 2.4. Based on Eq.(2.1) and (2.2), the "Winners" ("Losers") are the stocks whose returns are above (below) the market returns, whereas "Value" ("Growth") are the stocks whose prices are below (above) their fundamental value. The left figure plots the cumulative returns of long and short portfolios of asset-level momentum, and the right figure plots those of the asset-level value strategy. In each figure, the solid lines represents high DOX of 0.95, whereas the dotted line represents low DOX of 0.05. The blue lines show the cumulative returns of the long portfolio, which is "Winners" for momentum, and "Value" for value strategies. The red lines plot the short leg of the strategy, which is "Losers" for momentum and "Growth" for value strategies. Figure 2.4 shows that the effect of DOX on the long and short legs is symmetric. More specifically, in the left figure of Figure 2.4, lower DOX (i.e. the dotted line) increases the positive returns of "Winners" and further decreases the negative returns of "Losers", leading to higher momentum returns compared to higher DOX scenarios (i.e. the solid line). Similarly, for the value strategy, the right figure shows that higher DOX not only increases the returns of "Value" stocks, but also decreases the returns of "Growth" stocks, indicating that the higher

[8]↑Given each set of parameters, there exist multiple equilibria that make the calibrated covariance matrix converge. The simulation results displayed here are from one of the equilibria.

value premium under high DOX comes from the amplifying effect of DOX on both legs of the strategy.

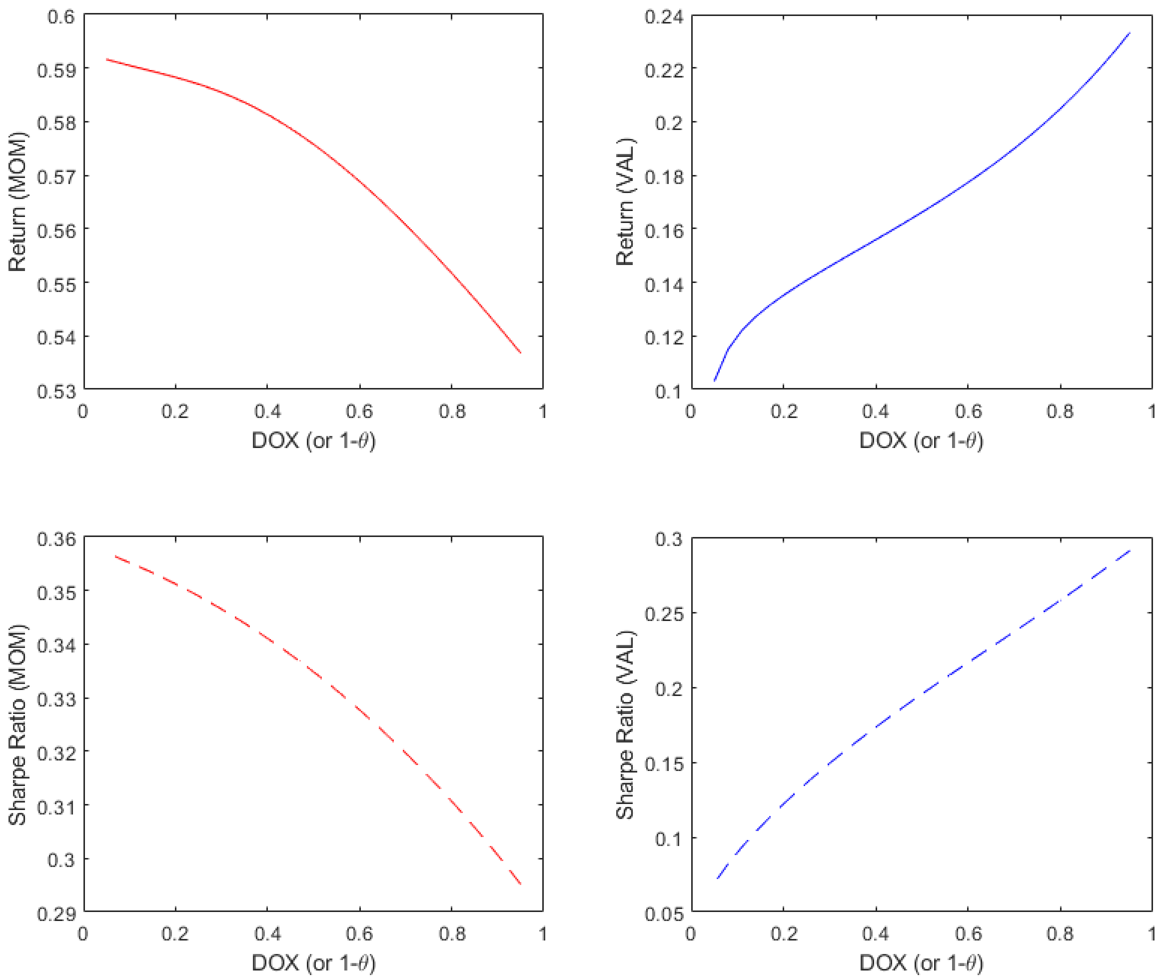

Figure 2.3. Extrapolation and the Profitability of Momentum and Value Strategies

This figure plots the simulated one-period returns and Sharpe ratios of asset-level momentum and value strategy in certain economy with different level of extrapolative bias in style chasers' expectation. The return is the one period change in wealth from implementing certain strategy. The Sharpe ratio is computed as the average one period change in wealth divided by the standard deviation of the one-period wealth change from implementing the strategy. The asset-level momentum strategy (MOM) buys (shorts) assets that performed better (worse) than average last period. The asset-level value strategy (VAL) buys (shorts) the assets trading below (above) their fundamental value. θ is a preset parameter, which ranges from 0.05 to 0.95. DOX is equal to $1-\theta$. The left part (the red lines) plots the returns and Sharpe ratios from implementing momentum strategy, and the right part (the blue lines) plot the returns and Sharpe ratios of value strategy.

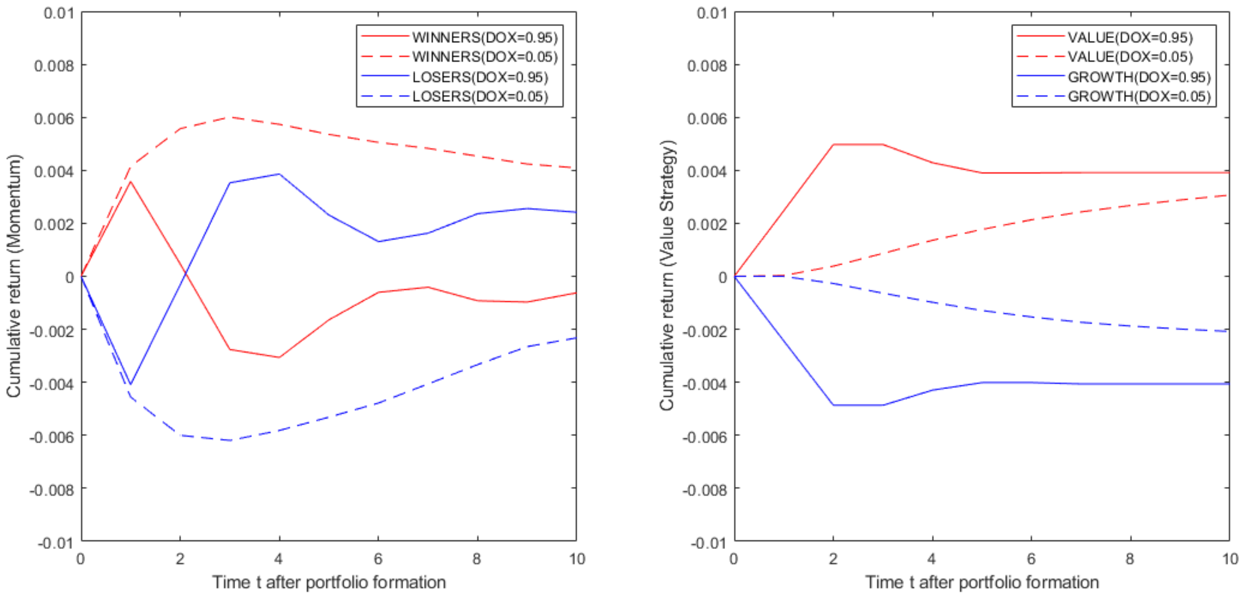

Figure 2.4. Extrapolation and Cumulative Returns of long/short portfolios of Momentum and Value Strategies

This figure plots the simulated cumulative returns of investing in the long and short legs of both momentum and value strategies. The x-axis is the time increment after the portfolio formation, which is at $t = 0$. The left figure plots the cumulative returns of long and short portfolios of asset-level momentum, and the right figure plots the cumulative returns of the long and short portfolios of asset-level value strategy. The detailed definition and construction are described in Section 2.2. In each figure, the solid lines represents high DOX of 0.95, whereas the dotted line represents low DOX of 0.05. The blue lines show the cumulative returns of the long portfolio, which is Winners for momentum, and Value for value strategies. The red lines show the cumulative returns of the short leg of the strategy, which is Losers for momentum and Growth for value strategies. At the portfolio formation time, Winners (Losers) are the stocks whose returns are above (below) the market returns, whereas Value (Growth) are the stocks whose prices are below (above) their fundamental value.

Superior Strategy: Combining Momentum and Value

In Proposition 8 in Barberis and Shleifer (2003)[1], it shows the optimal investment strategy of the arbitrageurs can be written as the following:

$$N_{\mathrm{i},t}^{A} = 2c[N_{\mathrm{i},t}^{MOM} + \phi(1-\theta)N_{\mathrm{i},t}^{VAL}], \tag{2.8}$$

where c is a positive constant, and $N_{i,t}^{MOM}$ and $N_{i,t}^{VAL}$ are the share demand of style-level momentum and value strategies for risky asset i at time t. This optimal strategy is the one that maximize the expected utility of the arbitrageurs, who know the correct prices evolution process in the economy. This combining strategy should mechanically deliver superior Sharpe ratio compared to simply implementing momentum or value strategy. In the simulation and later empirical tests, I replace the style-level strategies with asset-level strategies shown in Eq.(2.1) and Eq.(2.2) for simplicity.[9]

Table 2.1 reports the one-period change in wealth and Sharpe ratios of asset-level momentum, value, and the combining strategy under different level of extrapolation. ϕ is estimated within the simulation given each θ. In Table 2.1, DOX ranges from 0.05 to 0.95, and the corresponding calibrated ϕ ranges from 2.16 to 2.38. Consistent with the discussion in Section 8, the one-period wealth gain and Sharpe ratio decrease in DOX for momentum strategy, whereas increase in DOX for value strategy. The combining strategy which utilizes the different impact of DOX on the profitability of momentum and value strategy by putting different weights on value strategy under different DOX. More specifically, for higher DOX, value strategy becomes relatively more profitable compared to the economy with lower DOX, thus the weight on value strategy should be higher when the economy has higher value of DOX.[10] When θ is very close to 1, the combining strategy is very similar to momentum strategy. As shown in Table 2.1, when $DOX = 0.05$, the combining strategy has the average one-period wealth gain of 0.60 and Sharpe ratio of 0.36, which are only slightly higher than (or even equal to) that from just momentum strategy (one-period wealth gain of 0.59, and Sharpe ratio of 0.36). As DOX increases and the value strategy becomes more profitable, the combining strategy starts to provide much higher Sharpe ratio compared to only implementing either momentum or value strategy. More specifically, when $DOX = 0.95$, the Sharpe ratio of the combining strategy is 0.46, whereas the Sharpe ratio of momentum and value are 0.30 and 0.29, respectively. Overall, the combining strategy provides superior Sharpe ratios compared to the pure momentum and value strategy.

[9]↑In Proposition 7 of Barberis and Shleifer (2003)[1], they discuss that the style-level momentum and value strategies deliver greater or equal Sharpe ratios than the asset-level momentum and value strategies.

[10]↑Since ϕ is an implicit function of θ, it is not immediately clear how $\phi(1-\theta)$ changes with respect to θ. Based on my simulation results, $\phi(1-\theta)$ is decreasing function of θ.

Table 2.1. Model simulation on Momentum, Value, and Combining Strategies under different level of Extrapolation

This table reports the one-period change in wealth and Sharpe ratios of asset-level momentum, value, and the combining strategy in certain economy with different level of extrapolative bias in style chasers' expectation. The wealth gain per period is the one period change in wealth from implementing certain strategy. The Sharpe ratio is computed as the average one period change in wealth divided by the standard deviation of the one-period wealth change from implementing the strategy. The asset-level momentum strategy (MOM) buys (shorts) assets that performed better (worse) than average last period. The asset-level value strategy (VAL) buys (shorts) the assets trading below (above) their fundamental value. The combining strategy (COMB) is implemented through $N_{\mathrm{i},t}^{MOM} + \phi(1-\theta)N_{\mathrm{i},t}^{VAL}$, where $N_{\mathrm{i},t}^{MOM}$ and $N_{\mathrm{i},t}^{VAL}$ are the share demand of asset i at time period t for asset-level momentum and value strategy. θ is a preset parameter, which ranges from 0.05 to 0.95. DOX is equal to $1-\theta$, and ϕ is estimated in the simulation given each value of θ.

	Wealth gain per period			Sharpe Ratio		
DOX	MOM	VAL	COMB	MOM	VAL	COMB
0.05	0.59	0.10	0.60	0.36	0.07	0.36
0.20	0.59	0.14	0.65	0.35	0.12	0.38
0.50	0.58	0.17	0.77	0.33	0.20	0.41
0.80	0.55	0.20	0.91	0.31	0.26	0.44
0.95	0.54	0.23	1.02	0.30	0.29	0.46

2.3 Data and Methodology

The sample period for the main analyses is from December 1967 to October 2018, which has the available estimated DOX from Cassella and Gulen(2018)[2]. Following Cassella and Gulen(2018)[2], the estimation of DOX is based on these two surveys, the Investor Intelligence Survey (II) and a survey of retail investors conducted by the American Association of Individual Investors (AA). II collects investors' forecasts of stock market since 1963, and AA started from 1987. The DOX used in the following discussion is constructed using the DOX extracted from II during the period from December 1967 to May 1992, the DOX extracted from the principal component time-series of II and AA from June 1992 to October 2018. More specifically, the extrapolative expectations are modeled as follows:

$$Exp_t = a + b\sum_{\mathrm{i}=0}^{\infty}\omega_{\mathrm{i}}R_{t-(\mathrm{i}+1)\Delta t,t-\mathrm{i}\Delta t} \tag{2.9}$$

$$\omega_{\mathrm{i}} = \frac{\lambda^{\mathrm{i}}}{\sum_{k=0}^{\infty} \lambda^k}, 0 \leq \lambda < 1 \tag{2.10}$$

where Exp_t refers to extrapolators' expectations as of time t obtained from survey data, and R_{t_1,t_2} is the return realized between time t_1 and time t_2. Δt represents the frequency of return observations. Following previous literature, Δt is chosen to be 1/4, so the estimation uses quarterly returns. A lower λ implies that investors place higher weight on more recent observations, while earlier observations contribute less to an extrapolator's expectations. DOX, the degree of extrapolation, is defined as $1 - \lambda$.

Following Cassella and Gulen(2018)[2], the time-series of DOX is obtained by estimating Eq.(2.9) recursively by nonlinear least squares. The recursive estimation is performed in every month t using a rolling-window $(t - m + 1, t)$. The length of the rolling window, m is endogenized by combining estimates obtained using different window lengths. Specifically, firstly, for every month t, Eq.(2.9) is estimated for months $t-12$ to $t-1$. This 12-month period is referred to as the cross-validation period. Secondly, for each of these 12 months, DOX is estimated over three alternative rolling window sizes of prior 24, 36, and 48 months, as well as expanding window which includes all the prior observations. More specifically, in month $t-12$ the parameter estimates based on the 24-month rolling window are obtained using the survey data in the interval $[t - 36 + 1, t - 12]$. Similarly, the parameter estimates based on the 36-month rolling window are obtained using the survey data in $[t - 48 + 1, t - 12]$, and so on. Thirdly, for each of the twelve months in the cross-validation period, I calculate the one-month ahead forecast errors. For instance, the parameter estimates obtained in month $t-12$ using the 24-month rolling window are used to calculate the fitted survey expectations for month $t - 11$, $E\hat{X}P^{24}_{t-11}$. The one-month ahead forecast error, ϵ^{24}_{t-11}, is the difference between the actual survey expectation EXP^{24}_{t-11} and the fitted value $E\hat{X}P^{24}_{t-11}$. Similarly, the forecast errors are calculated for each of the 4 alternative window lengths, and for each of the 12 months in the cross-validation period. Then I use them to calculate four mean-squared forecast error (MSFE) metrics, $MSFE^{24}$, $MSFE^{36}$, $MSFE^{48}$, and $MSFE^{expanding}$, for month t. Finally, for each of the four moving windows, one DOX is estimated. The final estimate of DOX for month t is the weighted average of the four DOX candidates, using the inverse of the $MSFE$ (normalized to summing to 1) as weights.

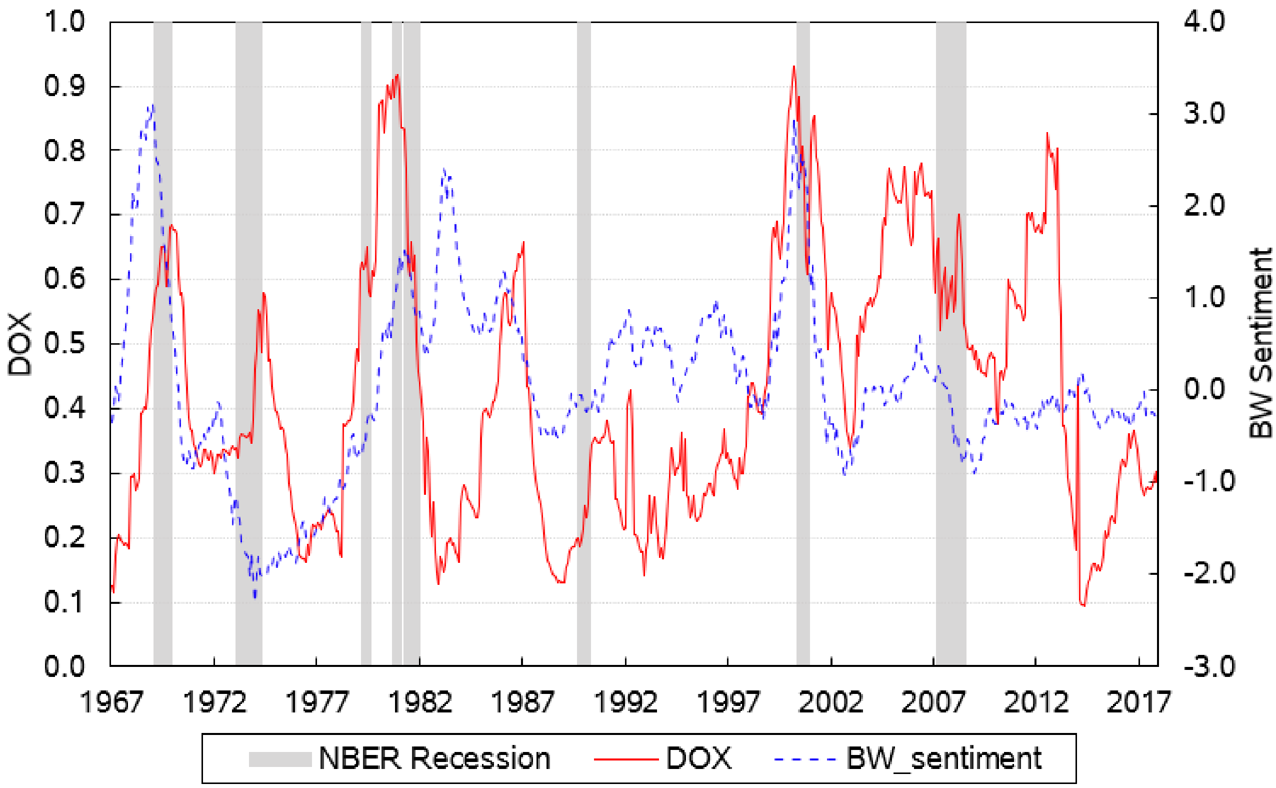

Figure 2.5. Time-series of DOX, December 1967- October 2008.
This figure plots the time series of DOX (red solid) and the investor sentiment index in Baker and Wurgler (2006)[55] (blue dotted), together with $NBER$ recessions (shaded areas), from December 1969 to October 2018. The left y-axis corresponds to the time series of DOX, while the right y-axis corresponds to the time series of $BW_sentiment$.

In Figure 2.5, I present the time-series plots of DOX, which is plotted along the time series of the Baker and Wurgler investor sentiment index in the blue dotted line. As the investor sentiment is more likely to be higher during the bubble period and lower during recession. However, degree of overextrapolation is capturing something different from either sentiment or recession.

Monthly stock returns are obtained from the Center for Research on Securities Prices (CRSP). I follow standard conventions and restrict the analysis to common stocks (Share

Codes 10 and 11) of firms listed in U.S., and traded on NYSE, Amex, or Nasdaq. Monthly returns are adjusted for delisting.[11] Stocks with price less than $1 are excluded.

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 tax credit (if available), minus the book value of preferred stock. Depending on availability, we use the redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock.[12] I use the shareholders' equity number as reported by Compustat. If these data are not available, I calculate shareholders' equity as the sum of common and preferred equity. If neither is available, shareholders' equity is defined as the difference between total assets and total liabilities. The earnings used in year t are total earnings before extraordinary items for the last fiscal year end in $t-1$. The cash flows used in year t are total earnings before extraordinary items, plus equity's share of depreciation, plus deferred taxes (if available) for the last fiscal year end in $t-1$. Based on Asness and Frazzini(2013)[58], I compute book-to-market ratios (B/M) on a monthly basis, where I 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. Similarly, for robustness, I also calculate earnings-to-price ratios (E/P) and cash-flow-to-price ratios (C/P) on a monthly basis, where earnings and operating cash flows are from last fiscal year and they are updated annually. Stocks with negative book equity (earnings, cash flows) are excluded when forming portfolios based on B/M (E/P, CF/P).

To construct the momentum strategy, I follow Jegadeesh and Titman(1993)[24] to construct the "J-M-K" momentum strategy, which includes the common stocks with available returns data in the J months preceding the portfolio formation date from which the buy and sell portfolios, and then skip M months, and hold for K months. At end of each month t, I calculate and sort the stock cumulative returns from month $t-J-1$ to month t into ten portfolios. The Decile 10 portfolio (i.e. Winner portfolio) contains the stocks with the

[11]↑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)[56]) and -55% for Nasdaq stocks (Shumway and Warther(1999)[57])

[12]↑On Ken French's website, it mentions "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.

previous J-month cumulative returns above the cross-sectional 90^{th} percentile, whereas the Decile 1 portfolio (i.e. Loser portfolio) includes the stocks that have the cumulative returns from the preceding J months below the cross-sectional 10^{th} percentile. I use the common stocks listed in NYSE, NASDAQ, and AMEX to find the cross-sectional breakpoints. The long-short portfolio (WML) is to buy the Winner portfolio and short the Loser portfolio. All decile portfolios and the WML portfolio are tracked for M months. For the brevity of the paper, I only report and discuss the "12-0-12" momentum strategy in the following empirical tests. The results are qualitatively similar when I look at "6-0-1", "6-0-6", "11-1-1", and "12-0-1" momentum strategies.

The value strategy is constructed by following Asness and Frazzini(2013)[58], where the B/M ratios are calculated on a monthly basis such that book equity is from the last fiscal year-end and market value is updated at the end of each month. Book equity is updated annually at the end of each June. They show that using a current price in the denominator is superior to the standard method of using prices at fiscal year-end as a proxy for the true B/P ratio, and this improvement can lead to a significantly better value-investing portfolio strategy. Therefore, at the end of each month t, stocks are sorted based on their valuation ratios (B/M, E/P, or C/P) and 10 decile portfolios are formed. Financial and utility firms are excluded when calculating their valuation ratios. I use the stocks that are listed in NYSE to find the cross-sectional breakpoints. Decile 1 is the portfolio with the lowest B/M (E/P, C/P) and it represents growth stocks, while Decile 10 is the portfolio with the highest B/M (E/P, C/P) and it represents value stocks. The value strategy (VMG portfolio) is defined as the return spread between Decile 10 and Decile 1 of portfolios sorted by B/M, E/P, or C/P. All decile portfolios and the VMG portfolio are tracked for 12 months.

2.3.1 Unconditional Performance of Momentum / Value Premium

Prior to the discussion on how DOX, I first document the unconditional performance of momentum and value premium in the sample period investigated in this paper. As discussed in the previous section, both momentum and value strategy portfolios are held for 12 months.

The returns reported are the average monthly returns over the 12-month holding period for each strategy.

Table 2.2 reports the equal-weighted average returns, Jensen's alphas, excess returns, volatility and Sharpe ratios of the portfolios in "12-0-12" momentum strategy and the value premium calculated by B/M, E/P, and C/P[13]. The portfolio formation date ranges from December 1967 to October 2018[14]. In Panel A of Table 2.2, the unconditional average monthly return for the "12-0-12" momentum strategy is 0.50% per month (with t-statistics of 2.71). The corresponding Jensen's alpha is 0.49% per month (with t-statistics of 2.63). These results indicate that the "12-0-12" momentum strategy is profitable during this sample period.

In Panel B of Table 2.2, I report the equal-weighted performance measures of different value strategies. In Panel B.1, the value/growth portfolios are formed based on B/M. In the last column, the unconditional average monthly return for the Value-Growth portfolio is 0.88% per month (with t-statistics of 4.32). The corresponding Jensen's alpha is 0.49% per month (with t-statistics of 2.63), suggesting that the equal-weighted value premium delivers the positive returns over this sample period, and the results cannot be explained by market risk. Similarly, the average value premium is 0.39% per month (with t-statistics of 2.53) and 0.51% per month (with t-statistics of 2.87) for portfolios formed on E/P and C/P, respectively. The corresponding Jensen's alphas for E/P and C/P portfolios are 0.40% (with t-statistics of 2.65) and 0.52% (with t-statistics of 2.96), respectively.

[13]↑Table 2.2 only reports the equal-weighted returns. The value-weighted results are qualitatively similar for momentum, and less profitable for value strategies. The results for other momentum strategies, such as "6-0-6" and "11-1-1" are also suggesting that those are profitable strategies in my sample period.
[14]↑Since each portfolio is tracked for 12 months, the last returns are from November 2019.

2.3.2 Momentum / Value Premium Conditional on Degree of Extrapolation

Based on the discussion of the conceptual framework in Section 2.2, the profitability of the momentum strategy and the value strategy varies with degree of overextrapolative bias in expectations. To empirically investigate the conditional profitability of momentum and value premium, I refer to Cassella and Gulen(2018)[2] and use the degree of extrapolative weighting in investors' beliefs (DOX) to measure investors' degree of over-extrapolation. A high DOX implies quicker reversion in extrapolators' beliefs, and entices arbitrageurs into correcting mispricing in the cross-section, leading stocks with low price-scaled ratios (i.e. growth stocks) to underperform in the subsequent period over stocks with high price-scaled ratios (i.e. value stocks), i.e., a value effect. On the other hand, a lower DOX implies more persistent extrapolative beliefs, which dissuade arbitrageurs from correcting the mispricing, and hence lead high (low) prices to be followed by even higher (lower) prices in the future, i.e., a momentum effect. Therefore, we should be able to observe higher value premium and lower momentum in the data following higher DOX, and vice versa. The data of DOX cover from December 1967 to October 2018, which is splitted into *High DOX*, *Mid DOX* and *Low DOX* based on the 70^{th} and 30^{th} percentiles of DOX. The performance of the momentum strategy and the value premium are then examined conditional on these three market states.

Table 2.3 reports monthly equal-weighted[15] portfolio returns for momentum and the value premium under scenarios with different levels of DOX. In Panel A the average returns, Jensen's alphas, and Sharpe ratios of the "12-0-12" momentum are reported, while Panel B reports the performance of value premium constructed using B/M, E/P, and C/P. The table also shows the difference in average returns and Jensen's alphas between *High DOX* and *Low DOX* states. The returns reported in this table are the average over the 12 months following each level of DOX.

[15] ↑The results for value-weighted returns are reported in the Appendix B.

Table 2.2. Unconditional Momentum and Value Premium, Equal-weighted, 1968-2018

This table reports the unconditional equal-weighted returns of momentum strategy 12-0-12 (in Panel A), and value premium (in Panel B). In Panel A, the momentum strategy is constructed at end of each month by sorting stocks into decile portfolios based on their cumulative 12-month returns, and then track them for 12 months. The value/growth decile portfolios are formed at the end of each month and tracked for 12 months. In the last column, I report the performance of the long-short portfolios (Winners-Losers for momentum, and Value-Growth for value premium). In Panel B, the value premium is calculated using B/M, E/P, and C/P, respectively. Stocks with price less than $1 are excluded at the time of portfolio formation. For each decile portfolio and the long-short portfolio, I report the following statistics: the average monthly returns of the 12-month holding period ($\bar{R}$), the t-statistics of $\bar{R}$ ($t(\bar{R})$), Jensen's alpha (α), and its corresponding t-statistics ($t(\alpha)$), the average excess returns over the 1-month T-bill rate ($\bar{R} - R_f$), the standard deviation of the excess returns (σ), and the Sharpe ratio (SR). The sample covers from Jan 1968 to November 2018.

Panel A. Momentum

Statistics	*D1 (Losers)*	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*	*D8*	*D9*	*D10 (Winners)*	*Winners - Losers*
$\bar{R}$	0.59	0.92	1.01	1.10	1.14	1.18	1.20	1.21	1.22	1.08	0.50
$t(\bar{R})$	[1.93]	[3.84]	[4.89]	[5.93]	[6.49]	[6.92]	[6.92]	[6.79]	[6.34]	[4.66]	[2.71]
α	0.14	0.48	0.58	0.66	0.71	0.75	0.77	0.78	0.78	0.64	0.49
$t(\alpha)$	[0.47]	[2.01]	[2.81]	[3.63]	[4.11]	[4.49]	[4.55]	[4.48]	[4.20]	[2.83]	[2.63]
$\bar{R} - R_f$	0.20	0.53	0.63	0.71	0.76	0.79	0.81	0.83	0.83	0.70	0.50
σ	2.73	2.14	1.86	1.66	1.57	1.51	1.52	1.57	1.71	2.11	1.70
SR	0.07	0.25	0.34	0.43	0.48	0.53	0.54	0.53	0.49	0.33	0.29

Panel B. Value Premium

Statistics	*D1 (Growth)*	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*	*D8*	*D9*	*D10 (Value)*	*Value - Growth*
					Panel B.1. B/M						
$\bar{R}$ R	0.57	0.89	1.01	1.10	1.14	1.18	1.24	1.31	1.40	1.45	0.88
$t(\bar{R})$	[2.44]	[4.39]	[5.07]	[5.58]	[5.94]	[6.13]	[6.31]	[6.44]	[6.33]	[5.28]	[4.32]
α	0.12	0.45	0.57	0.66	0.70	0.75	0.81	0.87	0.96	1.02	0.90
$t(\alpha)$	[0.52]	[2.27]	[2.93]	[3.44]	[3.74]	[3.98]	[4.21]	[4.37]	[4.39]	[3.69]	[4.42]
$\bar{R} - R_f$	0.18	0.50	0.62	0.71	0.75	0.79	0.85	0.92	1.01	1.07	0.88
σ	2.14	1.84	1.79	1.77	1.72	1.72	1.76	1.81	1.97	2.45	1.72
SR	0.09	0.27	0.35	0.40	0.44	0.46	0.48	0.51	0.51	0.43	0.51
					Panel B.2. E/P						
$\bar{R}$	0.87	1.08	1.10	1.14	1.19	1.24	1.28	1.31	1.36	1.26	0.39
$t(\bar{R})$	[3.97]	[5.61]	[6.05]	[6.42]	[6.71]	[7.12]	[7.06]	[6.88]	[6.75]	[5.21]	[2.53]
α	0.42	0.64	0.66	0.71	0.76	0.81	0.85	0.89	0.93	0.83	0.40
$t(\alpha)$	[1.94]	[3.37]	[3.72]	[4.05]	[4.34]	[4.73]	[4.78]	[4.74]	[4.71]	[3.42]	[2.65]
$\bar{R} - R_f$	0.48	0.69	0.71	0.75	0.80	0.85	0.89	0.93	0.98	0.87	0.39
σ	2.01	1.75	1.64	1.60	1.60	1.58	1.63	1.69	1.80	2.18	1.34
SR	0.24	0.39	0.43	0.47	0.50	0.54	0.55	0.55	0.54	0.40	0.29
					Panel B.3. C/P						
$\bar{R}$	0.82	1.03	1.12	1.20	1.24	1.27	1.30	1.34	1.35	1.33	0.51
$t(\bar{R})$	[3.79]	[5.41]	[5.96]	[6.47]	[6.50]	[6.62]	[6.58]	[6.57]	[6.46]	[5.17]	[2.87]
α	0.37	0.59	0.69	0.77	0.81	0.84	0.87	0.91	0.92	0.90	0.52
$t(\alpha)$	[1.73]	[3.14]	[3.70]	[4.20]	[4.32]	[4.45]	[4.47]	[4.54]	[4.44]	[3.47]	[2.96]
$\bar{R} - R_f$	0.43	0.64	0.74	0.81	0.85	0.88	0.91	0.95	0.96	0.94	0.51
σ	2.00	1.74	1.70	1.65	1.69	1.71	1.74	1.80	1.87	2.31	1.56
SR	0.21	0.37	0.43	0.49	0.50	0.51	0.52	0.53	0.51	0.41	0.33

Panel A of Table 2.3 shows that following periods with a low degree of over-extrapolation, momentum is large and significant, while momentum is not significantly profitable following high degree of over-extrapolation. More specifically, following *Low DOX*, the average momentum portfolio return is 1.00% per month over the 12-month post-formation period (t-statistic=4.94), whereas it is on average only 0.10% per month (t-statistic=0.24) following *High DOX*. The difference in average returns between *High DOX* and *Low DOX* periods is -0.90% per month (p-value=0.01). The results are similar for Jensen's alpha, suggesting that the difference cannot be explained by market risk. Furthermore, the table also reports the standard deviation of excess returns over 1-month T-bill rates (σ) and Sharpe ratios. It shows that not only the return of momentum is higher following *Low DOX* compared to *High DOX*, but the volatility of momentum returns is lower (1.06 and 2.27 following *Low DOX* and *High DOX*, respectively), hence the momentum strategy in the market-state with lower degree of over-extrapolation provides much better Sharpe ratios (0.94 and 0.04 for *Low DOX* and *High DOX*, respectively). The table shows that as the degree of over-extrapolation decreases, the magnitude of momentum effect increases, which is in line with the predictions of the model in Section 2.2.

The conditional performance of value premium is reported in Panel B of Table 2.3. For the brevity of the paper, only the results for the B/M value premium (Panel B.1) are discussed in details here, but the results for the value premium calculated using E/P and C/P are qualitatively similar. Panel B.1 shows that following periods with a high degree of over-extrapolation, value premium is large and significant. More specifically, following *High DOX*, the average monthly value premium is 1.29% over the 12 months after portfolio formation (t-statistic=3.08), whereas it is on average 0.51% per month (t-statistic=2.15) following *Low DOX*. The difference between *High DOX* and *Low DOX* periods is -0.78% per month (p-value=0.02). Furthermore, Panel B.2 and B.3 show that the value premium calculated by E/P and C/P is not significant following periods of *Low DOX*. Though the volatility of value premium is also higher for *High DOX* states (2.18 and 1.28 following *High DOX* and *Low DOX*, respectively), the Sharpe ratio for *High DOX* is still better (0.59 and 0.40 for *High DOX* and *Low DOX*, respectively). Different from the results for momentum,

Table 2.3. Momentum and Value Premium Conditional on Extrapolation, Equal-weighted, 1968-2018

This table reports the average equal-weighted returns of momentum (Panel A), and value premium (Panel B), conditional on the level of over-extrapolation (DOX). In Panel A, the momentum strategy is constructed at end of each month by sorting stocks into decile portfolios based on their cumulative 12-month returns, and then track them for 12 months. The value/growth decile portfolios are formed at the end of each month and tracked for 12 months. In the last column, I report the performance of the long-short portfolios (Winners-Losers for momentum, and Value-Growth for value premium). In Panel B, the value premium is calculated using B/M, E/P, and C/P, respectively. Stocks with price less than \$1 are excluded at the time of portfolio formation. For each decile portfolio and the long-short portfolio, I report the following statistics: the average monthly returns of the 12-month holding period ($\bar{R}$), the t-statistics of $\bar{R}$ ($t(\bar{R})$), Jensen's alpha (α), and its corresponding t-statistics ($t(\alpha)$), the average excess returns over the 1-month T-bill rate ($\bar{R} - R_f$), the standard deviation of the excess returns (σ), and the Sharpe ratio (SR). *High DOX* is defined as the states where DOX is greater than the 70^{th} percentile, and *Low DOX* is defined as the states where DOX is less than the 30^{th} percentile. *Mid DOX* represents the states where DOX is in between the 30^{th} and 70^{th} percentiles. The difference between *High DOX* and *Low DOX* is reported in the last column, and the corresponding p-values are reported in parenthesis. The sample covers from Jan 1968 to November 2018.

Panel A. Momentum (12-0-12)

Statistics	*All*	*High DOX*	*Mid DOX*	*Low DOX*	*High - Low*
$\bar{R}$	0.50	0.10	0.42	1.00	-0.90
$t(\bar{R})$	[2.71]	[0.24]	[2.14]	[4.94]	(0.01)
α	0.49	0.10	0.42	0.99	-0.89
$t(\alpha)$	[2.63]	[0.25]	[2.10]	[4.91]	(0.01)
σ	1.67	2.27	1.41	1.06	
SR	0.30	0.04	0.30	0.94	

Panel B. Value Premium

Panel B.1. B/M

Statistics	*All*	*High DOX*	*Mid DOX*	*Low DOX*	*High - Low*
$\bar{R}$	0.88	1.29	0.87	0.51	0.78
$t(\bar{R})$	[4.32]	[3.08]	[3.50]	[2.15]	(0.02)
α	0.90	1.29	0.89	0.53	0.75
$t(\alpha)$	[4.42]	[3.12]	[3.64]	[2.25]	(0.03)
σ	1.74	2.18	1.61	1.28	
SR	0.51	0.59	0.54	0.40	

Panel B.2. E/P

Statistics	*All*	*High DOX*	*Mid DOX*	*Low DOX*	*High - Low*
$\bar{R}$	0.39	0.68	0.27	0.25	0.43
$t(\bar{R})$	[2.53]	[2.09]	[1.40]	[1.41]	(0.10)
α	0.40	0.68	0.29	0.27	0.42
$t(\alpha)$	[2.65]	[2.13]	[1.54]	[1.52]	(0.12)
σ	1.35	1.71	1.27	0.97	
SR	0.29	0.40	0.21	0.26	

Panel B.3. C/P

Statistics	*All*	*High DOX*	*Mid DOX*	*Low DOX*	*High - Low*
$\bar{R}$	0.51	0.84	0.52	0.18	0.67
$t(\bar{R})$	[2.87]	[2.58]	[2.06]	[0.81]	(0.02)
α	0.52	0.84	0.53	0.19	0.65
$t(\alpha)$	[2.96]	[2.61]	[2.16]	[0.89]	(0.03)
σ	1.57	1.83	1.56	1.20	
SR	0.32	0.46	0.33	0.15	

the table shows that as the degree of over-extrapolation increases, the profitability of value premium also increases.

Table 2.4 reports the performance of the long and short legs of momentum and value premium conditional on degree of overextrapolation. In Panel A, we can see that the Winner portfolio generates on average 1.34% per month following low DOX months, while generates 0.94% per month following high DOX periods. The difference between high and low DOX states is -0.41% (p-value is 0.04), indicating that stocks that have been performing better in the past will continue to do better, and will generate significant higher returns with lower DOX in the market. As for the loser portfolio, the return is on average 0.34% per month following low DOX states and 0.82% per month following high DOX periods. The $High-Low$ difference for the loser portfolio is significant and 0.48% per month (p-value=0.03), suggesting that the stocks that have been performing poorly in the past will perform even worse when the market degree of extrapolation is low. The long and short leg performance for value strategies is reported in Panel B. The B/M value portfolio generates an average monthly return of 1.70% and 1.20% following high DOX and low DOX, respectively. The difference is 0.50% per month with p-value of 0.03. On the other hand, the B/M growth portfolio generates an average monthly return of 0.41% and 0.68% following high DOX and low DOX, respectively. The difference is -0.27% per month with p-value of 0.05. These results indicate that DOX has an "amplification" effect on both the long and short legs of momentum and value strategies. More specifically, the higher momentum (value premium) following low (high) DOX come from both the better performance of Winner (Value) and the worse performance of Loser (Growth). For momentum, the effect of DOX on the long and short legs are similar, whereas the effect of DOX on value premium is stronger on the long leg of the strategy.

Table 2.4. Long and Short Legs of Momentum and Value Premium Conditional on Extrapolation, Equal-weighted, 1968-2018

This table reports the average equal-weighted returns of the long and short legs of momentum (Panel A), and value premium (Panel B), conditional on the level of over-extrapolation (DOX). In Panel A, the momentum strategy is constructed at end of each month by sorting stocks into decile portfolios based on their cumulative 12-month returns, and then track them for 12 months. The value/growth decile portfolios are formed at the end of each month and tracked for 12 months. Decile 1 portfolio is the loser (growth) portfolio for momentum (value), and Decile 10 portfolio is the winner (value) portfolio for momentum (value). In the last column of each level of DOX, I report the performance of the long-short portfolios (WML for momentum, and VMG for value premium). In Panel B, the value premium is calculated using B/M, E/P, and C/P, respectively. Stocks with price less than $1 are excluded at the time of portfolio formation. For each decile portfolio and the long-short portfolio, I report the following statistics: the average monthly returns of the 12-month holding period ($\bar{R}$), the t-statistics of $\bar{R}$ ($t(\bar{R})$), Jensen's alpha (α), and its corresponding t-statistics ($t(\alpha)$), the average excess returns over the 1-month T-bill rate ($\bar{R} - R_f$), the standard deviation of the excess returns (σ), and the Sharpe ratio (SR). *High* DOX is defined as the states where DOX is greater than the 70^{th} percentile, and *Low* DOX is defined as the states where DOX is less than the 30^{th} percentile. *Mid* DOX represents the states where DOX is in between the 30^{th} and 70^{th} percentiles. The difference between *High* DOX and *Low* DOX is reported in the last column, and the corresponding p-values are reported in parenthesis. The sample covers from Jan 1968 to November 2018.

Panel A. Momentum

	High DOX			Mid DOX			Low DOX			High - Low		
Statistics	Winners	Losers	WML	Winners	Losers	WML	Winners	Losers	WML	Winners	Losers	WML
$\bar{R}$	0.92	0.82	0.10	1.01	0.59	0.42	1.34	0.34	1.00	-0.41	0.48	-0.90
$t(\bar{R})$	[2.11]	[1.39]	[0.24]	[2.99]	[1.38]	[2.14]	[4.08]	[0.88]	[4.94]	(0.04)	(0.03)	(0.01)
α	0.54	0.44	0.10	0.57	0.15	0.42	0.83	-0.16	0.99	-0.30	0.60	-0.89
$t(\alpha)$	[1.28]	[0.72]	[0.25]	[1.74]	[0.36]	[2.10]	[2.56]	[-0.40]	[4.91]	(0.05)	(0.02)	(0.01)
σ	2.38	3.36	2.27	2.12	2.63	1.41	1.78	2.04	1.06			
SR	0.22	0.13	-0.13	0.31	0.09	0.05	0.51	-0.04	0.54			

Table 2.4. Long and Short Legs of Momentum and Value Premium Conditional on Extrapolation, Equal-weighted, 1968-2018 (continued)

Panel B. Value Premium

Panel B.1. B/M

	High DOX			Mid DOX			Low DOX			High - Low		
Statistics	Value	Growth	VMG	Value	Growth	VMG	Value	Growth	VMG	Value	Growth	VMG
$\bar{R}$	1.70	0.41	1.29	1.47	0.60	0.87	1.20	0.68	0.51	0.50	-0.27	0.78
$t(\bar{R})$	[2.87]	[0.86]	[3.08]	[4.44]	[1.73]	[3.50]	[3.73]	[2.28]	[2.15]	(0.03)	(0.05)	(0.02)
α	1.31	0.02	1.29	1.04	0.16	0.89	0.70	0.17	0.53	0.60	-0.15	0.75
$t(\alpha)$	[2.20]	[0.05]	[3.12]	[3.21]	[0.46]	[3.64]	[2.14]	[0.57]	[2.25]	(0.02)	(0.07)	(0.03)
σ	3.25	2.58	2.18	2.21	2.11	1.61	1.70	1.63	1.28			
SR	0.40	0.01	0.41	0.50	0.12	0.32	0.45	0.16	0.07			

Panel B.2. E/P

	High DOX			Mid DOX			Low DOX			High - Low		
Statistics	Value	Growth	VMG	Value	Growth	VMG	Value	Growth	VMG	Value	Growth	VMG
$\bar{R}$	1.49	0.81	0.68	1.10	0.82	0.27	1.23	0.98	0.25	0.27	-0.17	0.43
$t(\bar{R})$	[3.04]	[1.97]	[2.09]	[3.35]	[2.49]	[1.40]	[4.23]	[3.42]	[1.41]	(0.05)	(0.07)	(0.10)
α	1.11	0.42	0.68	0.68	0.38	0.29	0.74	0.47	0.27	0.37	-0.05	0.42
$t(\alpha)$	[2.25]	[1.05]	[2.13]	[2.09]	[1.18]	[1.54]	[2.48]	[1.59]	[1.52]	(0.04)	(0.39)	(0.12)
σ	2.74	2.32	1.71	2.07	2.06	1.27	1.61	1.58	0.97			
SR	0.40	0.18	0.17	0.36	0.23	-0.06	0.50	0.35	-0.18			

Panel B.3. C/P

	High DOX			Mid DOX			Low DOX			High - Low		
Statistics	Value	Growth	VMG	Value	Growth	VMG	Value	Growth	VMG	Value	Growth	VMG
$\bar{R}$	1.62	0.78	0.84	1.25	0.74	0.52	1.13	0.95	0.18	0.50	-0.17	0.67
$t(\bar{R})$	[3.08]	[1.94]	[2.58]	[3.91]	[2.15]	[2.06]	[3.42]	[3.68]	[0.81]	(0.03)	(0.06)	(0.02)
α	1.24	0.40	0.84	0.83	0.30	0.53	0.64	0.44	0.19	0.60	-0.05	0.65
$t(\alpha)$	[2.35]	[1.00]	[2.61]	[2.60]	[0.88]	[2.16]	[1.89]	[1.66]	[0.89]	(0.02)	(0.59)	(0.03)
σ	2.96	2.30	1.83	2.09	2.11	1.56	1.78	1.47	1.20			
SR	0.42	0.17	0.25	0.43	0.18	0.10	0.39	0.36	-0.21			

In order to better characterize the dynamic of returns for momentum and value premium under different degrees of over-extrapolation, Figure 2.6 plots the cumulative returns of momentum and different value strategies over the 36 months after the portfolio formation, following *High DOX*, *Low DOX*, as well as the whole sample *ALL DOX*. The portfolio formation month t is identified as *High DOX* if the DOX at end of month t is above the sample 70^{th} percentile, and is identified as *Low DOX* if DOX in month t falls below its sample 30^{th} percentile. For each portfolio formed at month τ (i.e. the event month 0), I track its returns for 36 months, and the cumulative return at month t is the summation of monthly returns from portfolio formation month τ to month t. For each scenario of different DOX, I plot the average cumulative returns across portfolios. More specifically, in each graph of Figure 2.6, the blue solid line shows the cumulative returns for *Low DOX*, whereas the red solid line represents the return dynamics for *High DOX*. The black line plots the unconditional cumulative returns for each strategy. The top left figure plots the cumulative returns of momentum strategy. Consistent with the empirical results in Table 2.3, the cumulative returns of momentum is higher in the blue line (*Low DOX*) compared to the red line (*High DOX*). Furthermore, the pattern is very similar to the model implication shown in Figure 2.2. We can see that regardless of the over-extrapolation level, the momentum is more profitable in the short-term (up to 12 months post-formation), and then the cumulative returns start to decline. The profitability of momentum lasts longer (still positive cumulative return after 36 months) when the market has lower degree of over-extrapolation, whereas the momentum is no long profitable (cumulative returns of zero) after 12 months post-formation for states with high degree of over-extrapolation. The remaining three graphs plot the cumulative returns of value premium calculated using B/M, E/P, and C/P, respectively. In line with the discussion on the empirical results in Panel B of Table 2.3, the value premium is more profitable in *High DOX* (red line) than in *Low DOX* (blue line), and the value premium does not diminish over the 3 years after the portfolio formation.

Overall, the evidence in Table 2.3 and Figure 2.6 is consistent with the model implication in Section 2.2. Unconditionally, both momentum and value strategies are profitable. However, their profitability arises with different timing corresponding to the degree of over-

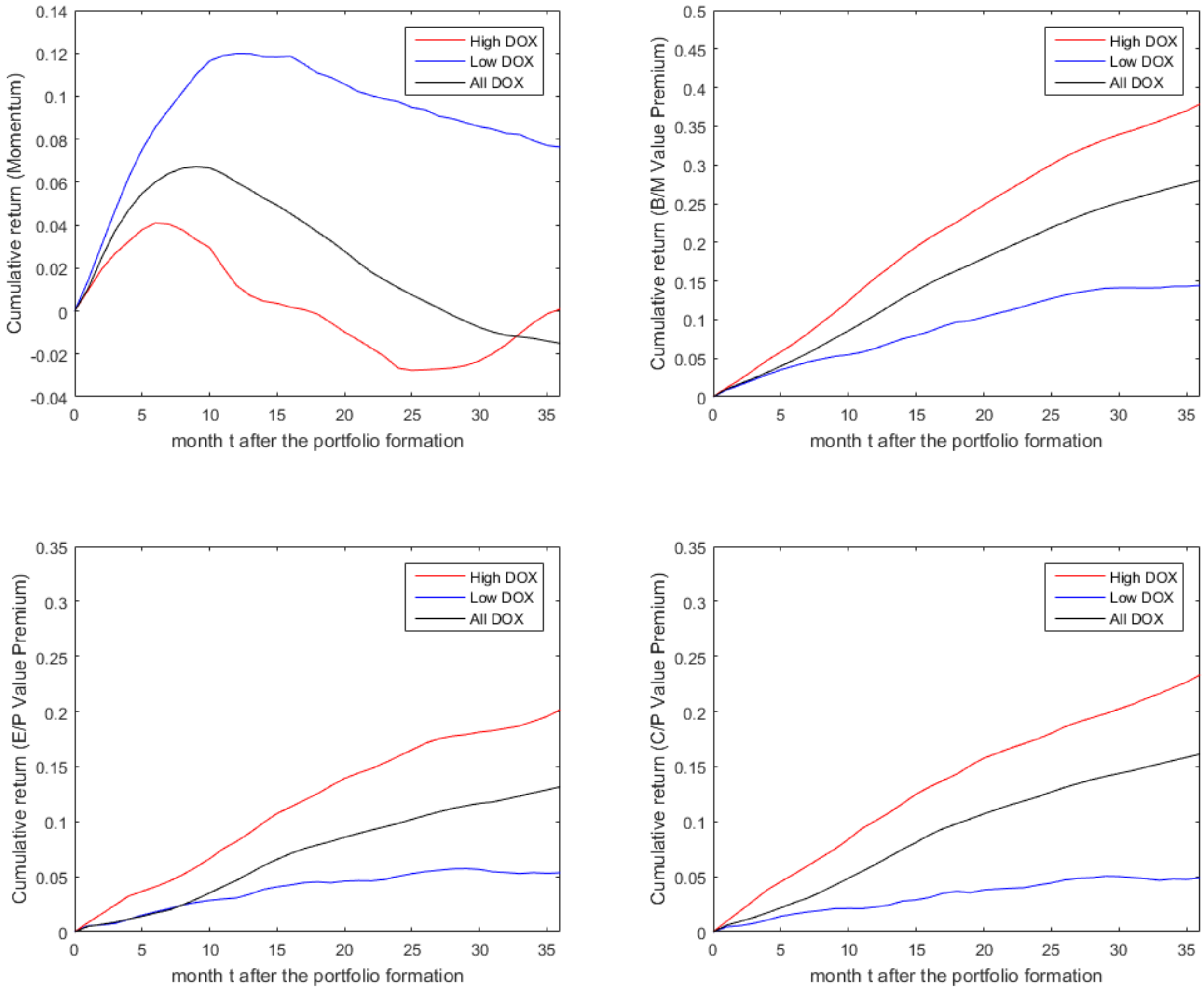

Figure 2.6. Extrapolation and the Cumulative Returns of Momentum and Value Premium

This figure plots the cumulative returns of the "12-0-12" momentum strategy and the value strategies constructed using B/M, E/P, and C/P. The x-axis shows the number of months after portfolio formation, which is at $t = 0$. Each portfolio is tracked for 36 months after formation. The momentum strategy is constructed at end of each month by sorting stocks into decile portfolios based on their cumulative 12-month returns. The value strategy is formed at end of each month using B/M, E/P, and C/P. Stocks with price less than $1 are excluded at the time of portfolio formation. The details of portfolio formation is discussed in Section 2.3. The time series of *DOX* cover from December 1967 to October 2018, which is splitted into *High DOX*, *Mid DOX* and *Low DOX* based on the $70^t h$ and $30^t h$ percentiles of *DOX*. In each figure, the blue solid line shows the average cumulative returns following months identified as *Low DOX*, whereas the red solid line represents the average cumulative returns for *High DOX*. The black line shows the unconditional cumulative returns. The cumulative return at month t is calculated as $\sum_{\tau=0}^{t} R_\tau$, where R_τ is the monthly return for the strategy in month τ after portfolio formation, and R_0 is set to be zero.

extrapolation. These results suggest that both momentum and the value premium are more likely to be an artifact of the mispricing caused by investors' expectation bias.

To investigate the effect of DOX on momentum and value premium in a way that allows to include other control variables, the following regression specifications are estimated:

$$R^{MOM}_{t+1,t+12} = a_1 DOX\ High + a_2 DOX\ Mid + a_3 DOX\ Low + \Gamma X_t + \epsilon_{t+1}, \tag{2.11}$$

$$R^{VAL}_{t+1,t+12} = a_1 DOX\ High + a_2 DOX\ Mid + a_3 DOX\ Low + \Gamma Y_t + \epsilon_{t+1}, \tag{2.12}$$

$$R^{MOM}_{t+1,t+12} = a_0 + bDOX_t + \Gamma X_t + \epsilon_{t+1}, \tag{2.13}$$

$$R^{VAL}_{t+1,t+12} = a_0 + bDOX_t + \Gamma Y_t + \epsilon_{t+1}, \tag{2.14}$$

where the dependent variables are the average future 12-month "12-0-12" momentum and value premium, *DOX High*, *DOX Mid* and *DOX Low* are dummy variables equal to 1 if DOX is greater than its sample 70^{th} percentile, in between the 30^{th} and 70^{th} percentiles, and below the 30^{th} percentile, respectively. Following Cassella and Gulen (2018)[2], DOX is the DOX extracted from II during the period from December 1967 to May 1992, the DOX extracted from the principal component time-series of II and AA from June 1992 to October 2018. X and Y are vectors of the other control variables corresponding to momentum and value premium. The control variables X in Eq.(2.11) and (2.13) include market volatility (Wang and Xu (2015)[51]), market illiquidity (Avramov, Cheng, and Hameed (2016)[52]), momentum gap (Huang (2019)[59]), the investor sentiment index in Baker and Wurgler (2006)[55]. The control variables for value premium in Y include the Sentiment Index of Baker and Wurgler (2006)[55], 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.

Table 2.5. Predicting Momentum/Value Premium, Equal-weighted, 1968-2018

This table reports the equal-weighted returns of momentum (Panel A), and value premium (Panel B), conditional on the degree of over-extrapolation (DOX). The following regression specifications are estimated:

$$R^{MOM}_{t+1,t+12}(or\ R^{VAL}_{t+1,t+12}) = a_0 + \Gamma X_t + \epsilon_{t+1}, \tag{2.15}$$

$$R^{MOM}_{t+1,t+12}(or\ R^{VAL}_{t+1,t+12}) = a_1 DOX\ High + a_2 DOX\ Mid + a_3 DOX\ Low + \Gamma X_t + \epsilon_{t+1}, \tag{2.16}$$

$$R^{MOM}_{t+1,t+12}(or\ R^{VAL}_{t+1,t+12}) = a_0 + bDOX_t + \Gamma X_t + \epsilon_{t+1}, \tag{2.17}$$

The dependent variables are the average future 12-month "12-0-12" momentum (Panel A) and different value premium (Panel B). *DOX High*, *DOX Mid* and *DOX Low* are dummy variables equal to 1 if DOX is greater than its sample 70^{th} percentile, in between the 30^{th} and 70^{th} percentiles, and below the 30^{th} percentile, respectively. Following Cassella and Gulen (2018)[2], DOX is the DOX extracted from II during the period from December 1967 to May 1992, the DOX extracted from the principal component time-series of II and AA from June 1992 to October 2018. X are vectors of the other control variables corresponding to momentum and value premium. The control variables X for dependent variable $R^{MOM}_{t+1,t+12}$ include market volatility (Wang and Xu, 2015), market illiquidity (Avramov, Cheng, and Hameed, 2016), momentum gap (Huang, 2015), and the investor sentiment index in Baker and Wurgler (2006). The control variables for value premium $R^{VAL}_{t+1,t+12}$ 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. Model (1), (3) and (5) estimate Eq(B.1), Eq(B.2) and Eq(B.3) without the control variables X, whereas Model (2), (4) and (6) include the control variables. The t-statistics are adjusted for serial correlation and heteroskedasticity and reported in brackets. The bottom of each panel reports the following statistics and tests: $\hat{a1} - \hat{a3}$ is the in-sample momentum/value premium wedge between high DOX and low DOX, and $p-Value(H_0 : \hat{a1} = \hat{a3})$ is the in-sample p-value of a test of the null-hypothesis that there is no difference in momentum/value following high versus low DOX. The sample covers from Jan 1968 to November 2019.

Panel A. Momentum 12-0-12

parameter	(1)	(2)	(3)	(4)	(5)	(6)
Int	0.005	0.019			0.011	0.023
	[2.71]	[2.28]			[3.32]	[2.46]
DOX High			0.001	0.008		
			[0.18]	[1.21]		
DOX Mid			0.004	0.011		
			[2.02]	[1.68]		
DOX Low			0.01	0.015		
			[4.87]	[2.51]		
DOX					-0.013	-0.011
					[-1.48]	[-1.59]
Macro controls	N	Y	N	Y	N	Y
N	611	611	611	611	611	611
Adj. R^2	0.078	0.181	0.115	0.201	0.024	0.125
$\hat{a1} - \hat{a3}$			-0.009	-0.007		
$p - Value(H_0 : \hat{a1} = \hat{a3})$			(0.008)	(0.007)		

Table 2.5 presents the predictive ability of DOX on the equal-weighted[16] momentum and value premium over 1968 to 2019. In Panel A of Table 2.5, the dependent variable is the equal-weighted average monthly return of the "12-0-12" momentum strategy over the 12 months after portfolio formation. Column (1) and (2) report the unconditional momentum returns with and without the macro control variables, which are both positively significant (t-stat=2.71 and 2.28, respectively). Column (3) and (4) estimate Eq.(2.11) with and without the macro control variables. In line with the results in Table 2.3, the coefficients on *DOX Low* are positively significant while the coefficients on *DOX high* are not significant. The bottom of Panel A reports two additional statistics: $\hat{a1} - \hat{a3}$ is the in-sample momentum wedge between high DOX and low DOX, and $p - Value(H_0 : \hat{a1} = \hat{a3})$ is the in-sample p-value of a test of the null-hypothesis that there is no difference in momentum following high versus low DOX. The difference between the coefficient on *DOX High* and *DOX low* is -0.007 (p-value=0.007) when control variables are included. Column (5) and (6) estimate Eq.(2.11) with and without control variables, and the coefficients on lagged DOX are negative.

Panel B of Table 2.5 repeat the estimation as in Panel A and replace the dependent variable with the equal-weighted average monthly return of different value premium over the 12 months post portfolio formation. Different from the results in Panel A, column (3) in Panel B.1 shows that the difference between the coefficient on *DOX High* and *DOX low* is significantly positive (0.008 with p-value=0.028), which is consistent with the conditional value premium results in Table 2.3. Furthermore, the coefficients on DOX are positive and significant. These results suggest that the effect of DOX on momentum and value premium are robust after controlling for other macro variables.

2.3.3 Extrapolation, Market Returns, and Patterns of Long/Short Portfolios in Momentum and Value

To further test the effect of extrapolation on momentum and value premium, this section investigate how extrapolation impact the long and short legs of momentum and value following good and bad market returns. Inspired by the findings of the extended style investing model proposed by Cassella, Chen, Gulen, and Petkova(2021)[40], the extrapolative

[16]↑The regression results for value-weighted returns are reported in the Appendix.

Table 2.5. Predicting Momentum/Value Premium, Equal-weighted, 1968-2018 (continued)

Panel B. Value Premium

Panel B1. B/M

parameter	(1)	(2)	(3)	(4)	(5)	(6)
Int	0.009	-0.020			0.001	-0.023
	[4.32]	[-3.34]			[0.38]	[-3.62]
DOX High			0.013	-0.014		
			[3.08]	[-2.10]		
DOX Mid			0.009	-0.016		
			[3.54]	[-2.70]		
DOX Low			0.005	-0.018		
			[2.36]	[-3.07]		
DOX					0.018	0.01
					[1.86]	[1.33]
Macro controls	N	Y	N	Y	N	Y
N	611	611	611	611	611	611
Adj. R^2	0.208	0.399	0.230	0.399	0.042	0.252
$\hat{a1} - \hat{a3}$			0.008	0.004		
$p - Value(H_0 : \hat{a1} = \hat{a3})$			(0.028)	(0.104)		

Panel B2. E/P

parameter	(1)	(2)	(3)	(4)	(5)	(6)
Int	0.004	-0.016			-0.001	-0.017
	[2.53]	[-3.88]			[-0.41]	[-3.73]
DOX High			0.007	-0.013		
			[2.09]	[-3.15]		
DOX Mid			0.003	-0.014		
			[1.37]	[-3.60]		
DOX Low			0.003	-0.014		
			[1.44]	[-3.29]		
DOX					0.012	0.002
					[1.61]	[0.46]
Macro controls	N	Y	N	Y	N	Y
N	611	611	611	611	611	611
Adj. R^2	0.076	0.265	0.092	0.258	0.031	0.204
$\hat{a1} - \hat{a3}$			0.004	0.001		
$p - Value(H_0 : \hat{a1} = \hat{a3})$			(0.108)	(0.901)		

Panel B3. C/P

parameter	(1)	(2)	(3)	(4)	(5)	(6)
Int	0.005	-0.02			-0.001	-0.022
	[2.87]	[-3.29]			[-0.34]	[-3.43]
DOX High			0.008	-0.014		
			[2.59]	[-2.50]		
DOX Mid			0.005	-0.015		
			[2.09]	[-2.70]		
DOX Low			0.002	-0.018		
			[0.95]	[-3.07]		
DOX					0.015	0.008
					[1.94]	[1.27]
Macro controls	N	Y	N	Y	N	Y
N	611	611	611	611	611	611
Adj. R^2	0.096	0.260	0.118	0.260	0.035	0.190
$\hat{a1} - \hat{a3}$			0.006	0.004		
$p - Value(H_0 : \hat{a1} = \hat{a3})$			(0.027)	(0.115)		

demand for each style also depends on the aggregate market performance. Intuitively, if the aggregate market is observed to be performing well, there will be additional extrapolative demand coming into the stock market from other asset classes, such as cash or bonds. It is likely that these additional extrapolative capital will be disproportionately invested in the relatively better performing stocks, such as the "Winners" or the "Growth" stocks. Thus, when the aggregate market returns are high, given the same degree of overextrapolation, the momentum return is more generated from the continuation of the good returns from the "Winners", whereas the value premium is mostly coming from the future underperformance of the growth stocks. On the contrary, if the aggregate market returns are low, there will be some extrapolative flows out of the stock market, and the outflows are more likely from selling the "Losers" or value stocks, which causes the "Losers" and value stocks to be severely underpriced. Hence in this scenario, the profitability of momentum is more likely to be generated by the worse returns of "Losers", and the value premium is mostly generated by the future good returns of value stocks.

To investigate the above conjecture formally, I perform independent bivariate sorts based on lagged market returns and DOX and split the sample to three groups along each of these two dimensions. Similarly with the definition of *High DOX*, *Mid DOX*, and *Low DOX*, each month is classified as "*Low Market*" if the previous 12-month cumulative market returns is below the 30^{th} percentile of the full-sample distribution, it is classified as "*High Market*" if the prior 12-month cumulative market return is above the 70^{th} percentile of the distribution, and it is classified as "*Mid Market*" otherwise. The market return is the monthly equal-weighted CRSP returns (including distributions). This procedure yields nine groups which are then rearranged in a 3-by-3 matrix. For each group, I report calculate the 12-month ahead returns and Jensen's alphas of momentum and value premium, as well as the long and short legs of both strategies.

Table 2.6. Extrapolation, Market Returns, Momentum and Value Premium, 1968-2018

This table reports the average equal-weighted returns of the long and short legs of momentum (Panel A), and value premium (Panel B), conditional on both past market returns and the level of over-extrapolation (DOX). The sample is double sorted in to 9 scenarios by prior-12-month market cumulative returns and DOX independently. For each decile portfolio and the long-short portfolio, I report the following statistics: the average monthly returns of the 12-month holding period ($\bar{R}$), the t-statistics of $\bar{R}$ ($t(\bar{R})$), Jensen's alpha (α), and its corresponding t-statistics ($t(\alpha)$). *High DOX* is defined as the states where DOX is greater than the 70^{th} percentile, and *Low DOX* is defined as the states where DOX is less than the 30^{th} percentile. *Mid DOX* represents the states where DOX is in between the 30^{th} and 70^{th} percentiles. *High Market* is defined as the states where prior 12-month cumulative market return is greater than its 70^{th} percentile, and *Low Market* is defined as the states where prior 12-month market returns is less than the 30^{th} percentile. *Mid Market* represents the states where prior 12-month cumulative market return is in between the 30^{th} and 70^{th} percentiles. The market return is the CRSP equal-weighted returns. The sample covers from Jan 1968 to November 2018.

Panel A. Momentum

		Mean Returns			Jensen's alpha		
		Low Market	Mid Market	High Market	Low Market	Mid Market	High Market
Low DOX	WmL	1.05	1.07	0.76	1.04	1.07	0.76
		[3.28]	[5.64]	[2.69]	[3.22]	[5.62]	[2.69]
	Winners	1.22	1.35	1.56	0.56	0.93	1.05
		[3.05]	[3.67]	[3.10]	[1.48]	[2.57]	[2.09]
	Losers	0.17	0.28	0.80	-0.49	-0.14	0.29
		[0.30]	[0.65]	[1.74]	[-0.88]	[-0.31]	[0.64]
Mid DOX	WmL	0.11	0.73	0.37	0.11	0.73	0.36
		[0.29]	[4.13]	[1.48]	[0.28]	[4.10]	[1.49]
	Winners	0.87	1.09	1.02	0.36	0.70	0.58
		[1.61]	[2.70]	[3.59]	[0.67]	[1.87]	[2.05]
	Losers	0.76	0.36	0.65	0.25	-0.03	0.21
		[0.98]	[0.79]	[1.66]	[0.33]	[-0.06]	[0.54]
High DOX	WmL	-0.65	0.64	0.30	-0.65	0.64	0.29
		[-0.83]	[2.40]	[0.83]	[-0.83]	[2.41]	[0.82]
	Winners	1.05	0.83	0.89	0.72	0.50	0.36
		[1.70]	[1.58]	[1.92]	[1.29]	[0.96]	[0.77]
	Losers	1.70	0.19	0.59	1.36	-0.14	0.07
		[1.64]	[0.30]	[1.36]	[1.28]	[-0.22]	[0.16]

Panel B. Value Premium

Panel B.1. B/M

		Mean Returns			Jensen's alpha		
		Low Market	Mid Market	High Market	Low Market	Mid Market	High Market
Low DOX	VmG	0.34	0.10	1.13	0.36	0.12	1.14
		[1.20]	[0.32]	[3.01]	[1.26]	[0.37]	[3.06]
	Value	1.40	0.78	1.56	0.92	0.31	1.03
		[3.71]	[1.54]	[4.18]	[2.41]	[0.59]	[2.63]
	Growth	1.06	0.68	0.43	0.56	0.19	-0.11
		[2.55]	[2.39]	[0.68]	[1.53]	[0.62]	[-0.18]
Mid DOX	VmG	1.48	0.36	0.91	1.50	0.38	0.92
		[3.98]	[1.51]	[2.52]	[4.07]	[1.59]	[2.57]
	Value	2.08	0.88	1.60	1.59	0.47	1.20
		[2.85]	[2.52]	[5.14]	[2.25]	[1.38]	[3.94]
	Growth	0.59	0.52	0.69	0.10	0.09	0.28
		[0.74]	[1.34]	[2.08]	[0.13]	[0.23]	[0.87]
High DOX	VmG	2.02	0.57	1.46	2.01	0.59	1.42
		[3.06]	[1.41]	[2.52]	[3.07]	[1.46]	[2.45]
	Value	3.15	0.90	0.61	2.85	0.46	0.18
		[3.02]	[1.49]	[2.42]	[2.73]	[0.76]	[0.54]
	Growth	1.13	0.34	-0.85	0.83	-0.13	-1.24
		[1.56]	[0.69]	[-1.16]	[1.26]	[-0.26]	[-1.48]

Table 2.6. Extrapolation, Market Returns, Momentum and Value Premium, 1968-2018 (continued)

Panel B.2. E/P

		Mean Returns			Jensen's alpha		
		Low Market	Mid Market	High Market	Low Market	Mid Market	High Market
Low DOX	VmG	0.40	-0.05	0.50	0.41	-0.04	0.50
		[1.53]	[-0.23]	[1.64]	[1.58]	[-0.17]	[1.68]
	Value	1.66	0.91	1.32	1.18	0.44	0.79
		[4.58]	[1.89]	[3.63]	[3.21]	[0.89]	[2.09]
	Growth	1.27	0.95	0.83	0.77	0.47	0.29
		[3.94]	[2.97]	[1.40]	[2.40]	[1.37]	[0.48]
Mid DOX	VmG	0.81	-0.13	0.29	0.82	-0.12	0.30
		[3.06]	[-0.75]	[0.95]	[3.14]	[-0.66]	[0.99]
	Value	1.58	0.51	1.33	1.10	0.10	0.94
		[2.13]	[1.52]	[4.21]	[1.52]	[0.32]	[2.99]
	Growth	0.78	0.64	1.05	0.28	0.22	0.64
		[1.09]	[1.64]	[3.32]	[0.42]	[0.56]	[2.07]
High DOX	VmG	1.28	0.03	0.99	1.27	0.05	0.95
		[2.61]	[0.09]	[2.36]	[2.62]	[0.15]	[2.28]
	Value	2.68	0.81	0.69	2.38	0.38	0.25
		[3.16]	[1.54]	[2.97]	[2.84]	[0.72]	[0.70]
	Growth	1.40	0.78	-0.30	1.10	0.33	-0.70
		[2.07]	[1.80]	[-0.51]	[1.80]	[0.78]	[-0.98]

Panel B.3. C/P

		Mean Returns			Jensen's alpha		
		Low Market	Mid Market	High Market	Low Market	Mid Market	High Market
Low DOX	VmG	-0.07	-0.25	0.87	-0.06	-0.24	0.88
		[-0.21]	[-0.92]	[3.92]	[-0.18]	[-0.88]	[3.99]
	Value	1.26	0.74	1.53	0.78	0.27	0.99
		[2.85]	[1.52]	[3.91]	[1.67]	[0.54]	[2.45]
	Growth	1.33	0.99	0.65	0.84	0.51	0.11
		[3.81]	[3.68]	[1.22]	[2.51]	[1.74]	[0.21]
Mid DOX	VmG	1.02	0.01	0.65	1.03	0.02	0.66
		[2.59]	[0.04]	[1.92]	[2.67]	[0.09]	[1.96]
	Value	1.68	0.65	1.54	1.19	0.24	1.15
		[2.54]	[1.93]	[4.64]	[1.85]	[0.74]	[3.39]
	Growth	0.65	0.64	0.89	0.16	0.22	0.49
		[0.87]	[1.59]	[2.70]	[0.22]	[0.54]	[1.49]
High DOX	VmG	1.43	0.24	1.04	1.43	0.25	1.01
		[2.57]	[0.76]	[2.41]	[2.57]	[0.80]	[2.35]
	Value	2.87	0.95	0.68	2.57	0.51	0.24
		[3.03]	[1.73]	[2.77]	[2.74]	[0.94]	[0.67]
	Growth	1.44	0.72	-0.36	1.14	0.26	-0.77
		[2.14]	[1.72]	[-0.62]	[1.85]	[0.64]	[-1.08]

The results of this analysis are presented in Table 2.6. Based on the discussion in the previous section, the momentum profitability is significant and concentrated in *Low DOX* scenarios. Furthermore, given the *DOX* being low, if the most recent market return is high, the corresponding alpha of momentum is 0.76% per month, with the “Winners” (“Losers”) generating 1.05% (0.29%) per month. However, if the most recent market return is low, the corresponding monthly alpha of "Winners" ("Losers") is on average 0.56% (-0.49%), which leads to the alpha of momentum portfolio is 1.04% per month. These results suggest that when the aggregate market has been performing badly (well), the degree of overextrapolation has larger impact on the short (long) leg of the momentum strategy.

Panel B of Table 2.6 reports the independent bivariate sorts for the value premium. Contrary to the findings in momentum, the value premium is higher when DOX is high and market returns have been either very high or very low. More specifically, in Panel B.1 of Table 2.6, the monthly alpha of value premium following *"High DOX, Low Market"* is on average 2.01%, of which the long leg generates 2.85% and the short leg only generates 0.83% per month. This suggests that when DOX is high and market returns have been low, the value stocks are more undervalued due to extrapolation, leading to larger reversal in later periods. On the other hand, *"High DOX, High Market"* indicates that the growth stocks are more likely to be more overpriced, hence we expect that the value premium is mostly coming from the underperformance of the growth stocks. The results in Panel B.1 are consistent with this conjecture. More specifically, following *"High DOX, High Market"*, the corresponding monthly alpha of "Value" ("Growth") is on average 0.18% (-1.24%), leading to the alpha of value premium is 1.42% per month. Overall, these additional results provide additional support on the effect of extrapolative demand on momentum and value premium.

2.3.4 Combining Momentum and Value Premium

Based on the Proposition 8 in Barberis and Shleifer (2003)[1] and the discussion in Section 2.2.2, there is a superior strategy that combines momentum and value strategy by applying different weights based on the market degree of over-extrapolation. The simple intuition is to invest more in momentum when DOX is low and invest more in value strategy when DOX is high. Since this "superior" strategy is derived from maximizing the expected utility of the arbitrageurs, we expect that this combining strategy delivers superior Sharpe ratio compared to simply implementing momentum or value strategy, rather than just better returns.

The most straightforward way to construct this combining strategy is to implement the following procedure: only investing in momentum when DOX is low, only investing in value strategy when DOX is high, and equally investing in both momentum and value for the remaining time. Same as the previous section, months are identified as *High DOX* if DOX in month t is above the sample 70^th percentile, and are identified as *Low DOX* if DOX in month t falls below its sample 30^th percentile. Table 2.7 presents the performance of the strategy that combines "12-0-12" momentum and different value strategy by applying the discrete weighting scheme. Regardless of the price-scaled valuation ratio to construct value premium, the combining strategy generates higher average returns and better Sharpe ratios compared to solely implementing momentum or value strategy unconditionally. More specifically, when combining momentum and the B/M value premium, the combo strategy provides 0.96% per month and Sharpe ratio of 0.27, whereas the momentum and value strategy generate average return of 0.51% and 0.92% per month, and Sharpe ratio of 0.10 and 0.20, respectively. The results are similar for value strategies constructed using E/P and C/P.

Another way to construct the combining strategy is to apply continuous weighting by directly using DOX. Building on Eq.(2.8), the weight is calculated as $\frac{1}{1+\phi*DOX}$ for momentum and $\frac{\phi*DOX}{1+\phi*DOX}$ on Value. According to the model, ϕ is also a function of DOX and should be estimated in the data. For now, phi is set to be 1.25, which is the calibrated number in Barberis and Shleifer (2003)[1], for simplicity. The last column of Table 2.8 reports the performance of this combo strategy, which still provides better Sharpe ratio compared to either momentum or value premium. Overall, the results in Table 2.7 and 2.8 provide empirical support to the model implication discussed in Section 2.2.2.

Table 2.7. Combining Momentum and Value Strategies (Discrete Weighting), Equal-weighted, 1968-2018

This table reports the performance of a combination strategy, which only invests in momentum strategy following *Low DOX* states, both momentum and value equally following *Mid DOX* states, and only in value strategy following *high DOX* states. The momentum strategy is constructed at end of each month by sorting stocks into decile portfolios based on their cumulative 12-month returns, and then track them for 12 months. The value/growth decile portfolios are formed at the end of each month and tracked for 12 months. In the last column, I report the performance of the combing strategy using the discrete weighting scheme. The value premium is calculated using B/M, E/P, and C/P, respectively. Stocks with price less than $1 are excluded at the time of portfolio formation. For each strategy, I report the following statistics: the average monthly returns of the 12-month holding period ($\bar{R}$), the t-statistics of $\bar{R}$ ($t(\bar{R})$), Jensen's alpha (α), and its corresponding t-statistics ($t(\alpha)$), the average excess returns over the 1-month T-bill rate ($\bar{R} - R_f$), the standard deviation of the excess returns (σ), and the Sharpe ratio (SR). Months are identified as *High DOX* if DOX in month t is above the sample 70^th percentile, and are identified as *Low DOX* if DOX in month t falls below its sample 30^th percentile. The t-statistics are reported in brackets and adjusted for serial correlation using Newey-West adjustment. The sample covers from Jan 1968 to November 2019.

Momentum (12-0-12) and B/M Value Premium			
Statistic	*Momentum*	*Value*	*Combo Strategy*
$\bar{R}$	0.51	0.92	0.96
$t(\bar{R})$	[2.36]	[4.05]	[5.81]
α	0.55	1.05	1.01
$t\alpha$	[2.74]	[4.78]	[6.02]
σ	5.24	4.51	3.53
SR	0.10	0.20	0.27
Momentum (12-0-12) and E/P Value Premium			
Statistic	*Momentum*	*Value*	*Combo Strategy*
$\bar{R}$	0.51	0.41	0.66
$t(\bar{R})$	[2.36]	[2.42]	[4.80]
α	0.55	0.51	0.70
$t\alpha$	[2.74]	[3.12]	[5.10]
σ	5.24	3.55	3.16
SR	0.10	0.12	0.21
Momentum (12-0-12) and C/P Value Premium			
Statistic	*Momentum*	*Value*	*Combo Strategy*
$\bar{R}$	0.51	0.54	0.76
$t(\bar{R})$	[2.36]	[2.66]	[5.16]
α	0.55	0.64	0.79
$t\alpha$	[2.74]	[3.24]	[5.40]
σ	5.24	4.30	3.47
SR	0.10	0.13	0.22

Table 2.8. Combining Momentum and Value Strategies (Continuous Weighting), Equal-weighted, 1968-2018

This table reports the performance of a combination strategy, which apply continuous weighting scheme on Momentum and Value strategies. The normalized weight is $\frac{1}{1+\phi*DOX}$ on Momentum and $\frac{\phi*DOX}{1+\phi*DOX}$ on Value. In this setting, ϕ is set to be 1.25, as the calibrated parameter in Barberis and Shleifer (2003). The momentum strategy is constructed at end of each month by sorting stocks into decile portfolios based on their cumulative 12-month returns, and then track them for 12 months. The value/growth decile portfolios are formed at the end of each month and tracked for 12 months. In the last column, I report the performance of the combing strategy using the continuous weighting scheme. The value premium is calculated using B/M, E/P, and C/P, respectively. Stocks with price less than $1 are excluded at the time of portfolio formation. For each strategy, I report the following statistics: the average monthly returns of the 12-month holding period ($\bar{R}$), the t-statistics of $\bar{R}$ ($t(\bar{R})$), Jensen's alpha (α), and its corresponding t-statistics ($t(\alpha)$), the average excess returns over the 1-month T-bill rate ($\bar{R} - R_f$), the standard deviation of the excess returns (σ), and the Sharpe ratio (SR). The t-statistics are reported in brackets and adjusted for serial correlation using Newey-West adjustment. The sample covers from Jan 1968 to November 2019.

Momentum (12-0-12) and B/M Value Premium			
Statistic	*Momentum*	*Value*	*Combo Strategy*
$\bar{R}$	0.51	0.92	0.72
$t(\bar{R})$	[2.36]	[4.05]	[6.78]
α	0.55	1.05	0.78
$t\alpha$	[2.74]	[4.78]	[7.36]
σ	5.24	4.51	2.80
SR	0.10	0.20	0.26
Momentum (12-0-12) and E/P Value Premium			
Statistic	*Momentum*	*Value*	*Combo Strategy*
$\bar{R}$	0.51	0.41	0.54
$t(\bar{R})$	[2.36]	[2.42]	[4.74]
α	0.55	0.51	0.59
$t\alpha$	[2.74]	[3.12]	[5.37]
σ	5.24	3.55	2.91
SR	0.10	0.12	0.18
Momentum (12-0-12) and C/P Value Premium			
Statistic	*Momentum*	*Value*	*Combo Strategy*
$\bar{R}$	0.51	0.54	0.59
$t(\bar{R})$	[2.36]	[2.66]	[5.24]
α	0.55	0.64	0.64
$t\alpha$	[2.74]	[3.24]	[5.79]
σ	5.24	4.30	2.97
SR	0.10	0.13	0.20

2.4 Conclusion

This paper tests directly for the role of over-extrapolation for momentum and value premium. The empirical design closely follows the implications of the style investing model proposed in Barberis and Shleifer (2003)[1], which allows return extrapolation to play a role in the cross-section for momentum and value premium. The strength and timing of momentum and value in the cross-section of stocks are a function of extrapolators' degree of over-extrapolation (DOX). This structural parameter of extrapolative expectations determines how quickly reverting extrapolative beliefs are. Since arbitrageurs in the model trade differently when faced with high versus low DOX, variation in DOX has implications for the profitability of momentum and value strategies in equilibrium. A high level of DOX implies quicker mean reversion in extrapolators' beliefs, and entices arbitrageurs into correcting mispricing in the cross-section, leading stocks with high price-fundamental ratios to underperform in the subsequent period over stocks with low price-fundamental ratios, i.e., a value effect. On the contrary, low levels of DOX imply persistent extrapolative beliefs, which dissuade arbitrageurs from correcting the mispricing, and hence lead high (low) prices to be followed by higher (lower) prices in the future, i.e., a momentum effect.

Relying on the results in Cassella and Gulen (2018)[2], who use survey data of US investors' return expectations to estimate the time-series variation in extrapolators' DOX, it becomes empirically possible to examine the conditional profitability of momentum and value premium. I find that following *Low DOX* periods, the average monthly momentum portfolio return is 1.00% over the 12-month post-formation period, whereas it is on average only 0.10% per month following *High DOX*. However, the value premium is on average 1.29% per month over the 12 months after portfolio formation, whereas it is on average 0.51% per month following *Low DOX*. Furthermore, the original style investing model provides a potential superior strategy which combines momentum and value strategy by applying different weights, which are corresponding to different degrees of overextrapolation. Intuitively, the combining strategy is implemented through putting relatively more weight on momentum when DOX is observed to be low, and putting relatively more weight on value strategy when DOX is perceived to be high. Empirically, I find that the combining strategies provide better Sharpe ratios than simply implementing either momentum or value strategy. Overall, the findings in this paper show that both momentum and value premium can be sourcing from a unifying behavioral factor, the return extrapolation.

3. EXTRAPOLATIVE DEMAND AND THE VALUE PREMIUM

3.1 Introduction

[1]In this chapter, I argue that the extrapolative demand derived from return extrapolation can also help explain some time-series pattern in the value premium. Different from Chapter 2, here in this chapter, the extrapolative demand not only can come from an increase in trading by within-equity extrapolators, but also can be due to an increase in demand by extrapolators coming from other asset classes, such as cash, bonds, and real estate. When stocks, on average, go up in response to positive cash-flow news, extrapolative demand for equities goes up. As return extrapolators are drawn into the equity market, not only they amplify the initial price jump of equities (causing overvaluation and eventual poor performance of the market), but furthermore, the stocks with relatively more positive cash-flow shocks and higher returns attract disproportionally more inflows from the extrapolators. As a result of the additional extrapolative demand for better-performing stocks, such stocks become relatively more overvalued (i.e. growth stocks) compared to stocks that experience relatively lower or even negative cash-flow shocks. 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 price go down, extrapolators move capital out of stocks, and the poor performing stocks experience disproportionally more outflows generated by extrapolators. As a result, such stocks become extremely undervalued (i.e. value stocks). The cross-sectional value premium is realized when these stocks' mispricing is corrected. The impact of extrapolative capital flows in and out of the stock market, as well as the resulted asymmetry in the demand allocated to different stocks, has been overlooked in the previous literature.

Prior theoretical work on cross-sectional predictability and extrapolative beliefs (as discussed in Chapter 2) suggests that the value premium can emanate from within-equity de-

[1]↑This chapter is based on an earlier version of my collaborated work "Market-wide Misvaluation and the Value Premium" by Cassella, Chen, Gulen, and Petkova (2021)[40].

mand shifts that are due to the relative performance of growth stocks over value stocks. However, the predictability of the value premium exhibits features that theories of within-equity extrapolation cannot easily accommodate. In particular, in these theories the overvaluation of growth stocks and the undervaluation of value stocks arise and subside simultaneously (i.e., extra demand for growth stocks comes from reduced demand for value stocks, resulting in a symmetric move in B/M ratios of value and growth stocks). Moreover, within-equity extrapolation theories not only posit that, on average, the mispricing in the short and the long leg of the value strategy should contribute equally to the profitability of the value strategy, but also that this regularity should be observed in every period. However, empirically this does not seem to be the case, as is evident in Figure 3.1 which shows that the way in which mispricing in the long and the short leg of the value strategy contribute to the value premium is heavily time-varying and asymmetric. It shows that the B/M ratio of value stocks and (minus) the B/M ratio of growth stocks contribute asymmetrically to the predictability of the future value premium. As the figure shows, there exist both periods in which the predictability of the value premium is more strongly linked to the undervaluation of value stocks (when the line is above 0) and periods in which the value premium appear to emanate more strongly from the correction of overpricing of growth stocks (when the line lies below zero).

While this asymmetry can be difficult to reconcile with within-equity theories of extrapolation, it can arise naturally in a richer theoretical framework where there are extrapolators who move capital in/out of equity[2], and do so unevenly among growth and value stocks. In such a framework, time variation in extrapolative demand to/from equities depends on both the degree of extrapolation bias and the performance of stocks on average. Such additional extrapolative inflows (outflows) amplify the overvaluation (undervaluation) of growth (value) stocks following good (poor) performance of the equity market. Thus, to understand variation in the expected value premium and the asymmetry pattern of value and growth stocks, an extended framework is called for, which not only accounts for the irrational demand for

[2] ↑For instance, Greenwood and Shleifer (2014)[20] provide evidence of positive correlation between investors' extrapolative expectations and fund flows.

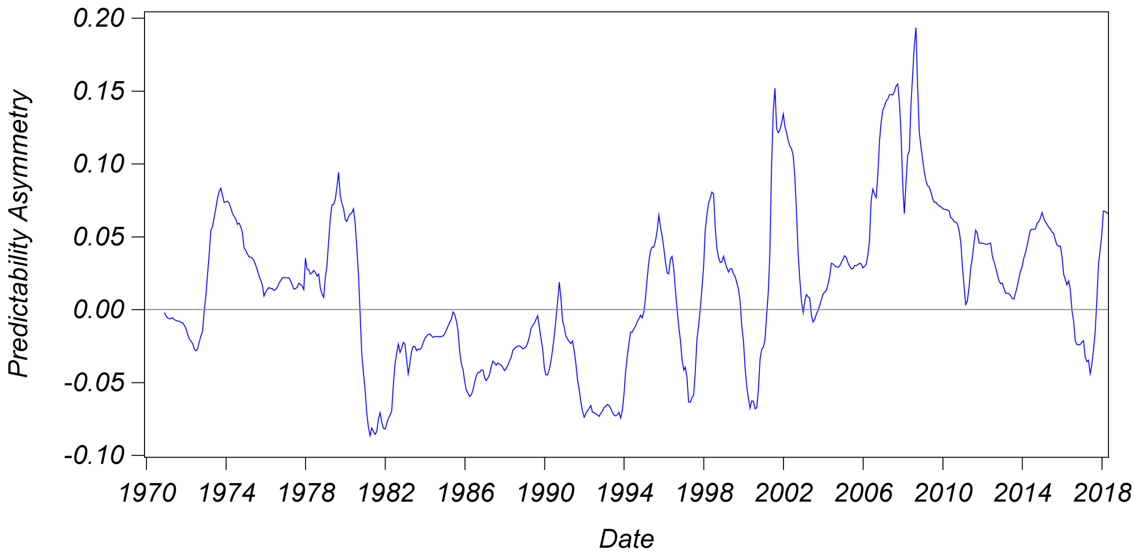

Figure 3.1. The Value Premium: Asymmetric Predictability
We estimate recursively the following bivariate regression of the future 12-month return of the value strategy on the lagged B/M of growth stocks and value stocks:

$$vmg_{t+12} = \alpha + \beta_V * bm_t^V + \beta_G * bm_t^G + \varepsilon_{t+12},$$

where vmg_{t+12} is the 12-month ahead value premium, bm_t^G is the B/M of growth stocks, and bm_t^V is the B/M of value stocks. Growth and value classification is based on a decile allocation of stocks following cross-sectional sorts on the B/M ratio. On average, $\beta_V > 0$ and $\beta_G < 0$, i.e., overvaluation among growth stocks (low bm_t^G) and undervaluation among value stocks (high bm_t^V) can both contribute to a higher future value premium. Therefore, we measure the extent to which the overvaluation of growth stocks and the undervaluation of value stocks contribute asymmetrically to the value premium by means of the difference $\beta_V - (-\beta_G)$. A positive value indicates the value premium is disproportionately linked to the undervaluation of value stocks, whereas a negative value indicates that the value premium stems disproportionately from the over-valuation of growth stocks. The documented asymmetry is also apparent in a full-sample regression. All quantities are in logs. Estimates are obtained using a rolling window of 36 months.

value and growth stocks within the equity market, but also accommodates the variation in the aggregate extrapolative capital flows in and out of the equity market.

To more formally investigate the implications of aggregate extrapolative demand for equities for cross-sectional return predictability, in Section 3.2, the style-investing model in Barberis and Shleifer (2003)[1] is extended by introducing the asset-class switchers who extrapolate returns at the equity market level. In the extended model, extrapolative demand for equities increases following good recent market returns. At the aggregate level, and akin to the result in Barberis, Greenwood, Jin, and Shleifer (2015)[9], the inflows of extrapolators' capital into the equity market cause overvaluation of the market. In the cross section, extrapolators' aggregate inflows are disproportionately allocated to growth stocks. This differential extrapolative demand for better performing growth stocks causes such stocks to become relatively more overvalued. A similar story holds for periods in which the market experiences negative returns, when extrapolators reduce their exposure to the overall equity market and disproportionately sell value stocks.

This extended model introduces two new predictions on the cross-sectional value premium. First, it suggests that the value premium is larger following periods of extreme market-wide over- or undervaluation.[3] Second, the model predicts that the cross-sectional value premium should largely stem from the overvaluation of growth stocks following periods in which stocks on average exhibit significant overvaluation and the undervaluation of value stocks following periods of significant market-wide undervaluation.

To empirically test the predictions of the extended model requires a measure of market-wide misvaluation. Coming up with a misvaluation measure that is implementable in real-time and without the benefit of hindsight, is not straightforward. In developing such a measure, the following criteria are considered: (i) the measure should capture the market-wide misvaluation in a way that is consistent with the model, and (ii) the misvaluation proxy should be a data-driven metric to avoid look-ahead bias. In the model, the valuation ratio of the market is the equally-weighted average of B/M ratios of all stocks, therefore, empirically the cross-sectional average of the B/M ratios of all stocks is used as a measure of market-wide valuation.[4] To measure the degree of market-wide *misvaluation*, a benchmark for the fair value of stocks is needed. To this end, the long-run historical distribution of the average firm-level B/M ratio is used as the valuation benchmark. This is based on the idea that the long-run B/M average represents the mean value to which 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.

[3]↑Following normal valuation periods, the value premium largely emanates from within-equity extrapolative demand shifts as in Barberis and Shleifer (2003)[1].
[4]↑Going forward, the market-wide or aggregate B/M ratio refers to the cross-sectional average of firm level B/M ratios.

Using this approach, two measures of market-wide misvaluation are proposed, both of which use the cross-sectional distribution of firm-level B/M ratios. The first measure compares the current cross-sectional average B/M ratio to the historical distribution of the (cross-sectional) average B/M ratio.[5] The periods in which the market-wide B/M ratio falls into the tails of the benchmark distribution signal significant market-wide misvaluation (*relative to* its valuation benchmark). 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. The first measure is denoted as RMV, short 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.

The second measure of market-wide misvaluation accounts for the possibility that the entire cross-sectional distribution of B/M ratios (rather than just the cross-sectional mean) contains additional information about whether stocks are misvalued, on average. When the recent cross-sectional distribution of individual B/M ratios deviates significantly to the right (left) of its historical benchmark distribution of B/M ratios, the overall market is likely to be undervalued (overvalued). The distance between the distribution of current firm-level B/M ratios and its historical benchmark distribution can be quantified by using the nonparametric Mann-Whitney U test. The test produces the Mann-Whitney z-statistic for large samples, which is denoted as RMV^{mwz}.[6]

Using these measures, the main predictions of the extended model can be tested empirically. In Section 3.4.2, the results show that, over the sample period from 1968 to 2018, the profitability of the value premium is *conditional* on the degree of market-wide misvaluation.

[5]↑More specifically, at each point in time, t, I use the previous 10 years of the time series of aggregate B/M ratios as the benchmark historical distribution of market-wide valuations. 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 relying on the idea that 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. Similar results can be obtained when using a 20-year rolling window.

[6]↑The corresponding p-value of this statistic is used to identify periods of significant over- or undervaluation. A significantly positive RMV^{mwz} means that the current cross-sectional distribution of B/M ratios shifts to the right relative to the benchmark distribution, indicating market-wide undervaluation. On the other hand, a significantly negative RMV^{mwz} means that the current cross-sectional distribution of B/M ratios shifts to the left relative to the benchmark distribution, signaling market-wide overvaluation.

For example, based on the first misvaluation measure, RMV, in 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 highly 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 overvalued), the value premium is 1.70% per month with high significance. More importantly, in the month following periods in which the aggregate B/M ratio does not fall into the tails of its historical benchmark distribution, the value premium is small and not statistically significant.[7] Similar patterns are obtained for the 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 down to 0.60% per month over the same investment horizon.[8] Similar results can be obtained with the RMV^{mwz} measure. 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.

For the second prediction of the model, the empirical results in Section 3.4.2 show that following a period of extreme market-wide under (over) valuation, the increase in the profitability of the value strategy will stem mainly from the good (poor) performance of value (growth) stocks. The results also show that following periods of normal valuations, the value premium is 0.60% on average and value and growth stocks contribute almost equally to this return spread. 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 the conceptual framework of Barberis and Shleifer (2003)[1] in Chapter 2, in which within-equity demand shifts explain the value premium in normal valuation periods. However, the story is different for the periods following extreme market-wide valuations. Consistent with the predictions of

[7]↑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.
[8]↑The existence of a significant 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. This is consistent both with Barberis and Shleifer (2003)[1] and the extended model.

the extended model, in the one-year horizon following market-wide overvaluation, the value premium is mainly driven by the poor performance of growth stocks. For example, of the 1.22% monthly value premium 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 periods of market-wide undervaluation, the value premium is mainly driven by the poor performance of value stocks. For example, of the 2.80% monthly value premium 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. 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.

Next, some evidence is provided to support the main mechanism of the model, which is related to return extrapolation and extrapolative demand. The main premise here is that when investors become excited about stocks in general, they are particularly excited about growth stocks; and that when they are depressed about the stock market, they are particularly depressed about value stocks. The reason for this is that when stocks on average receive good cash-flow news, these good news are concentrated in growth stocks, pushing their returns higher than those of value stocks, which in turn attracts extrapolators disproportionately more to growth stocks. To this end, the empirical results show that, compared to value stocks, growth stocks do experience significantly higher cash flow shocks (as measured by standardized unexpected earnings) for four quarters leading up to significant market-wide overvaluation. The associated cumulative returns experienced by growth stocks are substantial. For example, over the four quarters leading up to significant market-wide overvaluation, growth stocks experience 73.75% return compared to value stocks' -8.64% cumulative return over the same period. Similarly, over the four quarters leading up to significant market-wide undervaluation, value stocks experience -40% return compared to growth stocks' 21.65% cumulative return over the same period.[9]

Finally, the documented conditional profitability of the value premium could have alternative explanations such as variation in the conditional risk exposures of value and growth stocks (e.g., Petkova and Zhang (2005)[60]) or variation in the value spread (e.g., Cohen, Polk, and Vuolteenaho (2003)[53]). I find that, although the conditional market betas of value and growth stocks vary in the right direction, their magnitude is not high enough to capture the size of the value premium following periods of extreme market-wide misvaluation. Furthermore, I show that the predictive ability of the measures of relative market-wide misvaluation for the value premium survives in the presence of the value spread as an additional predictor.

This chapter contributes to a growing literature on the timing of cross-sectional portfolio returns (e.g., Cooper, Gutierrez, and Hameed (2004)[50], Ali, Daniel, and Hirshleifer (2017)[61], Lou and Polk (2019)[19]). 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)[62], Cohen, Polk, and Vuolteenaho (2003)[53], Asness et al (2021)[63], Baba Yara, Boons, and Tamoni (2021)[64]). This work differs from these prior studies both empirically and conceptually. From an empirical standpoint, it is shown that even after controlling for the value spread used in Cohen, Polk, and Vuolteenaho (2003)[53], as well as other variables, the degree of market-wide misvaluation continues to display significant predictive power for the value strategy. Conceptually, this work shows theoretically and empirically that both cross-sectional and aggregate-level return extrapolation can predict the return of the value strategy. In addition, the theory proposed in this chapter implies that there is asymmetry in the sources of the value premium in good and bad times.

Ever since the value premium was included as part of an asset-pricing model by Fama and French (1993)[41], abundant research debating the sources of the value premium has

[9]↑The pattern is similar in the most recent quarter leading up to significant market-wide misvaluation. During the quarter leading up to significant market-wide overvaluation (undervaluation) growth stocks experience 13.98% (3.04%) return compared to -1.52% (-13.47%) return for value stocks.

emerged. While some argue that the difference in returns between value and growth stocks reflects compensation for risk,[10] others argue that the value effect is a result of mispricing.[11] The second contribution of this work is to document that the value premium is only evident following extreme valuation periods. This cannot be easily reconciled with traditional risk-based stories. The evidence prensented in this chapter provides some supports that the value premium is likely linked to return extrapolation and errors in expectations.

3.2 Conceptual Framework: an Extension from Barberis and Shleifer (2003)

In this section, the original style investing model in Barberis and Shleifer (2003)[1] is extended to a stylized model of financial markets with two types of return extrapolators. One of the key features of the model is the interaction between aggregate demand for equities and the cross-sectional demand within equities for value and growth stocks. The implications about the value premium derived from this model are summarized in Section 3.2.2.

3.2.1 Model Setup

Following the framework of Barberis and Shleifer (2003)[1] that examines an economy populated by extrapolators who form expectations based on past returns, 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 $D_{\mathrm{i},T}$ to be paid at the final date T. The final dividend equals

$$D_{\mathrm{i},T} = D_{\mathrm{i},0} + \epsilon_{\mathrm{i},1} + ... + \epsilon_{\mathrm{i},T}, \tag{3.1}$$

[10]↑For example, Fama and French (1993)[41] link the value premium to distress risk, Lettau and Wachter(2007) [65] offer an explanation based on cash-flow duration, Campbell, Polk, and Vuolteenaho (2010)[66] 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)[67] explain the value premium based on the covariance of cash-flow growth with consumption in the long run, Koijen, Lustig, and Van Nieuwerburgh (2017)[68] argue that the value premium reflects compensation for macroeconomic risk, Zhang (2005)[54] offers an explanation based on costly reversibility and a countercyclical price of risk.

[11]↑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, Lakonishok, Shleifer, and Vishny (1994)[44].

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

$$\epsilon_t = (\epsilon_{1,t}, ..., \epsilon_{2n,t}) \sim N(0, \Sigma_D), \text{ i.i.d. over time.} \tag{3.2}$$

The price per share of risky asset i at time t is $P_{\mathrm{i},t}$ and, for simplicity, the return of risky asset i between time $t-1$ and t is

$$\Delta P_{\mathrm{i},t} = P_{\mathrm{i},t} - P_{\mathrm{i},t-1}. \tag{3.3}$$

Following the style investing model of Barberis and Shleifer (2003)[1], assume that some investors in the economy categorize risky assets into different groups, referred to as styles, and these investors form their demand for risky assets at the style level. Within each style, investors do not distinguish individual stocks when formulating their demand. Risky assets are categorized into two styles, X and Y. Risky assets 1 through n are in style X, and risky assets $n+1$ through $2n$ are in style Y. We denote the value of each style and the market portfolio (a weighted average of risky styles X and Y) as $P_{X,t}$, $P_{Y,t}$, and $P_{M,t}$, respectively, where

$$P_{X,t} = \frac{1}{n}\sum_{\mathrm{i}\in X} P_{\mathrm{i},t}, \quad P_{Y,t} = \frac{1}{n}\sum_{\mathrm{j}\in Y} P_{\mathrm{j},t}, \quad P_{M,t} = \frac{1}{2n}\sum_{l\in X or Y} P_{l,t}. \tag{3.4}$$

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

$$\Delta P_{X,t} = P_{X,t} - P_{X,t-1}, \quad \Delta P_{Y,t} = P_{Y,t} - P_{Y,t-1}, \quad \Delta P_{M,t} = P_{M,t} - P_{M,t-1}. \tag{3.5}$$

Furthermore, we assume that the cash-flow shock covariance matrix has the same structure as in the original model, so that

$$\Sigma^D_{\mathrm{ij}} = \begin{cases} 1 & \mathrm{i} = \mathrm{j}, \\ \psi_M^2 + \psi_S^2 & \text{i,j in the same style, i} \neq \text{j}, \\ \psi_M^2 & \text{i,j in different styles.} \end{cases} \tag{3.6}$$

There are three types of investors in the model: style switchers, asset-class switchers, and fundamental traders. Both style switcher and asset-class switchers have extrapolative expectations, so that they use style's or market's past performance to form their expectations. More specifically, the investment policy of style switchers contains the following two features. First, style switchers allocate their funds at the style level. Second, their demand for one style depends on the style's past performance relative to other styles. As a result, at each point in time, style switchers demand the same number of shares for styles X and Y but with opposite signs. To capture these two features, we write the style switchers' demand for shares of asset i in style X at time t as

$$N_{\mathrm{i},t}^{SS} = \frac{1}{n}\sum_{k=1}^{t-1}\theta^{k-1}(\Delta P_{X,t-k} - \Delta P_{Y,t-k}) = \frac{N_{X,t}^{SS}}{n}, \tag{3.7}$$

where θ is a constant with $0 < \theta < 1$, which measures the weight style switchers put on the more recent returns of each style. Similarly, the style switchers' demand for shares of asset j in style Y at time t is

$$N_{\mathrm{j},t}^{SS} = \frac{1}{n}\sum_{k=1}^{t-1}\theta^{k-1}(\Delta P_{Y,t-k} - \Delta P_{X,t-k}) = \frac{N_{Y,t}^{SS}}{n}. \tag{3.8}$$

The equations above reinforce the idea that style switchers' demand for all assets from a given style is the same since they allocate their funds at the style level.

This model extends Barberis and Shleifer (2003)[1] by introducing an additional type of investors that are referred as asset-class switchers. Similar to style chasers, asset-class switchers demand risky assets at the style level and form expectations about the aggregate market based on its past performance. Their distinctive feature is that they observe the aggregate market performance and reallocate funds accordingly between risky assets and cash. Specifically, when asset-class switchers observe that the aggregate market has done well, they decide to invest more in risky assets. While doing so, they allocate their funds to the better-performing styles in the market. On the other hand, when they observe that the aggregate market has performed poorly, they decide to withdraw their funds from risky assets by selling relatively worse-performing styles in the market.

Suppose that asset-class switchers have CARA preferences. To determine their demand for a risky asset, asset-class switchers solve

$$\underset{N_{M,t}^{AS}}{\text{Max}} \; E_t^{AS}[-\mathrm{e}^{-\gamma(W_t^{AS}+N_{M,t}^{AS}(\tilde{P}_{M,t+1}-P_{M,t}))}], \tag{3.9}$$

where $P_{M,t}$ is defined in Eq.(3.4). If conditional market price changes follow a Normal distribution, the optimal market holding of asset-class switchers, $N_{M,t}^{AS}$, is given by

$$N_{M,t}^{AS} = \frac{1}{\gamma} \times Var_t^{AS}(\Delta P_{M,t+1})^{-1} E_t^{AS}[\Delta P_{M,t+1}]. \tag{3.10}$$

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

$$E_t^{AS}(\Delta P_{M,t+1}) = \theta E_{t-1}^{AS}(\Delta P_{M,t}) + (1-\theta)\Delta P_{M,t-1}, \tag{3.11}$$

which implies

$$E_t^{AS}(\Delta P_{M,t+1}) = (1-\theta)\sum_{k=1}^{t-1}\theta^{k-1}\Delta P_{M,t-k}. \tag{3.12}$$

Combining Eq.(3.10) and Eq.(3.12), we can write the demand function of asset-class switchers as

$$N_{M,t}^{AS} = \sum_{k=1}^{t-1}\theta^{k-1}\Delta P_{M,t-k}. \tag{3.13}$$

The equation above shows that asset-class switchers' demand for risky assets is an increasing function of the past performance of the market.

Without loss of generality, suppose that style X has a relatively higher return than style Y. To capture the idea that asset-class switchers' demand for risky assets will be directed mainly to the better-performing styles within the market, the asset-class switchers' demand for shares of asset i in style X, $N_{\mathrm{i},t}^{AS}$, is written as

$$N_{\mathrm{i},t}^{AS} = \begin{cases} 2N_{M,t}^{AS} & \text{if } N_{M,t}^{AS} > 0 \\ 0 & \text{if } N_{M,t}^{AS} \leq 0. \end{cases} \tag{3.14}$$

Similarly, the asset-class switchers' demand for shares of asset j in style Y, $N_{\mathrm{j},t}^{AS}$, is written as

$$N_{\mathrm{j},t}^{AS} = \begin{cases} 0 & \text{if } N_{M,t}^{AS} > 0 \\ 2N_{M,t}^{AS} & \text{if } N_{M,t}^{AS} \leq 0. \end{cases} \tag{3.15}$$

Combining style switchers' and asset-class switchers' demand, total share demand from extrapolators, N_t^E, is

$$N_t^E = N_t^{SS} + N_t^{AS}, \tag{3.16}$$

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

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

$$\underset{N_t^F}{\mathrm{Max}} \;\; E_t^F[-\mathrm{e}^{-\gamma(W_t^F + N_t^F(\tilde{P}_{t+1} - P_t))}], \tag{3.17}$$

where

$$N_t^F = (N_{1,t}^F, ..., N_{2n,t}^F), \quad P_t = (P_{1,t}, ..., P_{2n,t}). \tag{3.18}$$

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

$$N_t^F = \frac{1}{\gamma} \times Var_t^F(\Delta P_{t+1})^{-1} E_t^F[\Delta P_{t+1}]. \tag{3.19}$$

Therefore, in contrast to style-switchers and asset-class switchers, who extrapolate past prices, fundamental traders are forward-looking in their expectations about prices.

As in Barberis and Shleifer (2003)[1], 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.(3.19) results in

$$P_t = E_t^F(P_{t+1}) - \gamma Var_t^F(\Delta P_{t+1})(Q - N_t^E), \tag{3.20}$$

where N_t^E is defined in Eq.(3.16). The price forecast of fundamental traders is based on their conditional expectation of the final dividend, D_T. At time $T-1$, we have

$$E_{T-1}^F(P_T) = E_{T-1}^F(D_T) = D_{T-1}. \tag{3.21}$$

Following the derivation of the original model of Barberis and Shleifer (2003)[1], we roll Eq.(3.20) forward iteratively and further assume that $Var_t^F(\Delta P_{t+1}) = V$ and $E_t^F(N_{t+k}^E) = \bar{N}^E$. Therefore, it follows that

$$P_t = D_t - \gamma V(Q - N_t^E) - (T - t - 1)\gamma V(Q - \bar{N}^E). \tag{3.22}$$

Dropping the non-stochastic terms, we obtain

$$P_t = D_t + \gamma V(N_t^{SS} + N_t^{AS}). \tag{3.23}$$

This equation reveals that fundamental traders cannot push prices back to fundamental values. In this model, as in the original Barberis and Shleifer (2003)[1] model, fundamental traders cannot eliminate mispricing. Therefore, demand shifts by style-switchers and asset-class switchers can influence the price of risky assets.[12]

3.2.2 Impulse Response Functions

The stylized model above represents a conceptual framework for the analysis of value and growth styles in the presence of switchers with extrapolative beliefs. To understand the

[12]↑Barberis and Shleifer (2003)[1] point out that if institutions are the style-switchers in the model, then the model is consistent with evidence in Gompers and Metrick(2001)[69] that institutional demand influences security prices.

effect of switchers on the prices of value and growth stocks, the model is used to generate impulse response functions. Following Barberis and Shleifer (2003)[1], some of the driving parameters in the model aren set to the following values: $\psi_M = 0.25$, $\psi_S = 0.5$, $\theta = 0.95$, $\gamma = 0.093$, and $\sigma_\epsilon = 3$. Suppose that the price covariance matrix has the same structure as the cash-flow covariance matrix Σ_D. I set $T = 30$, $\boldsymbol{Q} = \mathbf{0}$, and $n = 50$, so that there are 100 risky assets in a zero net supply, of which the first 50 belong to style X and the last 50 belong to style Y. At $t = 0$, the initial price of risky assets $D_{\mathrm{i},0}$ is \$50. The following three cases are simulated: a benchmark case in which the aggregate market receives a zero cash-flow shock, an overvalued market in which the market receives a positive shock, and an undervalued market in which the market receives a negative shock. In the benchmark case, the only active extrapolators are the style switchers. In the other two cases, asset-class switchers also enter the market.

The impulse response functions are obtained from a simulation that follows several steps. The initial value of V is set to Σ_D. Then for a given randomly-generated shock, Eq.(3.23) is used to calculate the prices of risky assets. This is used to calculate a new price covariance matrix $\hat{V}$. Then use $\hat{V}$ to calculate a new set of prices for risky assets. This process is repeated until $\hat{V}$ converges. The model convergence can be achieved for a wide range of parameter choices.[13]

Benchmark Case

In the benchmark scenario, the aggregate market receives a net zero cash-flow shock. Styles X and Y receive a one-time shock at $t = 1$, where

$$\epsilon_{\mathrm{i},1} = \kappa,\ \epsilon_{\mathrm{i},t} = 0,\ t > 1,\ \forall \mathrm{i} \in X, \tag{3.24}$$

$$\epsilon_{\mathrm{j},1} = -\kappa,\ \epsilon_{\mathrm{j},t} = 0,\ t > 1,\ \forall \mathrm{j} \in Y, \tag{3.25}$$

[13]↑Consistent with Barberis and Shleifer (2003)[1], for these parameter values, style returns in the benchmark case have a standard deviation 1.3 times the standard deviation of cash-flow shocks. In this model, style returns have a standard deviation 1.33 times the standard deviation of cash-flow shocks. The higher return volatility in our model comes from the additional demand of asset-class switchers.

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 level. In the cross section of risky assets, style X receives a positive cash-flow shock, while style Y receives a negative cash-flow shock. As a result, style X has a higher return than style Y, which leads to style switchers buying more of style X and decreasing their holdings in style Y. Figure 3.2 shows the evolution of prices for the aggregate market, $P_{M,t}$, style X, $P_{X,t}$, and style Y, $P_{Y,t}$, defined in Eq.(3.4), after a one-time cash-flow shock with $\kappa = 1$ at $t = 1$.

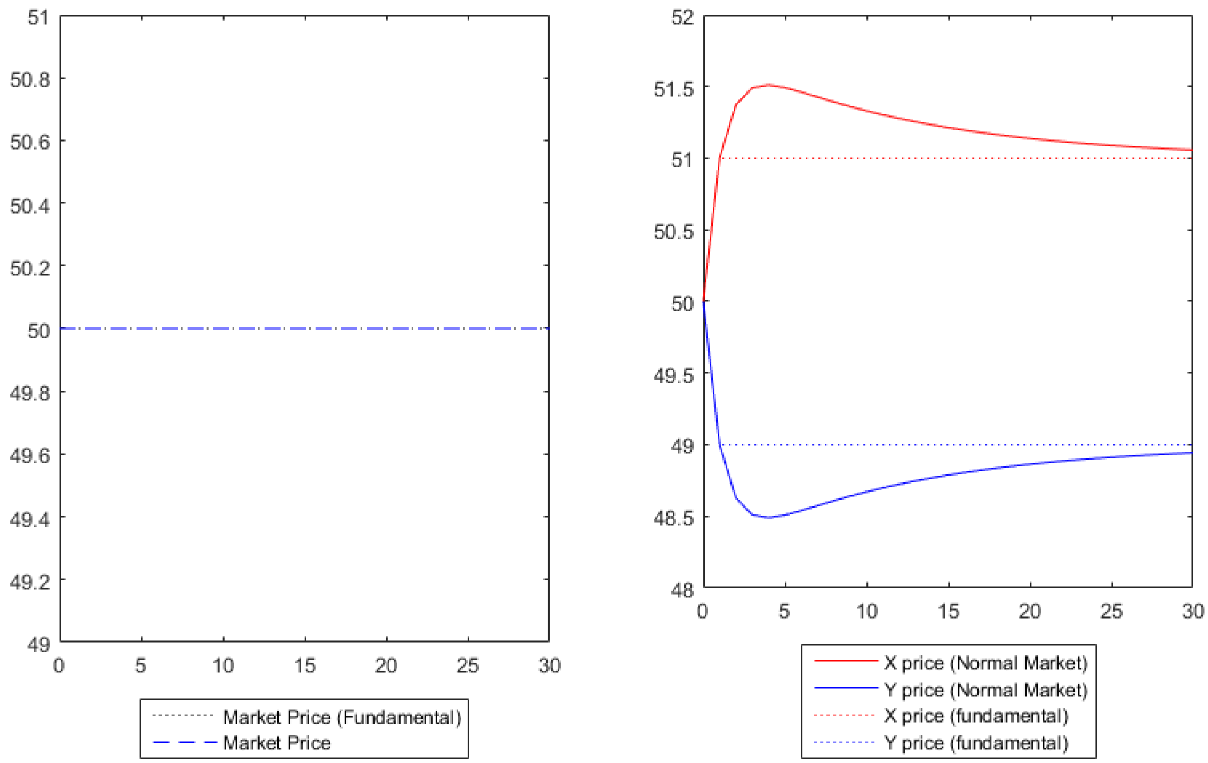

Figure 3.2. Price Impulse Responses to Style-level Cash-flow Shocks with Only Style Switchers
The left figure plots the evolution of the aggregate market price after a one-time style-level cash-flow shock. In the right figure, the solid lines show the evolution of prices for style X (blue solid line) and style Y (red solid line). Prices for both X and Y are initially \$50. At time $t = 1$, style X receives a \$1 per share cash-flow shock, while style Y receives a -\$1 per share cash-flow shock. For comparison, dashed lines show fundamental values, or prices without extrapolators.

In the right panel of Figure 3.2, consistent with the style investing model of Barberis and Shleifer (2003)[1], the good cash-flow news about X pushes its price up to \$51 at $t = 1$. This attracts style switchers' attention and increases their demand for X. The presence of style switchers leads to a substantial deviation of X's price from its fundamental value. Similarly, for style Y, the negative cash-flow news pushes Y's price down to \$49 at $t = 1$, which leads to style switchers moving away from Y and into X. Style switchers 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 fundamental values. In the right panel of Figure 3.2, in the presence of only style switchers, price deviations from fundamental values are symmetric for X and Y. Thus, at the aggregate level, the market price does not deviate from its fundamental value (left panel). We refer to this case as the normal market state. This result indicates that, in the benchmark case, mispricing exists only at the style-level, but not at the aggregate market level. The value premium would be realized as the mispricing is corrected.

Overvalued Market

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

$$\epsilon_{\mathrm{i},1} = \kappa_X,\ \epsilon_{\mathrm{i},t} = 0,\ t > 1,\ \forall \mathrm{i} \in X, \tag{3.26}$$

$$\epsilon_{\mathrm{j},1} = \kappa_Y,\ \epsilon_{\mathrm{j},t} = 0,\ t > 1,\ \forall \mathrm{j} \in Y, \tag{3.27}$$

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. I further assume that asset-class switchers' demand for risky assets will be fulfilled by investing in relatively better preforming risky styles. More specifically, the cash flow shocks are set to $\kappa_X = 2.5$ and $\kappa_Y = 0.5$. At the aggregate level, the market price of risky assets increases from \$50 to \$51.5. After observing this, extrapolative asset-class switchers decide to increase their holdings in risky assets by investing in the better-performing style X only. In the cross section of risky assets, style X receives relatively better cash-flow news than style Y, leading to a higher return for style X. As a result, style switchers still buy more of style X and decrease their holdings of style Y. Figure 3.3 shows the evolution of prices for the market, $P_{M,t}$, style X, $P_{X,t}$, and style Y, $P_{Y,t}$, defined in Eq.(3.4), after a one-time cash-flow shock with $\kappa_X = 2.5, \kappa_Y = 0.5$ at $t = 1$.

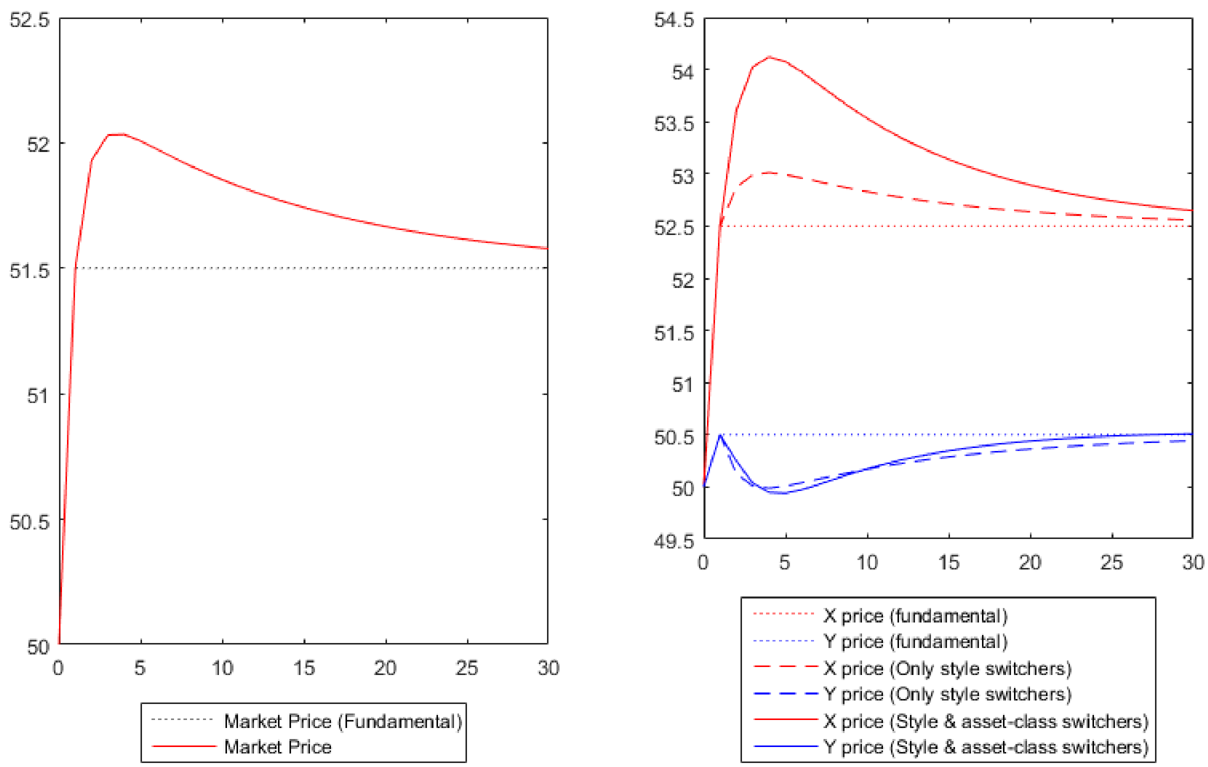

Figure 3.3. Price Impulse Responses to Cash-flow Shocks with Style Switchers and Asset-class Switchers in an Overvalued Market

The left figure plots the evolution of aggregate market price of risky assets after the one-time style-level cash-flow shocks. In the right figure, the solid lines show the evolution of prices of style X (the blue solid line) and Y (the red solid line) in the presence of both style switchers and asset-class switchers. For comparison, the dashed lines show the prices of X and Y with only style switchers in the economy. The dotted lines show the fundamental values, or the prices without extrapolators. Prices of both X and Y are initially \$50. At time $t = 1$, style X receives \$2.5 per share cash-flow shock, while style Y receives \$0.5 per share cash-flow shock.

The left panel of Figure 3.3 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 fundamental value, we refer to this scenario as an overvalued market.

The right panel of Figure 3.3 shows, in the cross section, style-level price impulse responses with both style switchers and asset-class switchers present (solid lines), and only style switchers present (dashed lines). The positive cash-flow news about X and Y pushes their prices up to \$52.5 and \$50.5, respectively, at $t = 1$ (dotted lines). The relative outperformance of X attracts style switchers' attention and increases their demand for X. To finance their additional demand for X, style switchers sell some of their holdings in Y. As a result, style switchers push Y's price down and away from its fundamental value, while they drive X's price even higher. In the presence of asset-class switchers, their additional demand for style X creates an even higher increase in X's price, resulting in asymmetric price changes in styles X and Y.

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

The impulse response functions in Figure 3.3 reveal the first implication of this extended model for the behavior of the value premium.

***Model 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 val-*

uation. In addition, the larger the magnitude of overvaluation of the market, the larger a 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 the growth style.

Undervalued Market

The third scenario is that the aggregate market receives net negative cash-flow news. In this case, both styles X and Y receive a one-time shock at $t = 1$, where

$$\epsilon_{\mathrm{i},1} = \kappa_X,\ \epsilon_{\mathrm{i},t} = 0,\ t > 1,\ \forall \mathrm{i} \in X, \tag{3.28}$$

$$\epsilon_{\mathrm{j},1} = \kappa_Y,\ \epsilon_{\mathrm{j},t} = 0,\ t > 1,\ \forall \mathrm{j} \in Y, \tag{3.29}$$

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. I further assume that asset-class switchers' lower demand for risky assets will be fulfilled by selling relatively underperforming risky styles. More specifically, the cash flow shocks are set to $\kappa_X = -0.5$ and $\kappa_Y = -2.5$. At the aggregate level, the market price of risky assets decreases from \$50 to \$48.5, which prompts asset-class switchers to leave the risky asset market by selling the underperforming style Y. In the cross section, where style switchers play a more important role, style X still receives relatively better cash-flow news than style Y. This leads to an increase in the price of X and a decrease in the price of Y. As a result, style switchers buy more of style X and decrease their holdings of style Y. Figure 3.4 shows the evolution of prices for the market, $P_{M,t}$, style X, $P_{X,t}$, and style Y, $P_{Y,t}$, defined in Eq.(3.4), after a one-time cash-flow shock with $\kappa_X = -0.5, \kappa_Y = -2.5$ at $t = 1$.

Similar to the case of an overvalued market, the left panel of Figure 3.4 shows that asset-class switchers observe the decline in market price at $t = 1$ and decide to decrease their holdings in risky assets. Their outflows cause the market price to decrease even further, therefore, deviating from fundamental value. The right panel of Figure 3.4 shows the results in the cross section. In contrast to the case of an overvalued market, asset-class switchers sell style 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 styles X and Y compared to style switchers. Therefore, in the case of an undervalued market, asset-class switchers amplify style switchers' demand as well. When the price of style Y reverts back to fundamental value, the price change is larger in magnitude than under the benchmark case.

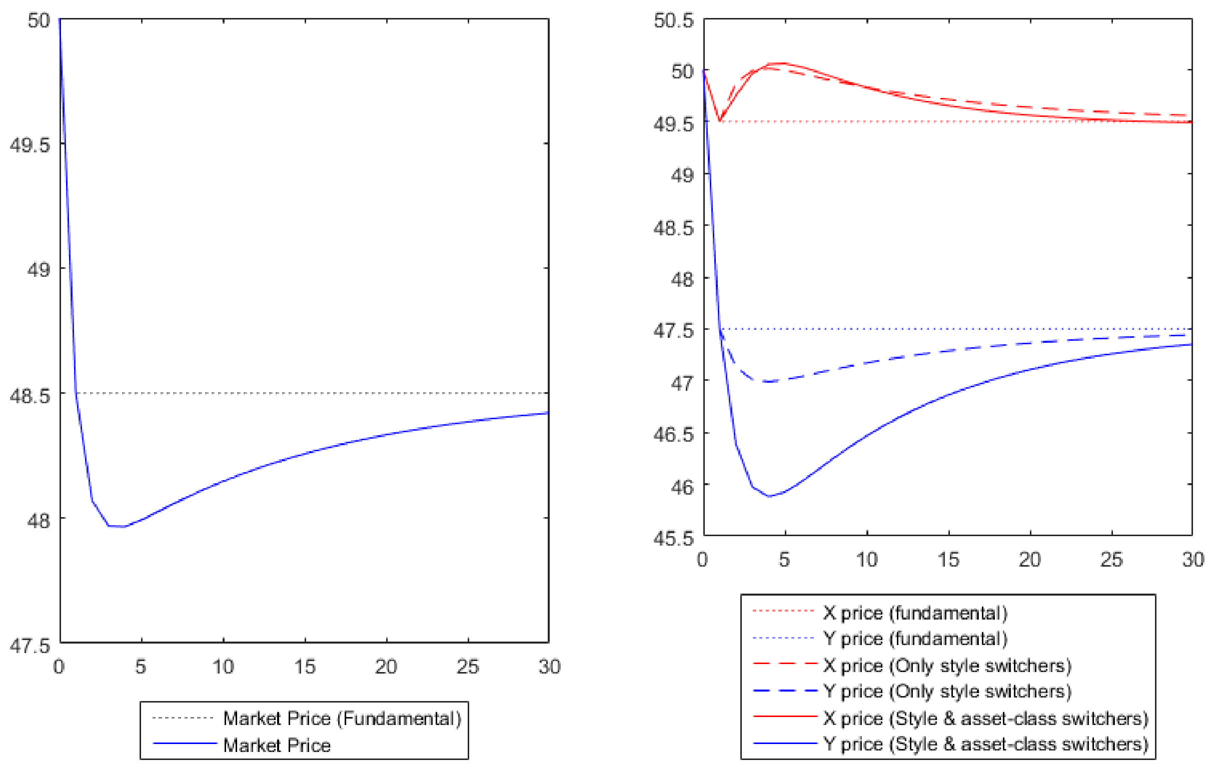

Figure 3.4. Price Impulse Responses to Cash-flow Shocks with Style Switchers and Asset-class Switchers in an Undervalued Market

The left figure plots the evolution of aggregate market price of risky assets after the one-time style-level cash-flow shocks. In the right figure, the solid lines show the evolution of prices of style X (the blue solid line) and Y (the red solid line) in the presence of both style switchers and asset-class switchers. For comparison, the dashed lines show the prices of X and Y with only style switchers in the economy. The dotted lines show the fundamental values, or the prices without extrapolators. Prices of both X and Y are initially 50. At time $t = 1$, style X receives -\$0.5 per share cash-flow shock, while style Y receives -\$2.5 per share cash-flow shock.

The impulse response functions in Figure 3.4 reveal the second implication of the extended model for the behavior of the value premium.

Model 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, the larger the correction will be needed for prices to revert back 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 value style.*

Simulation under Different Degrees of Over- or Undervaluation

Based on the analysis so far, the model implies that the value premium will be higher in cases in which the aggregate market is under- or overvalued. The profitability of implementing a value strategy is also expected to be higher in cases of a higher degree of under- or overvaluation of the market.

To illustrate the implications of the model numerically, I use simulated data. Under the framework of the model, growth and value styles are identified by using a price-to-fundamental ratio, P/F. A style is defined as growth if $P/F > 1$, while a style is defined as value if $P/F < 1$. The same parameter values are used as in the previous simulation. The simulation results are summarized in Table 3.1, which examines several scenarios from our model with different levels of market under- or overvaluation.

In Table 3.1, *Market condition* indicates whether the market is undervalued, normal, or overvalued. *Shock to growth* and *Shock to value* show the cash-flow shocks given to styles X and Y in different scenarios. *Shock to market* is the average of *Shock to growth* and *Shock to value*. 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. *Max of Price gap* is the maximum of the price difference between styles X and Y. *Growth price deviation* and *Value price deviation* are the maximum of the absolute difference between price and fundamental value for styles X and Y, respectively. *Growth 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. *Value 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. *Value premium (%)* is the difference between *Value return (%)* and *Growth return (%)*. *Dollar gain from value strategy ($)* is the wealth increase of buying one share of the value style and shorting one share of the growth style at t, and selling the value style and buying back the growth style at T. Time t is the time when the price of the growth style reaches its peak and the price of the value style reaches its bottom.

The results indicate that, in normal times, the value premium is 1.82% emanating from within-class style switching. The value premium is much larger when the aggregate market has deviated from fundamental value. More specifically, when the aggregate market receives a shock of $1.5 per share, the value premium is 3.84%. On the other hand, when the aggregate market receives a shock of -$1.5 per share, the value premium is 4.33%. Furthermore, in an overvalued market, the value premium mostly results from the relative underperformance of growth stocks. In an undervalued market, the value premium is mostly driven by the relative outperformance of value stocks.

This model also provides implications on the optimal timing of implementing a value strategy. When we observe significant deviations from fundamental value at the aggregate level, the optimal time to buy value stocks and short growth stocks is when the market P/F has reached its peak or bottom. This result sheds light on the time-series properties of the value premium. Namely, the value premium is higher following times when the aggregate P/F deviates significantly from its normal valuation, which will be proxied by the long-run average of the aggregate P/F ratio.[14]

[14]↑As will be explained later, significant deviation will be calculated as the period in which the P/F ratio of the market falls into the tails of its long-run historical distribution. This implicitly assumes that the long-run average reflects the normal or fair valuation of the market. We note that even when the aggregate market is fairly priced on average, it is possible to have misvaluation at an individual stock level, and the value premium will mainly be driven by asset-class level style switching.

Table 3.1. Model Simulation of Value Premium under Different Levels of Market-Wide Under- or Overvaluation

This table reports the simulated results related to value premium under different level of market-wide overvaluation or undervaluation. *Market condition* indicates whether the market is undervalued, normal, or overvalued. *Shock to growth stocks* and *Shock to value stocks* show the cash-flow shocks given to style X and Y in different scenarios. *Shock to market* is the average of *Shock to growth stocks* and *Shock to value stocks*. If *Shock to market*$= 0$, then we define the case as normal market. If *Shock to market*> 0, then we define the case as overvalued market. If *Shock to market*< 0, then we define the case as undervalued market. *Max(Price gap)* is the maximum of the price difference between style X and Y. *Growth stock price deviation* and *Value stock price deviation* are the maximum of the absolute difference between price and fundamental value for style X and Y, respectively. *Growth return (%)* is calculated as $\frac{P_{X,T}-P_{X,t}}{P_{X,t}}$, where t is the time when X's price reaches to the peak, and T is the terminal date. *Value return (%)* is calculated as $\frac{P_{Y,T}-P_{Y,t}}{P_{Y,t}}$, where t is the time when Y's price reaches to the bottom, and T is the terminal date. *Value premium (%)* is the difference between *Value return (%)* and *Growth return (%)*.

Market condition	Shock to market	Shock to growth	Shock to value	Max of Price gap	Growth price deviation	Value price deviation	Growth return (%)	Value return (%)	Value premium (%)
Overvalued	1.5	2.5	0.5	4.17	1.62	0.56	-2.72	1.12	3.84
Overvalued	1.0	2.0	0.0	3.81	1.26	0.55	-2.15	1.09	3.23
Overvalued	0.5	1.5	-0.5	3.45	0.90	0.55	-1.56	1.05	2.60
Normal	0.0	1.0	-1.0	3.02	0.51	0.51	-0.88	0.94	1.82
Undervalued	-0.5	0.5	-1.5	3.45	0.55	0.90	-1.00	1.71	2.72
Undervalued	-1.0	0.0	-2.0	3.81	0.55	1.26	-1.06	2.45	3.51
Undervalued	-1.5	-0.5	-2.5	4.17	0.56	1.62	-1.12	3.21	4.33

3.3 Data

The sample period for the main analyses is January 1962 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 U.S., and traded on NYSE, Amex, or Nasdaq. Monthly returns are adjusted for delisting.[15] Stocks with price less than $1, financial firms, and utility firms are excluded from the sample.

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 tax credit (if available), minus the book value of preferred stock. Depending on availability, I use the redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock.[16] I use the shareholders' equity number as reported by Compustat. If these data are not available, I calculate shareholders' equity as the sum of common and preferred equity. If neither is available, shareholders' equity is defined as the difference between total assets and total liabilities. The earnings used in year t are total earnings before extraordinary items for the last fiscal year end in $t-1$. The cash flows used in year t are total earnings before extraordinary items, plus equity's share of depreciation, plus deferred taxes (if available) for the last fiscal year end in $t-1$. Based on Asness and Frazzini (2013)[58], the book-to-market ratios (B/M) are calculated on a monthly basis, where the book equity is from the last fiscal year end and market value is updated at the end of every month. Book equity is updated annually, at the end of each June. Similarly, for robustness, I also calculate earnings-to-price ratios (E/P) and cash flow-to-price ratios (CF/P) on a monthly basis, where earnings and operating cash flows are from last fiscal year and they are updated annually. Stocks with negative book equity (earnings, cash flows) are excluded when forming portfolios based on B/M (E/P, CF/P). To measure flows to domestic equity

[15]↑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)[56]) and -55% for Nasdaq stocks (Shumway and Warther (1999)[57])

[16]↑On Ken French's website, it mentions "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.

and bond funds, I obtain data from the Investment Company Institute (ICI). Appendix A contains detailed descriptions of data sources, sample coverage, and variable calculations.

3.4 Methodology and Results

The conceptual framework outlined in Section 3.2 implies that the magnitude of the value premium will vary conditionally on the state of market-wide valuation. In particular, the model predicts that the value premium will be larger following market-wide under- or overvaluation. The test of this implication is proceeded in two steps. First, construct measures of market-wide misvaluation based on aggregate B/M ratios. Then, document the conditional performance of the value premium following periods of market-wide under- and overvaluation.

3.4.1 Market-wide Misvaluation Measures

This section starts with 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.[17] To identify periods of market-wide under- or overvaluation, a data-driven and recursively-updated approach is proposed, which does not suffer from a look-ahead bias. Specifically, for each month t in the sample, I use the past 10 years of the time series of market-wide B/M ratios from $t-119$ to $t-1$, and 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. This measure is referred to as relative market-wide valuation, denoted as RMV. The values for the RMV measure are in the interval (0,1]. Periods of significant market-wide misvaluation are identified using the tails of the RMV variable. For example, if the current market-wide B/M is in the bottom 5% of the benchmark historical distribution, it is denoted as $RMV_{0.05}$ and designated as a period of market-wide overvaluation. If the most recent market-wide B/M is in the top 5% of the historical distribution, it is denoted

[17]↑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).

as $RMV_{0.95}$ and designated as a period of market-wide undervaluation.[18] Therefore, the subscript of RMV represents the placement of the most recent market-wide B/M ratio in the recursively estimated historical benchmark distribution. Finaaly, the normal times are defined 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 use pre-specified filters to define misvaluation, I let the historical data drive the definition of market valuation states.

The RMV measure is an intuitive measure of market-wide valuation, however, since it is based on a cross-sectional average, it may be sensitive to the extreme valuation of just a few stocks. In addition, it does not take into account the higher moments of the cross-sectional B/M distribution. To ensure that the main results are robust to the presence of outliers and to use the full information embedded in the cross-sectional distribution of B/M, an alternative measure is proposed 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, one 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. Based on the implications of the extended model in Section 3.2, following these periods, the value premium is likely to be large. To 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, I employ the Mann-Whitney[70] U test. The test produces the Mann-Whitney z-statistic for large samples, denoted as MWZ, which is used to test the null hypothesis that the current cross-sectional distribution of valuation ratios is the same as the historical benchmark.

Based on the MWZ statistic, I calculate an alternative market-wide valuation measure, denoted as RMV^{mwz}. Specifically, in each month t, I obtain the cross section of firm-level B/M ratios as the current distribution of valuations. For this measure, the historical bench-

[18]↑For robustness, I use the 5^{th}, 10^{th}, 20^{th}, 80^{th}, 90^{th}, and 95^{th} percentiles of the historical distribution of the market-wide B/M to define the tails of the distribution.

mark distribution is constructed by pooling all cross-sectional distributions of B/M ratios from $t-119$ to $t-1$. Then I extract the centiles (from 1^{st} to 99^{th}) from the current distribution to form an approximate current distribution, and also extract the centiles from the historical benchmark distribution to form an approximate benchmark distribution. The Mann-Whitney U-test is conducted by using the two approximate distributions, which produces the final statistics as z-statistics. Therefore, the values of the RMV^{mwz} measure are actually 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, three levels of significance are examined and the corresponding RMV^{mwz} are denoted as $RMV_{0.01}^{mwz-}$, $RMV_{0.05}^{mwz-}$, and $RMV_{0.10}^{mwz-}$, where "-" stands for a negative z-statistic.[19] 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. Similarly, the three levels of significance are 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, the normal times are defined 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.[20]

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

[20]↑One other potential measure is market's P/E ratio, which is essentially equivalent to the value-weighted average of individual stocks' P/E ratios. This measure is not used 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 in horizons 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.

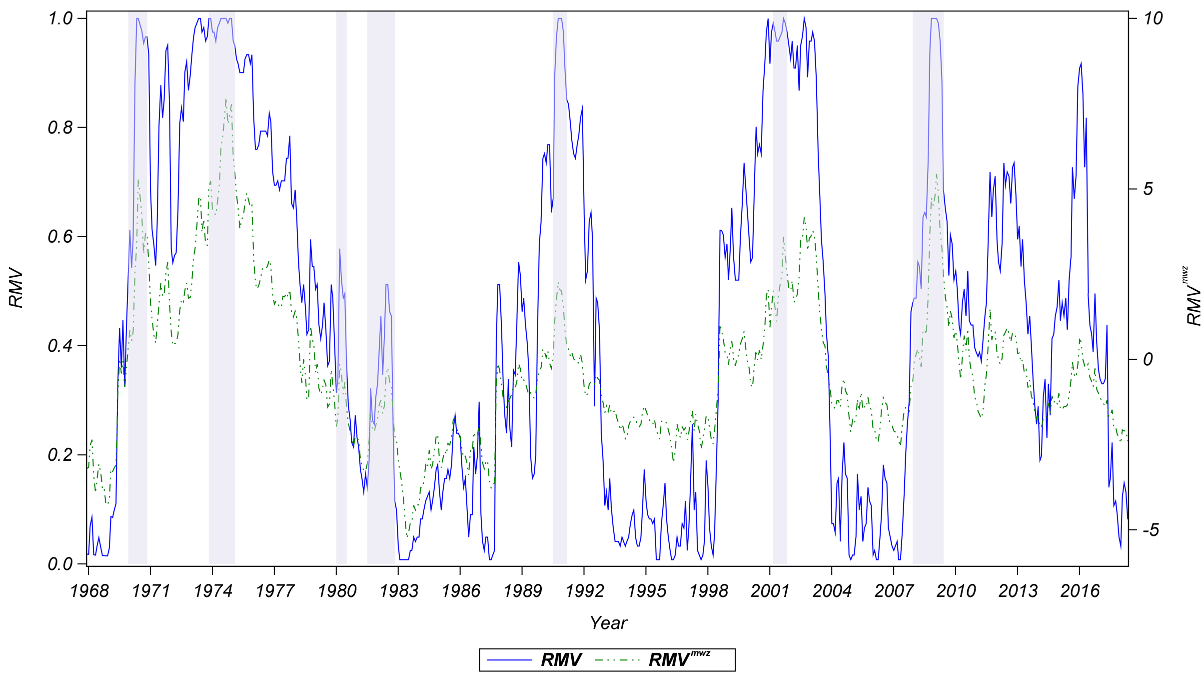

Figure 3.5. Time Series of RMV and RMV^{mwz}

This figure plots the time series of RMV (blue solid) and RMV^{mwz} (green dotted), together with $NBER$ recessions (shaded areas), from January 1968 to December 2018. The left y-axis corresponds to the time series of RMV, while the right y-axis corresponds to the time series of RMV^{mwz}. Detailed variable definitions are in Appendix A.

Figure 3.5 plots the time series of RMV (left axis) and RMV^{mwz} (right axis) over the entire sample period, together with NBER recession periods. Higher (lower) levels of RMV and RMV^{mwz} correspond to market-wide undervaluation (overvaluation). The figure shows that both measures of market-wide valuation line up with historical periods during which the market has been described as under- or overvalued. For example, the low values of both RMV and RMV^{mwz} in the buildup to the Tech Bubble period correspond to states of market overvaluation. The gradual increase in the values of RMV and RMV^{mwz} during the recent Great Recession indicates that the market was undervalued by the end of the recession and

Also note that extrapolative beliefs exhibit a mean reverting behavior in shorter horizons (results are available upon request), thus making the RMV measures a more appropriate metric within our framework. Moreover, since I am measuring the value premium using equal-weighted portfolio returns, using equal weighting to measure market-wide misvaluation is internally consistent. Nevertheless, when using market's P/E ratio (measured as the value-weighted P/E ratio of individuals stocks) and classify value and growth stocks using P/E sorts, we find that the value-weighted value-premium is only significant following states of market-wide misvaluation. (As expected, the pattern is weaker compared to equal-weighted results.)

subsequently experienced a correction. It is interesting to note that while both measures tend to spike during NBER recessions, periods of undervaluation happen during expansions as well. This suggests that RMV and RMV^{mwz} contain information independent of the business cycle as measured by NBER recessions.

3.4.2 Value Premium Conditional on Market-Wide Misvaluation

Within the framework of the model in Section 3.2, the RMV and RMV^{mwz} measures can be viewed as signals which indicate when extrapolators have been active for a while in pushing prices away from fundamental values. Therefore, price corrections should be observed in the data following extreme market-wide valuations. For example, in periods in which the market-wide B/M ratio is way above historical levels, the right tail of the distribution of individual B/M ratios is also likely to be significantly above historical levels. This implies that value stocks have become so undervalued that a reversal in their prices is imminent. Similarly, if the market-wide B/M ratio is significantly below historical benchmarks, then the left tail of the distribution of individual B/M ratios is also likely to be significantly below historical levels. This implies that growth stocks have become so expensive that a reversal in their prices is likely. This section examines the performance of the value premium conditional on three market-wide states: overvaluation, undervaluation, and normal times, as measured by RMV and RMV^{mwz}.

Table 3.2 reports monthly equal-weighted portfolio returns for value stocks, growth stocks, and the value premium under scenarios with different degrees of market-wide misvaluation. In Panel A market-wide misvaluation is measured using RMV, while in Panel B it is measured using RMV^{mwz}. The table also shows under each valuation scenario the average market-wide B/M ratio, the average returns over the 12 months before misvaluation, the one month following market-wide misvaluation, and the 12 months following misvaluation. This examines the whole pattern of returns around times characterized by market-wide over- or undervaluation.

Panel A of Table 3.2 shows that following periods with a high degree of 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 over the first 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. This is in line with the predictions of our model in Section 3.2.

Following periods with high degree of 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 first 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.

Table 3.2 also reports the average returns of value and growth stocks over a 12-month period before portfolio formation. The evidence shows that before portfolio formation, growth stocks tend to experience a run-up in price leading to market-wide overvaluation relative to a normal market. Value stocks, on the other hand, tend to experience a decline in price before portfolio formation in an undervalued market. On average, across all valuation measures, the prices of growth stocks tend to decline after portfolio formation in an overvalued market. In an undervalued market, the prices of value stocks tend to increase after portfolio formation.

Next, in Panel B of Table 3.2, the analysis in Panel A of Table 3.2 is repeated by substituting our RMV measure with RMV^{mwz}. A comparison between the results in Panels A and B of Table 3.2 reveals that RMV and RMV^{mwz} measures identify similar under- and overvaluation periods, i.e., they have a similar number of observations and average valuation levels. Using RMV^{mwz}, the table shows that following periods with a high degree of market-wide overvaluation, the value premium one month after formation varies from 0.93% to 2.45% per month depending on the significance level of MWZ. Following periods with a high degree of market-wide undervaluation, the value premium one month after formation varies from 2.65% to 3.32% per month depending on the significance level of MWZ, and it is statistically

Table 3.2. Market-wide Misvaluation and the Value Premium, 1968-2018

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. Variable definitions are described in Appendix A. 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 measure market-wide misvaluation by RMV (Panel A) and RMV^{mwz} (Panel B). In each panel, 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 previous 12 months, the next 1 month, and the next 12 months. Newey-West t-statistics are reported in brackets.

Panel A. Using RMV misvaluation measure

				12 months prior			1 month			12 months		
condition	N	Market B/M	Value spread	V	G	VmG	V	G	VmG	V	G	VmG
Overvalued ($RMV_{0.05}$)	85	0.54	2.05	-0.11	5.05	-5.16	1.22	-1.02	2.24	0.58	-0.71	1.29
				[-0.30]	[10.82]	[-14.61]	[2.21]	[-1.67]	[5.97]	[1.72]	[-2.36]	[3.47]
Overvalued ($RMV_{0.10}$)	129	0.55	2.07	-0.35	4.64	-4.99	1.22	-0.48	1.70	0.94	-0.28	1.22
				[-1.02]	[11.96]	[-15.22]	[2.62]	[-0.82]	[4.30]	[2.74]	[-0.92]	[4.05]
Overvalued ($RMV_{0.20}$)	195	0.59	2.06	-0.73	4.22	-4.95	1.31	-0.18	1.49	1.03	-0.09	1.12
				[-2.31]	[10.93]	[-17.08]	[3.78]	[-0.42]	[5.02]	[3.65]	[-0.36]	[4.50]
Normal (RMV_{normal})	285	0.79	2.12	-1.35	4.07	-5.41	1.36	1.37	-0.01	1.56	0.96	0.60
				[-3.55]	[9.81]	[-11.61]	[3.03]	[3.25]	[-0.03]	[4.40]	[2.87]	[2.64]
Undervalued ($RMV_{0.80}$)	120	1.18	2.41	-3.20	2.30	-5.50	2.94	0.02	2.91	3.31	0.75	2.56
				[-5.00]	[4.26]	[-9.03]	[2.83]	[0.03]	[4.19]	[3.74]	[1.18]	[4.92]
Undervalued ($RMV_{0.90}$)	91	1.26	2.43	-3.74	1.75	-5.49	3.47	0.05	3.42	3.63	0.83	2.80
				[-5.16]	[3.13]	[-8.13]	[2.93]	[0.05]	[4.15]	[3.59]	[1.14]	[4.80]
Undervalued ($RMV_{0.95}$)	67	1.29	2.44	-4.62	1.00	-5.61	3.95	0.66	3.29	3.96	0.97	2.99
				[-8.32]	[1.99]	[-7.90]	[2.52]	[0.69]	[2.88]	[3.18]	[1.10]	[4.16]

Panel B. Using RMV^{mwz} misvaluation measure

				12 months prior			1 month			12 months		
condition	N	Market B/M	Value spread	V	G	VmG	V	G	VmG	V	G	VmG
Overvalued ($RMV^{mwz-}_{0.01}$)	86	0.64	2.05	-0.19	4.60	-4.78	1.01	-1.44	2.45	0.49	-0.89	1.38
				[-0.36]	[6.72]	[-10.51]	[1.65]	[-1.96]	[6.08]	[1.42]	[-2.16]	[4.20]
Overvalued ($RMV^{mwz-}_{0.05}$)	179	0.63	2.06	-1.06	4.14	-5.20	1.20	0.36	0.84	1.10	0.28	0.82
				[-4.22]	[12.82]	[-18.89]	[3.66]	[1.04]	[3.11]	[3.80]	[1.07]	[3.64]
Overvalued ($RMV^{mwz-}_{0.10}$)	234	0.62	2.07	-0.87	4.12	-4.99	0.95	0.02	0.93	0.97	0.00	0.98
				[-3.14]	[11.59]	[-17.98]	[2.47]	[0.05]	[2.82]	[3.21]	[-0.01]	[3.79]
Normal (RMV^{mwz}_{normal})	233	0.75	2.18	-1.64	4.26	-5.90	1.53	1.24	0.29	1.57	0.90	0.67
				[-3.76]	[8.46]	[-10.42]	[3.21]	[2.23]	[0.83]	[4.65]	[2.47]	[2.70]
Undervalued ($RMV^{mwz+}_{0.10}$)	133	1.20	2.27	-2.44	2.28	-4.72	3.12	0.48	2.65	3.37	1.02	2.34
				[-3.28]	[4.93]	[-9.46]	[3.03]	[0.68]	[3.96]	[4.08]	[1.80]	[4.52]
Undervalued ($RMV^{mwz+}_{0.05}$)	118	1.23	2.29	-2.28	3.13	-5.41	2.43	0.99	1.44	2.80	1.07	1.73
				[-4.11]	[7.39]	[-10.48]	[3.51]	[1.59]	[2.39]	[5.25]	[2.58]	[4.51]
Undervalued ($RMV^{mwz+}_{0.01}$)	78	1.32	2.28	-3.08	1.44	-4.52	3.85	0.53	3.32	4.31	1.32	3.00
				[-3.19]	[2.33]	[-7.92]	[2.70]	[0.62]	[3.57]	[3.80]	[1.91]	[4.09]

significant. Following normal times, the value premium one month after formation is not significant.

Overall, the evidence in Panel B of Table 3.2 is consistent with the main results obtained in Panel A. Both market-wide misvaluation measures show that the value premium is larger following periods of extreme market-wide valuation. These results suggest that the unconditional value premium is largely accounted for by the periods in which market prices deviate significantly from fundamentals.

It is interesting to note that, following normal times 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% in Panel A and 0.67% in Panel B 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 B.4 of the Appendix B), the value premium is not significantly different from zero (it is even significantly negative in some cases) following normal 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 coming from extreme market-wide misvaluation states.

Another implication of the model in Section 3.2 is that, in contrast to normal valuation times, following periods of overvaluation (undervaluation) the value premium will be driven primarily by the downward (upward) price correction of growth (value) stocks. The findings in Table 3.2 are consistent with this implication. Relative to normal times, growth stocks depreciate significantly more than value stocks following market-wide overvaluation, and this results in a large value premium.[21] On the other hand, relative to normal times, value stocks appreciate significantly more than growth stocks following market-wide undervaluation, driving the value premium.[22]

[21]↑For example, in Panel A, the difference between the return of value stocks one month after $RMV_{0.10}$ and the return of value stocks one month after normal valuation is -0.14% (1.22% vs. 1.36%). For growth stocks, this difference is -1.85% (-0.48% following $RMV_{0.10}$ vs. 1.37% following normal valuation). This pattern is more pronounced when we measure value premium over a year following portfolio formation. We also conduct a test for the significance of the difference between -0.14% and -1.85% based on GMM. The χ^2 statistic is 11.34 with a p-value of 0.0008.

[22]↑For example, in Panel A of Table 3.2, the difference between the return of value stocks one month after $RMV_{0.90}$ and the return of value stocks one month after normal valuation is 2.11% (3.47% vs. 1.36%). For

Table 3.3. Market-wide Misvaluation and Decile Portfolio Returns, 1968-2018

This table reports the next 12-month average returns (in %) of value stocks (V), growth stocks (G), the value premium (VmG), and the other decile portfolios formed on stock-level B/M under different market-wide misvaluation scenarios (RMV and RMV^{mwz}). Variables definitions are described in detail in Appendix A. At the end of each month, we calculate B/M and sort stocks listed in NYSE, NASDAQ and AMEX by their B/M ratios into decile portfolios. The top decile is defined as value stocks, while the bottom decile is defined as growth stocks. In each panel, we report the number of months under different scenarios of RMV (RMV^{mwz}), and the next-12-month average returns of 10 decile portfolios and VmG. Newey-West t-statistics are reported in brackets. Panel A reports the results for using RMV to identify misvaluation states. Panel B reports results for using RMV^{mwz} to identify misvaluation states.

Panel A. Using RMV misvaluation measure

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]

Panel B. Using RMV^{mwz} misvaluation measure

condition	N	V (D10)	D9	D8	D7	D6	D5	D4	D3	D2	G (D1)	VmG (D10-D1)
Overvalued ($RMV_{0.01}^{mwz-}$)	86	0.49	0.55	0.44	0.45	0.30	0.20	0.15	0.00	-0.21	-0.89	1.38
		[1.42]	[1.78]	[1.40]	[1.37]	[0.98]	[0.62]	[0.44]	[-0.01]	[-0.63]	[-2.16]	[4.20]
Overvalued ($RMV_{0.05}^{mwz-}$)	179	1.10	1.11	1.05	1.01	0.99	0.96	0.92	0.84	0.67	0.28	0.82
		[3.80]	[4.63]	[4.76]	[4.62]	[4.56]	[4.53]	[4.25]	[3.90]	[3.04]	[1.07]	[3.64]
Overvalued ($RMV_{0.10}^{mwz-}$)	234	0.97	0.95	0.91	0.87	0.83	0.78	0.73	0.63	0.46	0.00	0.98
		[3.21]	[3.97]	[3.99]	[3.96]	[3.85]	[3.64]	[3.52]	[3.14]	[2.19]	[-0.01]	[3.79]
Normal (RMV_{normal}^{mwz})	233	1.57	1.48	1.39	1.33	1.32	1.32	1.31	1.23	1.11	0.90	0.67
		[4.65]	[5.13]	[5.26]	[5.12]	[4.94]	[4.91]	[4.60]	[4.26]	[3.73]	[2.47]	[2.70]
Undervalued ($RMV_{0.10}^{mwz+}$)	133	3.37	2.49	2.21	1.99	1.80	1.63	1.56	1.39	1.26	1.02	2.34
		[4.08]	[4.17]	[4.01]	[3.82]	[3.59]	[3.28]	[3.00]	[2.61]	[2.42]	[1.80]	[4.52]
Undervalued ($RMV_{0.05}^{mwz+}$)	118	2.80	2.15	1.95	1.78	1.65	1.53	1.51	1.35	1.25	1.07	1.73
		[5.25]	[5.45]	[5.31]	[5.07]	[4.77]	[4.37]	[4.11]	[3.57]	[3.36]	[2.58]	[4.51]
Undervalued ($RMV_{0.01}^{mwz+}$)	78	4.31	3.15	2.81	2.58	2.29	2.09	2.03	1.83	1.66	1.32	3.00
		[3.80]	[4.04]	[4.08]	[4.00]	[3.79]	[3.50]	[3.31]	[2.91]	[2.67]	[1.91]	[4.09]

Table 3.3 further examines the types of stocks that drive the value premium following different states of market-wide misvaluation. This table reports the average returns of decile B/M portfolios over the 12 months following different market-wide misvaluation scenarios. To the extent that Decile 5 represent the performance of the average stock, the value premium could be examined in the context of value and growth stocks return deviations with respect to the average stock. Results in Table 3.3 are consistent with the conjecture that the value premium is driven by the correction of growth stocks' extreme overvaluation in up markets and value stocks' extreme undervaluation in down markets. For example, following market-wide overvaluation as defined by $RMV_{0.10}$, 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 as defined by $RMV_{0.90}$, 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 those of 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%). Similar results hold for using RMV^{mwz} as a market-wide misvaluation measure in Panel B of Table 3.3.

In Table 3.4, Jensen's alphas are reported for value stocks, growth stocks, and the value premium under different market-wide misvaluation scenarios. This table shows alphas for the one month following misvaluation and average alphas for the 12 months following misvaluation. The results in Table 3.4 using risk-adjusted returns are similar to the findings in Table 3.2. 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

growth stocks, this difference is -1.32% (0.05% following $RMV_{0.90}$ vs. 1.37% following normal valuation). The GMM test for the significance of the difference between 2.11% and -1.32% has a χ^2 statistic of 9.97 with a p-value of 0.0016.

Table 3.4. Market-wide Misvaluation and the Value Premium (Jensen's Alpha), 1968-2018

This table reports monthly alphas (in %) for value stocks (V), growth stocks (G), and the value premium (VmG) under different scenarios of market-wide misvaluation. Variable definitions are described in Appendix A. 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 measure market-wide misvaluation by RMV (Panel A) and RMV^{mwz} (Panel B). In each panel, we report the number of months under different valuation scenarios, the next-month Jensen's alphas, and the next-12-month average Jensen's alphas of V, G, and VmG. Newey-West t-statistics are reported in brackets.

Panel A. Using RMV misvaluation measure

Market condition	N	V (1 month)	G (1 month)	VmG (1 month)	V (12 months)	G (12 months)	VmG (12 months)
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]

Panel B. Using RMV^{mwz} misvaluation measure

Market condition	N	V (1 month)	G (1 month)	VmG (1 month)	V (12 months)	G (12 months)	VmG (12 months)
Overvalued ($RMV^{mwz-}_{0.01}$)	86	1.55	-0.83	2.38	1.41	-0.94	2.35
		[3.85]	[-2.25]	[6.21]	[11.97]	[-9.03]	[19.73]
Overvalued ($RMV^{mwz-}_{0.05}$)	179	0.63	-0.29	0.92	0.58	-0.3	0.88
		[2.47]	[-1.32]	[3.34]	[7.93]	[-4.74]	[11.01]
Overvalued ($RMV^{mwz-}_{0.10}$)	234	0.49	-0.51	0.99	0.41	-0.53	0.94
		[1.47]	[-1.94]	[3.03]	[4.35]	[-7.07]	[9.75]
Normal (RMV^{mwz}_{normal})	233	0.57	0.16	0.42	0.57	0.16	0.41
		[2.16]	[0.52]	[1.22]	[7.33]	[1.82]	[4.11]
Undervalued ($RMV^{mwz+}_{0.10}$)	133	2.86	0.18	2.68	2.86	0.18	2.68
		[4.34]	[0.69]	[3.95]	[14.25]	[2.30]	[13.16]
Undervalued ($RMV^{mwz+}_{0.05}$)	118	1.76	0.22	1.53	1.76	0.23	1.53
		[3.54]	[0.86]	[2.76]	[11.85]	[2.96]	[9.33]
Undervalued ($RMV^{mwz+}_{0.01}$)	78	3.41	0.03	3.37	3.41	0.04	3.37
		[3.75]	[0.17]	[3.58]	[12.06]	[0.53]	[11.74]

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 $RMV_{0.90}$). Panel A of Table 3.4 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 Panel A of Table 3.4, 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 with a p-value of 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 Panel A of Table 3.4, 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 with a p-value of 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.[23]

In Panel B of Table 3.4, I use the RMV^{mwz} measure of market-wide misvaluation and find results similar to the ones in Panel A. Interestingly, in Panel B, following normal times for the market (RMV^{mwz}_{normal}), the 1-month alpha of the value premium and the average alpha of the value premium over the next 12 months are not statistically significant.

The results so far show that our measures of market-wide misvaluation, RMV and RMV^{mwz}, are significant predictors of the magnitude of the value premium. Next, I perform a multiple regression analysis to test whether the results are robust to including other

[23]↑I also compute the Jensen's alphas for decile portfolios based on B/M by repeating the analysis in Table 3.3. The results are similar to the ones reported on Table 3.3 and they are available upon request.

variables that have been shown to predict the value premium. For example, previous studies have examined 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)[53], Asness et al (2000)[62], Asness et al (2021)[63]). 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 and RMV^{mwz} measures. The RMV and RMV^{mwz} measures capture the extent to which market-wide valuation shifts relative to the historical benchmark. They distinguish periods of undervaluation and overvaluation from normal market-wide valuation periods. In addition, I control for other potential predictors of the value premium including market volatility, the Sentiment Index of Baker and Wurgler (2006)[55][24], 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),[25] and the dividend yield of the market portfolio (DIV).

The two proposed measures of market-wide misvaluation, RMV and RMV^{mwz}, are such that their extremely low or extremely high values are positively associated with the subsequent value premium. To control for this quality of the measures in a way that makes it possible to include them in a multiple regression with other continuous variables, they are transformed as follows. A new variable, called the degree of market misvaluation, DOM, is defined as $(RMV - 0.5)^2$ in the case of RMV and $|RMV^{mwz}|$ in the case of RMV^{mwz}[26] and examine the following specification:

$$Value\,premium_{t,t+h} = b_0 + b_1 * DOM_t + b_2 * Value\,spread_t + b_3 * X_t + \epsilon_{t,t+h}, \tag{3.30}$$

where the dependent variable is the future h-month value premium, DOM is either $(RMV - 0.5)^2$ or $|RMV^{mwz}|$, $Value\,spread$ is defined as the difference between the log B/M of value and growth stocks, and X is a vector of the other control variables.

[24]↑The investor sentiment index of Baker and Wurgler (2006)[55] is obtained from Jeffrey Wurgler's website.
[25]↑The data on bond yield are obtained from the website of the Federal Reserve Bank of St. Louis.
[26]↑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.

Table 3.5 presents results for horizons $h = 3, 6, 12$. The table shows that the predictive ability of DOM, which is a function of the magnitude of RMV and RMV^{mwz}, for the future profitability of value-minus-growth strategies is economically and statistically significant by itself and also after controlling for value spread and other variables explained above.[27] This holds for all return horizons. The predictive ability of the value spread is sensitive to the inclusion of the 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 3.5 suggest that the market-wide misvaluation measures, RMV and RMV^{mwz}, are distinct from the value spread and other predictive variables. They contain independent predictive power for the future performance of the value premium.

3.5 Mechanism

In this section, we focus on providing evidence related to the main mechanism of our framework. We first document the behavior of cash flows and returns for value and growth stocks in the run up to market-wide misvaluation, and then explore the return extrapolation channel in more detail.

3.5.1 Value and Growth Cash Flows and Return Dynamics in Pre-Formation

According to our model, when the aggregate market experiences good (bad) cash-flow news they tend to be disproportionately concentrated in growth (value) stocks. This, in turn, drives the returns of growth (value) stocks higher (lower), catches the attention of extrapolators, and eventually leads to market-wide overvaluation (undervaluation). In this section, we present evidence consistent with this mechanism. We document that growth stocks have more positive earnings surprises during the periods leading up to market-wide overvaluation. Value stocks, on the other hand, have more negative earnings shocks during the periods leading up to market-wide undervaluation.

[27]↑Comparable results can be obtained when using $|RMV - 0.5|$ to define DOM. For example, in Panel A of Table 3.5, 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 using DOM measured by $|RMV - 0.5|$, the coefficient of DOM is 6.04 with a t-statistic of 4.87. Similar results hold for $h = 6, 12$.

Table 3.5. Market-Wide Misvaluation and Predictability of the Value Premium, 1968-2018

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 either $(RMV - 0.5)^2$ (Panel A) or $|RMV^{mwz}|$ (Panel B). $Value\,spread$ is defined as 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. Detailed variable definitions are in Appendix A. Newey-West t-statistics are reported in brackets.

Panel A. $DOM = (RMV - 0.5)^2$

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

Panel B. $DOM = |RMV^{mwz}|$

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

Specifically, we compute the standardized unexpected earnings (SUE) of value and growth portfolios as the median SUE of stocks within each portfolio. We then we track both the SUE and the following returns of value and growth portfolios over the 4 separate quarters leading up to market-wide misvaluation. Results are presented in Table 3.6.

Panel A1 of Table 3.6 shows that, unconditionally, value stocks experience negative earnings surprises while growth stocks experience positive earnings surprises in all 4 lagged quarters.[28] However, leading up to periods of significant market-wide overvaluation ($RMV_{0.05}$) growth stocks have higher SUE than under normal times (RMV_{normal}). On the other hand, leading up to periods of significant market-wide undervaluation ($RMV_{0.95}$) value stocks have lower SUE than under normal times. This holds for all 4 lagged quarters and for different degrees of relative market-wide misvaluation. Panel A2 of Table 3.6 reveals that growth stocks experience large positive cumulative returns in the 4 quarters leading up to market-wide overvaluation, while value stocks experience large negative cumulative returns in the 4 quarters leading up to market-wide undervaluation.

In Panels B1 and B2 of Table 3.6, I repeat the analysis in Panels A1 and A2, respectively, using the RMV^{mwz} measure to infer market-wide misvaluation. The results are very similar to the ones reported when using RMV.

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

Table 3.6. Market-wide Misvaluation, Unexpected Earnings, and Stock Returns

This table reports the standardized unexpected earnings (SUE) and cumulative returns for value (V) and growth (G) portfolios prior to different states of market-wide misvaluation. In Panels A1 and A2, we use the RMV measure of market-wide misvaluation, while in Panels B1 and B2 we use the RMV^{mwz} measure. In each panel we identify 7 market-wide valuation states based on the level of RMV and RMV^{mwz}. For each valuation state, Panels A1 and B1 report average SUE for stocks in the value and growth portfolio, 1 to 4 quarters prior to portfolio formation. Portfolio SUE is measured as the median SUE of stocks within the portfolio. Panels A2 and B2 report cumulative portfolio returns 1 to 4 quarters prior to portfolio formation. Newey-West t-statistics are reported in brackets. The sample period is 1972-2018.

Panel A1. Standardized Unexpected Earnings, % (Using RMV misvaluation measure)

		Lagged 1Q		Lagged 2Q		Lagged 3Q		Lagged 4Q	
condition	N	V	G	V	G	V	G	V	G
Overvalued ($RMV_{0.05}$)	85	-0.75	0.24	-1.04	0.25	-1.11	0.26	-1.02	0.27
		[-3.43]	[30.65]	[-2.83]	[27.92]	[-2.62]	[24.02]	[-2.31]	[22.37]
Overvalued ($RMV_{0.10}$)	129	-0.70	0.24	-0.89	0.26	-0.96	0.26	-0.87	0.27
		[-3.44]	[23.32]	[-3.07]	[26.49]	[-2.97]	[24.91]	[-2.70]	[25.82]
Overvalued ($RMV_{0.20}$)	195	-0.71	0.24	-0.83	0.26	-0.86	0.27	-0.78	0.27
		[-3.77]	[23.36]	[-3.67]	[23.20]	[-3.56]	[22.75]	[-3.41]	[22.03]
Normal (RMV_{normal})	285	-0.88	0.23	-0.85	0.24	-0.75	0.25	-0.61	0.26
		[-4.92]	[10.10]	[-5.73]	[9.91]	[-6.08]	[9.63]	[-5.11]	[9.67]
Undervalued ($RMV_{0.80}$)	120	-2.16	0.18	-1.59	0.18	-1.23	0.18	-0.94	0.17
		[-2.71]	[9.93]	[-3.84]	[9.68]	[-3.82]	[9.59]	[-3.71]	[9.33]
Undervalued ($RMV_{0.90}$)	91	-2.37	0.17	-1.56	0.17	-1.29	0.17	-0.96	0.17
		[-2.60]	[9.63]	[-3.49]	[9.66]	[-3.50]	[9.40]	[-3.22]	[9.34]
Undervalued ($RMV_{0.95}$)	67	-2.29	0.18	-1.24	0.18	-1.07	0.17	-0.83	0.16
		[-1.91]	[8.16]	[-2.66]	[9.00]	[-2.74]	[9.79]	[-2.58]	[10.89]

Panel A2. Cumulative Portfolio Returns, % (Using RMV misvaluation measure)

		Cumret [-1Q,0]		Cumret [-2Q,0]		Cumret [-3Q,0]		Cumret [-4Q,0]	
condition	N	V	G	V	G	V	G	V	G
Overvalued ($RMV_{0.05}$)	85	-0.04	16.09	-2.02	35.01	-4.24	55.13	-6.83	79.71
		[-0.03]	[7.32]	[-0.79]	[7.40]	[-1.13]	[7.05]	[-1.53]	[7.46]
Overvalued ($RMV_{0.10}$)	129	-1.68	13.98	-4.47	29.95	-6.66	49.84	-8.64	73.75
		[-1.52]	[6.67]	[-2.03]	[6.92]	[-2.12]	[7.55]	[-2.23]	[8.47]
Overvalued ($RMV_{0.20}$)	195	-4.03	11.84	-7.05	26.81	-9.66	44.75	-11.39	65.91
		[-4.33]	[7.26]	[-3.92]	[7.56]	[-3.72]	[8.09]	[-3.35]	[8.57]
Normal (RMV_{normal})	285	-5.13	13.76	-9.11	29.39	-12.65	46.50	-16.60	63.11
		[-3.22]	[6.90]	[-3.13]	[6.83]	[-3.45]	[6.90]	[-4.20]	[7.36]
Undervalued ($RMV_{0.80}$)	120	-11.02	5.15	-22.45	10.49	-31.70	17.06	-37.60	29.85
		[-4.49]	[2.20]	[-5.39]	[2.55]	[-5.96]	[2.99]	[-6.81]	[3.33]
Undervalued ($RMV_{0.90}$)	91	-13.47	3.04	-24.91	6.18	-33.72	11.77	-40.05	21.65
		[-4.20]	[1.22]	[-4.57]	[1.31]	[-5.43]	[1.87]	[-6.72]	[2.62]
Undervalued ($RMV_{0.95}$)	67	-16.60	0.97	-31.29	-0.37	-40.96	2.74	-47.43	10.88
		[-6.44]	[0.51]	[-7.4]	[-0.12]	[-9.39]	[0.57]	[-12.16]	[1.49]

3.5.2 Value Premium and Investors Expectation Error

Lakonishok, Shleifer, and Vishny (1994)[44] suggest that since investors tie their expectations of future performance to past performance, they are excessively optimistic about growth stocks and excessively pessimistic about value stocks. If investors make such mistakes in forming their expectations on average, these mistakes could be reflected in the aggregate market valuation. To the extent that the value premium arises from mispricing due to overextrapolating past stock returns, the periods when the value premium is strongest should be associated with higher extrapolative bias in investors' expectations. Therefore, as the value premium is being realized, we should observe a pattern of expectation revisions and expectation errors consistent with an ex-ante extrapolative bias in prices.

To test this idea, I measure expectation errors and revisions using the following two empirical proxies: earnings announcement period returns and the change in analyst target price forecasts. Both of these measures capture different dimensions of market expectation-related adjustments following portfolio formation, and in both measures, we uncover evidence which supports the argument that the value premium is associated with price corrections following periods of over-extrapolation.

Earnings Announcement Period Returns

I analyze the market's response to earnings news to infer the presence of biased expectations. La Porta et al (1997)[71] examine earnings announcement period returns conditional on firms' B/M ratios. They find that growth (value) firms have negative (positive) earnings announcement returns in the one-year period following portfolio formation. This is consistent with these portfolios containing systematically biased expectations of future profitability. We extend their analysis to examine earnings announcement period returns across value (growth) portfolios conditional on the deviation of the aggregate B/M from its historical benchmark.

The firms' earnings announcement returns are calculated as cumulative size-adjusted returns during a three-day window (-1, +1) for four quarters after portfolio formation. Panel A of Table 3.7 presents the results, using aggregate B/M to measure market misvaluation (RMV). Across all valuation ratios, unconditionally, growth (value) firms have negative

Table 3.6. Market Misvaluation, Unexpected Earnings, and Stock Returns (continued)

Panel B1. Standardized Unexpected Earnings, % (Using RMV^{mwz} misvaluation measure)

		Lagged 1Q		Lagged 2Q		Lagged 3Q		Lagged 4Q	
condition	N	V	G	V	G	V	G	V	G
Overvalued ($RMV^{mwz-}_{0.01}$)	86	-0.98	0.26	-1.40	0.28	-1.60	0.29	-1.50	0.30
		[-3.52]	[19.10]	[-3.73]	[20.29]	[-3.90]	[15.09]	[-3.62]	[11.38]
Overvalued ($RMV^{mwz-}_{0.05}$)	179	-0.84	0.25	-0.86	0.26	-0.80	0.27	-0.67	0.27
		[-4.71]	[13.91]	[-5.19]	[13.9]	[-5.39]	[13.65]	[-5.23]	[13.65]
Overvalued ($RMV^{mwz-}_{0.10}$)	234	-0.87	0.24	-0.91	0.26	-0.90	0.28	-0.78	0.28
		[-4.30]	[16.93]	[-4.24]	[16.43]	[-4.19]	[15.60]	[-4.00]	[14.91]
Normal (RMV^{mwz}_{normal})	233	-0.96	0.24	-0.89	0.25	-0.76	0.25	-0.62	0.25
		[-5.08]	[9.56]	[-6.66]	[9.47]	[-7.21]	[9.37]	[-5.45]	[9.29]
Undervalued ($RMV^{mwz+}_{0.10}$)	133	-1.67	0.21	-1.32	0.21	-1.06	0.20	-0.84	0.19
		[-2.13]	[8.67]	[-2.95]	[7.98]	[-3.11]	[7.76]	[-2.82]	[8.27]
Undervalued ($RMV^{mwz+}_{0.05}$)	118	-1.49	0.21	-1.20	0.21	-1.02	0.21	-0.83	0.20
		[-3.07]	[10.88]	[-4.21]	[10.45]	[-4.53]	[10.33]	[-4.23]	[10.51]
Undervalued ($RMV^{mwz+}_{0.01}$)	78	-2.12	0.20	-1.37	0.20	-1.02	0.19	-0.85	0.18
		[-1.76]	[9.14]	[-2.39]	[8.66]	[-2.60]	[9.37]	[-2.88]	[10.13]

Panel B2. Cumulative Portfolio Returns, % (Using RMV^{mwz} misvaluation measure)

		Cumret [-1Q,0]		Cumret [-2Q,0]		Cumret [-3Q,0]		Cumret [-4Q,0]	
condition	N	V	G	V	G	V	G	V	G
Overvalued ($RMV^{mwz-}_{0.01}$)	86	-1.58	13.13	-2.86	31.88	-5.62	49.66	-7.80	72.19
		[-0.84]	[4.07]	[-0.77]	[4.22]	[-1.11]	[4.40]	[-1.29]	[4.88]
Overvalued ($RMV^{mwz-}_{0.05}$)	179	-4.91	12.88	-9.08	27.35	-12.02	44.87	-14.27	64.77
		[-5.69]	[8.57]	[-5.89]	[9.08]	[-5.59]	[9.29]	[-5.4]	[9.69]
Overvalued ($RMV^{mwz-}_{0.10}$)	234	-3.91	12.57	-7.65	26.71	-10.41	44.14	-12.81	63.55
		[-3.91]	[7.33]	[-4.4]	[7.97]	[-4.39]	[8.69]	[-4.63]	[9.39]
Normal (RMV^{mwz}_{normal})	233	-7.14	12.82	-12.19	28.92	-16.49	46.62	-19.49	67.66
		[-4.52]	[5.95]	[-4.28]	[6.12]	[-4.16]	[5.99]	[-4.10]	[6.22]
Undervalued ($RMV^{mwz+}_{0.10}$)	133	-7.21	7.12	-14.92	14.38	-22.17	21.64	-28.89	28.29
		[-2.49]	[2.97]	[-3.08]	[3.23]	[-3.49]	[3.84]	[-3.66]	[3.72]
Undervalued ($RMV^{mwz+}_{0.05}$)	118	-7.63	9.09	-14.41	20.67	-21.25	32.09	-27.18	45.03
		[-3.36]	[4.62]	[-3.68]	[5.05]	[-4.24]	[5.66]	[-4.77]	[5.94]
Undervalued ($RMV^{mwz+}_{0.01}$)	78	-10.35	4.97	-19.50	9.74	-26.64	14.23	-33.21	18.13
		[-2.81]	[1.70]	[-3.09]	[1.80]	[-3.01]	[1.72]	[-3.52]	[1.84]

(positive) earnings announcement returns in the one-year period following portfolio formation. This is consistent with the evidence in La Porta et al (1997)[71]. Panel A of Table 3.7 further shows that when there is undervaluation at the aggregate level, earnings announcement returns for value stocks are larger than in the periods of both overvaluation and no significant market misvaluation. For example, following extreme market undervaluation periods ($RMV_{0.95}$), average 3-day CAR for value firms is 5.72% compared to 1.43% and 2.04% for extreme overvaluation ($RMV_{0.05}$) and normal periods, respectively. Thus, the evidence shows that investors are positively surprised by the earnings announcements for value stocks subsequent to portfolio formation in undervalued market states. This is consistent with investors having overly pessimistic expectations regarding value stocks before portfolio formation.

During the year following significant aggregate overvaluation, the earnings announcement returns of growth stocks are lower and more negative than in the case of undervaluation. Hence, investors' expectations about the future prospects of growth stocks are too high before portfolio formation, and prices react negatively to earnings announcements of these firms. Overall, the results from Table 3.7 are consistent with the conjecture that stocks with larger expectation errors are those whose valuations are likely to comove with the aggregate market valuation. These expectation errors likely stem from over-extrapolation of past performance.

Price Target Revisions

To further examine the presence of extrapolative beliefs in the data, we use an alternative measure of expectation errors: analysts' price target revisions (REV). The benefit of this analysis is that I can directly examine price target revisions for a set of sophisticated investors. This allows us to mitigate concerns associated with inferring expectation errors and revisions indirectly from short-window stock price changes. The limitation of this approach is that not all firms have analyst coverage and the resulting sample will contain larger, more profitable firms with better information environments (e.g., [Lang and Lundholm (1996)[72]). In addition, previous literature documents that I/B/E/S analysts issue optimistic forecasts in general and display reluctance to downgrade their previous forecasts

Table 3.7. Market-wide Misvaluation and Investor Expectation Errors for Value and Growth Stocks

This table reports average investor expectation errors about value and growth stocks under different degrees of market misvaluation (RMV). Variable definitions are described in Appendix A. At the end of each month, we calculate B/M, E/P, and CF/P and sort stocks listed on NYSE, NASDAQ and AMEX by these ratios. The top decile is defined as value stocks, while the bottom decile is defined as growth stocks. The proxies for investor expectation errors include 3-day cumulative abnormal return (CAR, in Panel A) and change in analyst price target (%, in Panel B). For each proxy in each panel, I report the number of months under different scenarios of RMV calculated using B/M, E/P, and CF/P, the average expectation error proxy for value stocks, growth stocks, and the difference between value and growth stocks. The t-statistics are reported in brackets.

Panel A. 3-day CAR of Earnings Announcement

	B/M			E/P			CF/P		
condition	N	Value	Growth	N	Value	Growth	N	Value	Growth
Overvalued ($RMV_{0.05}$)	85	1.43	-2.21	66	1.12	-0.80	79	0.85	-0.98
		[6.41]	[-12.89]		[4.92]	[-4.14]		[3.3]	[-5.88]
Overvalued ($RMV_{0.10}$)	129	1.72	-1.89	109	1.13	-0.57	121	0.93	-0.84
		[9.35]	[-12.26]		[6.27]	[-3.96]		[4.73]	[-6.29]
Overvalued ($RMV_{0.20}$)	195	1.67	-1.64	158	1.20	-0.41	172	0.92	-0.76
		[11.11]	[-13.92]		[7.39]	[-3.03]		[5.89]	[-7.41]
Normal (RMV_{normal})	285	2.04	-1.53	316	1.56	0.11	279	1.52	-0.04
		[11.42]	[-12.24]		[10.6]	[1.37]		[8.94]	[-0.51]
Undervalued ($RMV_{0.80}$)	120	5.04	-0.96	126	2.96	0.26	149	3.58	-0.13
		[19.45]	[-5.76]		[13.96]	[1.70]		[16.37]	[-1.02]
Undervalued ($RMV_{0.90}$)	91	5.25	-0.85	72	3.38	0.50	92	4.30	-0.04
		[17.87]	[-4.37]		[10.74]	[2.88]		[14.47]	[-0.23]
Undervalued ($RMV_{0.95}$)	67	5.72	-0.87	46	3.73	0.84	53	4.56	0.13
		[15.73]	[-3.50]		[8.33]	[4.23]		[10.32]	[0.60]

Panel B. Change in Analyst Price Target

	B/M			E/P			CF/P		
condition	N	Value	Growth	N	Value	Growth	N	Value	Growth
Overvalued ($RMV_{0.05}$)	19	-28.22	35.61	16	-8.40	18.05	16	-4.32	10.51
		[-14.43]	[20.13]		[-7.14]	[9.59]		[-13.69]	[8.88]
Overvalued ($RMV_{0.10}$)	29	-26.78	35.62	29	-8.43	16.19	27	-3.86	10.95
		[-17.08]	[24.93]		[-10.89]	[12.95]			[-6.7]
[10.08]									
Overvalued ($RMV_{0.20}$)	49	-25.77	35.85	41	-8.85	15.54	40	-3.06	11.96
		[-21.83]	[28.06]		[-14.9]	[16.64]		[-5.64]	[11.17]
Normal (RMV_{normal})	113	-25.62	31.34	124	-13.07	10.31	120	-9.37	12.94
		[-13.67]	[16.11]		[-14]	[13.75]		[-9.27]	[16.73]
Undervalued ($RMV_{0.80}$)	42	-31.17	25.34	51	-23.94	5.14	56	-24.83	0.66
		[-8.22]	[6.78]		[-15.6]	[2.28]		[-16.46]	[0.36]
Undervalued ($RMV_{0.90}$)	35	-34.29	23.39	25	-27.99	2.26	34	-27.88	-3.20
		[-8.69]	[5.85]		[-10.77]	[0.62]		[-13.39]	[-1.61]
Undervalued ($RMV_{0.95}$)	28	-32.01	27.65	15	-34.17	-6.13	16	-29.87	-5.67
		[-6.8]	[6.00]		[-10.19]	[-1.92]		[-8.11]	[-1.72]

(Scherbina (2004)[73]).[29] To mitigate concerns related to this potential bias in the data, we use revisions in analyst forecasts to capture the change in analysts' expectations.

The analysis in this section requires the creation of a new sample at the intersection with the main sample and the Adjusted I/B/E/S Detail File of Price Targets. Revisions in analysts' target prices (REV) are defined as the difference between the consensus in price targets and the average of the past 12-month consensus price targets, scaled by the average of the past 12-month consensus price targets.

Panel B of Table 3.7 presents mean analyst earnings forecast errors (FE), conditional on different RMV states. I find that in both the full analyst sample and across portfolios, the mean values of FE are positive, which is consistent with analysts' forecasts being optimistically biased. Focusing on forecast errors, we find that the unconditional mean forecast error for value stocks is lower than that for growth stocks in most cases. This indicates that analysts issue less optimistic forecasts for value stocks compared to growth stocks. This result is likely due to the optimistic bias of analysts who feel more uncertain about value stocks than growth stocks. Following market undervaluation, analyst forecast errors for value stocks are lower than those in normal times in the case of using E/P and CF/P to measure valuation. This indicates that analysts become more pessimistic about value stocks when the overall market is down. Following an overvalued market, analyst forecast errors for growth stocks are larger than those in normal times across all three valuation measures. This indicates that analysts are more likely to issue overly optimistic forecasts for growth stocks when the overall market is doing well.

Panel B of Table 3.7 presents results for target price revisions for value and growth stocks under different RMV scenarios. The price target revisions are measured before portfolio formation. I find that across all valuation states analysts are more pessimistic (optimistic) about value (growth) stocks. Furthermore, I find that analysts are more likely to revise their target price downward for value firms before the overall market is undervalued. This result

[29]↑The optimistic bias in analyst forecasts can be attributed to two reasons. First, analysts are inclined to issue more optimistic forecasts if they feel less accountable in uncertain environments. Second, high uncertainty will generally lead to more spread out private signals about future earnings. Analysts who receive a low private signal are more inclined to choose to keep quiet, which will bias the mean of the reported forecasts further up.

holds across all three valuation measures. This is in line with the conjecture that investors display more pessimistic expectations for value stocks in a declining market. Using B/M, we also find that analysts are more likely to revise their target price upward for growth firms before the overall market becomes overvalued. This is consistent with investors being more optimistic about growth stocks in a rising market.

3.5.3 Fund Flows within/across Asset Classes

In this section, I examine investor demand for different styles within the stock market as well as their demand across asset classes. Previous studies have also examined investor demand for various asset classes. For example, Frazzini and Lamont (2008)[74] show that retail investors actively reallocate their funds across different mutual funds. More specifically, investors allocate more funds to high-sentiment stocks, such as growth stocks. Frazzini and Lamont (2008)[74] refer to this observation as the "dumb money" effect since individual retail investors lose wealth in the long run. Ben-Rephael, Kandel, and Wohl (2012)[75] show that exchange flows from bond funds to equity funds are higher when the stock market experiences higher excess returns. In this section, I provide further evidence about investor demand for different styles and asset classes, conditional on the degree of market-wide misvaluation (RMV). In particular, I measure three aspects of investor demand: flows to equity and bond funds, flows between equity and bond funds within fund families, and flows to value and growth equity funds.

I begin by analyzing investor flows to equity and bond funds. According to the framework outlined in Section 3.2, investors would base their allocation to equity and bonds based on aggregate market valuation. Following Ben-Rephael, Kandel, and Wohl (2012)[75], we calculate net flows as: "new sales" minus "redemption" plus "exchanges in" minus "exchanges out," which are obtained from the Investment Company Institute (ICI). Panel A of Table 3.8 reports the average past 6-month fund flows to equity and bonds under different RMV levels. The results show that equity funds experience outflows before the stock market is designated as undervalued by the RMV measure. On the other hand, there are significant inflows into equity funds before the stock market is classified as overvalued. The results remain robust across different degrees of RMV and across using E/P or CF/P to measure market valuation.

Next, I look at net exchange flows from bond funds to equity funds over the previous 1, 3, and 6 months. Ben-Rephael, Kandel, and Wohl (2012)[75] argue that net exchanges reflect asset allocation decisions of mutual fund investors on shifting between bonds and equity, while net sales and redemptions are influenced by long-term savings and withdrawals. Therefore, I only focus on past net exchange, $NEIO$, from bond to equity funds, calculated as "exchanges in" minus "exchanges out" for equity funds within fund families. A positive $NEIO$ indicates exchange into equity funds from bond funds, while a negative $NEIO$ shows exchange out from equity funds into bond funds. We expect to see a significantly positive $NEIO$ before the stock market becomes overvalued. This would indicate that investors switch more wealth to equity funds from bond funds, which contributes to future market overvaluation. On the other hand, we expect a significantly negative $NEIO$ before the stock market reaches its undervaluation level. This would indicate that as investors flee from the stock market, they push prices further down and away from fundamental values. In Panel B of Table 3.8, I report the average past 1-month and 6-month $NEIO$ of equity and bond funds under different levels of RMV. Consistent with our predictions, across different degrees of RMV, $NEIO$ is significantly positive before overvaluation states and significantly negative before undervaluation states.

Table 3.8. Market-wide Misvaluation and Fund Flows

This table reports fund flows to bond funds and equity funds, net exchange flows to equity funds, and average flows to value and growth funds under different degrees of market misvaluation (RMV). Variable definitions are described in Appendix A. Flows to bond funds, equity funds, and net exchange into and out of equity funds (NEIO) are obtained from Ben-Rephael, Kandel and Wohl (2012). Value (growth) funds are identified based on fund names. The panels report average fund flows to bond and equity funds over the previous 6 months (Panel A), average net exchange from bond funds to equity funds over the current month and the previous 6 months (Panel B), and average aggregate flows to value and growth funds over the last 6 months (Panel C). In each panel, I report the number of months under different scenarios for RMV. In each panel, RMV is calculated using B/M, E/P, or CF/P. The t-statistics are reported in brackets.

Panel A. Average fund flows to Bond and Equity funds over last 6 months

	B/M			E/P			CF/P		
condition	N	Bond	Equity	N	Bond	Equity	N	Bond	Equity
Overvalued ($RMV_{0.05}$)	51	0.25	0.77	34	0.37	0.88	48	0.39	0.80
		[3.42]	[10.01]		[3.28]	[9.03]		[5.4]	[9.98]
Overvalued ($RMV_{0.10}$)	80	0.19	0.78	55	0.38	0.87	76	0.27	0.78
		[3.01]	[12.8]		[3.98]	[10.25]		[4.33]	[12.00]
Overvalued ($RMV_{0.20}$)	110	0.16	0.74	82	0.33	0.83	101	0.18	0.75
		[2.88]	[13.64]		[4.35]	[12.29]		[2.85]	[13.25]
Normal (RMV_{normal})	142	0.35	0.21	166	0.30	0.26	141	0.36	0.25
		[7.00]	[4.89]		[7.73]	[6.46]		[7.69]	[5.62]
Undervalued ($RMV_{0.80}$)	54	0.14	0.07	58	-0.01	0.07	64	0.11	0.05
		[2.29]	[1.15]		[-0.11]	[1.51]		[1.68]	[1.03]
Undervalued ($RMV_{0.90}$)	40	0.14	-0.02	26	-0.12	0.06	36	0.01	-0.08
		[2.81]	[-0.31]		[-1.23]	[0.82]		[0.24]	[-1.42]
Undervalued ($RMV_{0.95}$)	31	0.19	-0.06	15	0.01	-0.12	18	-0.05	-0.08
		[3.41]	[-1.05]		[0.08]	[-1.23]		[-0.71]	[-0.94]

In summary, the results in Panels A and B of Table 3.8 are in line with the behavior of asset-class switchers described in the framework of Section 3.2. Investors tend to switch their funds into the equity market in states characterized by overvaluation (i.e., low aggregate B/M, E/P, or CF/P ratios). This continuous switch contributes to market overvaluation. In states characterized by undervaluation (i.e., high aggregate B/M, E/P, or CF/P ratios), investors tend to leave equities toward safer assets, and this contributes to market undervaluation.

Finally, I analyze flows to value and growth funds. The sample of funds includes actively managed, diversified US equity mutual funds. To identify value and growth funds, I rely on fund names.[30] For example, if a fund's name contains the words "Value Fund", "Value Strategy", "Value Portfolio", or some other combination of these words, I classify it as a value fund.[31] A similar identification is used for growth funds.

The aggregate flows to a style category, s, is calculated as

$$Aggregate\_flow_{s,t} = \frac{\sum_{\mathrm{i}=1}^{N} \left[TNA_{\mathrm{i},t} - TNA_{\mathrm{i},t-1} \times (1 + RET_{\mathrm{i},t})\right]}{\sum_{\mathrm{i}=1}^{N} TNA_{\mathrm{i},t-1}} \tag{3.31}$$

in which $TNA_{\mathrm{i},t}$ is the total net assets of mutual fund i in style s at time t, and $RET_{\mathrm{i},t}$ is the return of mutual fund i in style s at time t, net of fees. The numerator simply aggregates individual fund flows within value and growth categories.

Panel C of Table 3.8 reports average aggregate flows over the last 6-months to value and growth funds under different levels of RMV. The results show that during 6 months prior to the market becoming classified as overvalued, both value and growth funds have positive fund inflows. Using B/M to measure RMV, before the market becomes extremely overvalued ($RMV_{0.05}$), growth funds experience significantly higher inflows than value funds. Similar results hold for E/P and CF/P measures of RMV, and for the other two levels of

[30] ↑This approach is motivated by the evidence in Cooper, Gulen, and Rau(2005)[76]. They show that flows to mutual funds are related to the investment style implied by the funds' names. Specifically, mutual funds that change their names to include a recent hot style in their names (i.e., value or growth) experience abnormal inflows. More importantly, it does not matter whether the name change is purely cosmetic. Therefore, even though running a style regression is arguably a better way to identify funds' actual investment styles, classifying funds based on styles implied by their names helps us to better understand how irrational or extrapolative flows are allocated across funds.

[31] ↑However, if a fund's name contains the words "Values" (as in "Christian Values Fund"), I do not classify that fund as a value fund.

Table 3.8. Market-wide Misvaluation and Fund Flows (continued)

Panel B. Net exchange from bond funds to equity funds, NEIO

	B/M			E/P			CF/P		
condition	N	lag1M	lag6M	N	lag1M	lag6M	N	lag1M	lag6M
Overvalued ($RMV_{0.05}$)	51	0.02	0.03	34	0.06	0.06	48	0.02	0.03
		[1.54]	[3.94]		[2.97]	[4.73]		[1.55]	[3.55]
Overvalued ($RMV_{0.10}$)	80	0.03	0.03	55	0.05	0.05	76	0.02	0.03
		[2.23]	[4.68]		[2.53]	[5.12]		[1.90]	[3.97]
Overvalued ($RMV_{0.20}$)	110	0.03	0.03	82	0.04	0.04	101	0.03	0.03
		[2.41]	[4.99]		[2.86]	[5.44]		[2.23]	[4.74]
Normal (RMV_{normal})	141	0.00	0.00	163	0.00	-0.01	141	0.00	0.00
		[0.12]	[-0.46]		[-0.25]	[-1.28]		[-0.37]	[-0.43]
Undervalued ($RMV_{0.80}$)	50	-0.06	-0.08	56	-0.05	-0.06	59	-0.04	-0.06
		[-2.19]	[-5.56]		[-3.26]	[-4.88]		[-1.93]	[-5.01]
Undervalued ($RMV_{0.90}$)	38	-0.10	-0.10	26	-0.08	-0.07	33	-0.09	-0.10
		[-3.28]	[-6.60]		[-2.97]	[-3.98]		[-3.82]	[-6.10]
Undervalued ($RMV_{0.95}$)	31	-0.13	-0.12	15	-0.14	-0.11	18	-0.12	-0.12
		[-4.35]	[-7.47]		[-3.52]	[-5.71]		[-3.39]	[-5.12]

Panel C. Average aggregate flows to Value and Growth funds over last 6 months

	B/M			E/P			CF/P		
condition	N	Value	Growth	N	Value	Growth	N	Value	Growth
Overvalued ($RMV_{0.05}$)	72	1.78	2.42	56	1.65	2.72	62	1.82	2.66
		[9.10]	[3.60]		[6.50]	[3.10]		[8.50]	[3.40]
Overvalued ($RMV_{0.10}$)	104	1.67	1.96	79	1.68	2.23	93	1.80	2.13
		[11.10]	[4.07]		[8.31]	[3.52]		[11.90]	[3.98]
Overvalued ($RMV_{0.20}$)	153	1.54	1.59	119	1.72	1.87	130	1.76	1.81
		[11.80]	[4.65]		[10.80]	[4.36]		[12.90]	[4.63]
Normal (RMV_{normal})	203	-0.04	0.64	230	0.14	0.51	221	0.04	0.49
		[-0.61]	[2.35]		[1.94]	[2.63]		[0.54]	[2.45]
Undervalued ($RMV_{0.80}$)	69	-0.40	1.18	76	-0.49	1.53	74	-0.51	1.50
		[-1.34]	[1.64]		[-1.89]	[1.92]		[-1.94]	[1.83]
Undervalued ($RMV_{0.90}$)	53	-0.20	0.57	34	-1.25	0.68	44	-0.78	0.56
		[-0.59]	[0.88]		[-2.22]	[0.67]		[-1.80]	[0.71]
Undervalued ($RMV_{0.95}$)	35	-0.18	0.22	21	-0.97	0.20	24	-0.68	0.53
		[-0.20]	[0.25]		[-1.35]	[0.14]		[-1.11]	[0.41]

RMV that are associated with overvaluation. Furthermore, 6 months prior to the market becoming undervalued, value funds experience cash outflows while growth funds continue to have inflows. When market-wide undervaluation is identified as $RMV_{0.80}$, value funds experience significantly higher outflows than growth funds. Similar results hold when using E/P and CF/P to measure RMV. When undervaluation is identified as $RMV_{0.90}$ or $RMV_{0.95}$, value funds continue to experience outflows relative to growth funds.

Overall, the results in Panel C of Table 3.8 are consistent with the behavior of style switchers described in the framework of Section 3.2. The evidence shows that investors tend to direct their funds disproportionately more towards growth styles in a rising market. In contrast, in a declining market, investors tend to withdraw their funds disproportionately more out of value styles.

3.5.4 Time-Varying Market Beta of Value and Growth Stocks

The results so far reveal that the performance of the value strategy is conditional on severe market-wide misvaluation periods, as measured by RMV (RMV^{mwz}). States in which the market is extremely over- or undervalued may be correlated with good or bad macroeconomic conditions. Previous research has documented that the market betas of value and growth stocks are different, depending on the state of the economy. For example, using the expected market risk premium as a measure of economic states, Petkova and Zhang (2005)[60] document that value stock betas tend to be higher than growth stock betas in bad times, while growth stock betas tend to be higher than value stock betas in good times. This finding is consistent with a risk-based explanation for the value premium. To examine whether the profitability of the value premium 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 different states of market-wide valuation as measured by RMV (RMV^{mwz}).

The market betas of value and growth portfolios are extimated using six-month rolling market model regressions with daily data.[32] Table 3.9 reports the market betas of value and

[32]↑Following Daniel and Moskowitz (2016)[77], I use ten lags of the market return in estimating market betas every day, using a regression specification of the form $r_{i,t} = \beta_0 r_{m,t} + \beta_1 r_{m,t-1} + ... + \beta_{10} r_{m,t-10} + \epsilon_{i,t}$.

Table 3.9. Market-wide Misvaluation and Market Betas of Value and Growth Stocks, 1968-2018

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 (RMV or RMV^{mwz}). The sample covers the period from January 1968 to December 2018. Variable definitions are described in Appendix A. 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. In each panel, we report the number of months 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. We report Newey-West t-statistics in brackets under the coefficient estimates.

Panel A.Using RMV misvaluation measure					
condition	N	Value Beta	Growth Beta	VmG Beta	VmG Alpha
Overvalued ($RMV_{0.05}$)	85	0.92	1.06	-0.14	1.18
				[-3.41]	[7.44]
Overvalued ($RMV_{0.10}$)	129	0.94	1.07	-0.13	1.19
				[-3.98]	[9.01]
Overvalued ($RMV_{0.20}$)	195	0.96	1.10	-0.14	1.08
				[-5.19]	[9.60]
Normal (RMV_{normal})	285	1.27	1.03	0.24	-0.29
				[6.68]	[-2.05]
Undervalued ($RMV_{0.80}$)	120	1.56	0.95	0.62	1.44
				[10.68]	[4.32]
Undervalued ($RMV_{0.90}$)	91	1.57	0.95	0.62	2.01
				[9.33]	[5.01]
Undervalued ($RMV_{0.95}$)	67	1.57	0.94	0.63	2.47
				[7.67]	[5.02]
Panel B.Using RMV^{mwz} misvaluation measure					
condition	N	Value Beta	Growth Beta	VmG Beta	VmG Alpha
Overvalued ($RMV_{0.01}^{mwz-}$)	86	0.91	1.13	-0.23	1.36
				[-5.91]	[6.95]
Overvalued ($RMV_{0.05}^{mwz-}$)	179	0.93	1.13	-0.20	1.02
				[-7.24]	[8.96]
Overvalued ($RMV_{0.10}^{mwz-}$)	234	0.97	1.12	-0.14	0.80
				[-5.42]	[6.94]
Normal (RMV_{normal}^{mwz})	233	1.26	1.01	0.26	-0.40
				[6.82]	[-2.47]
Undervalued ($RMV_{0.10}^{mwz+}$)	133	1.60	0.93	0.66	1.57
				[12.16]	[5.42]
Undervalued ($RMV_{0.05}^{mwz+}$)	118	1.59	0.93	0.66	1.61
				[11.52]	[5.72]
Undervalued ($RMV_{0.01}^{mwz+}$)	78	1.60	0.93	0.67	2.19
				[8.69]	[7.27]

growth portfolios conditional on different levels of RMV (Panel A) and RMV^{mwz} (Panel B). In both panels, following periods of overvaluation, growth stocks have significantly higher betas than value stocks and, following periods of undervaluation, value stocks have significantly higher betas than growth stocks.

Table 3.9 also reports the alphas of the value-minus-growth strategy in different states of RMV (RMV^{mwz}). The results show that the alphas are statistically significant for all specifications corresponding to an overvalued or undervalued market. In states of normal market-wide valuation, the alpha of the value-minus-growth strategy is negative and statistically significant. However, its magnitude is relatively small. Overall, the evidence in Table 3.9 reveals that the spread in betas between value and growth stocks in different states of RMV (RMV^{mwz}) is not large enough to explain the magnitude of the value premium following periods of over- or undervaluation. It is unlikely that the previous results are driven by differences in market exposure between value and growth stocks.

3.6 Robustness Tests

In this section, I perform several additional tests to examine the robustness of the main results. Specifically, I use alternative valuation ratios to B/M and we use value-weighted portfolio returns.

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. I substitute B/M with two other fundamental-to-price ratios that have been used previously, earnings-to-price (E/P) and cash flow-to-price (CF/P), to sort stocks into value and growth and to define the market-wide misvaluation measures RMV and RMV^{mwz}. Value and growth portfolios are still equally-weighted. Table B.3 in Appendix B reports the average returns of value, growth, and value-growth portfolios for 12 months before, one month after, and 12 months after portfolio formation, using E/P and CF/P as valuation ratios. The results in Table B.3 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.

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.

While previously I use equally-weighted value and growth portfolios, here I also study value-weighted portfolios. To save space, I report results that replicate the analysis in Tables 3.2 and 3.5 only, using value-weighted returns. The results are presented in Tables B.4 and B.5 of Appendix B. Table B.4 shows that the value-weighted value premium is large and significant following periods of market-wide under- or overvaluation. A notable result in Table B.4 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 (using both RMV and RMV^{mwz}). 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 B.5 in Appendix B shows that the predictability of DOM (as defined through RMV and RMV^{mwz}) 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)[55], 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.

3.7 Conclusion

In this chapter, a stylized model of financial markets is developed, which links time-series variation in the value premium to return extrapolation. The intuition of this extended 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 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 the end of the period. 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 bad 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.

Two main implications of the model are tested. First, the model predicts that the value premium is stronger following periods of extreme market-wide over- or undervaluation. Second, the 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 this chapter are consistent with the predictions of our model. Using the deviation of the aggregate B/M ratio from its historical benchmark as a measure of market-wide misvaluation, the results show that the profitability of the value premium is large and significant following periods of market-wide over- or undervaluation. The value premium either does not exist or very low following periods of normal valuation.

I provide further evidence that, around periods of market-wide misvaluation, the pattern of investor demand for equities and different equity styles is also consistent with the framework of the model. In particular, I show that equity funds experience outflows before periods of significant market-wide undervaluation and inflows before periods of significant market-wide overvaluation. Furthermore, in a rising market, investors direct their capital disproportionately more towards growth styles. In contrast, in a declining market, value styles experience a disproportionate withdrawal of investor funds.

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

This work 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 provided suggests that the value premium is likely linked to return extrapolation and errors in investor expectations.

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A. VARIABLE DEFINITIONS

Below I describe the calculation of the main variables used in this study.

- **Book-to-market ratio,** B/M: following Asness and Frazzini (2013), the firm-level B/M is calculated on a monthly basis, where the book equity is from the last fiscal year end, and the market value is updated at the end of each month. Book value of equity is shareholders' equity (item SEQ) minus preferred stock plus deferred taxes (item TXDITC). We measure preferred stock using liquidation value (item PSTKL), redemption value (item PSTKR) or carrying value (item PSTK) in this order, depending on availability. If SEQ is missing, we measure book value of equity as common equity (item CEQ) plus carrying value of preferred stock (item PSTK). Finally, if CEQ is missing, we measure book value of equity as total assets (item AT) minus total liabilities (item LT).[1] The market B/M in month t is the average of firm-level B/M, winsorized at 1% and 99%. Firms with negative B/M are excluded. Source: COMPUSTAT and CRSP. Coverage: January 1952 - June 2018.

- **Earnings-to-price ratio,** E/P: the firm-level E/P is calculated on a monthly basis, where the earnings used in year t are the total earnings before extraordinary items for the last fiscal year end in t-1, and the market value is updated at the end of each month. The market E/P is the average of firm-level E/P, winsorized at 1% and 99%. Firms with negative E/P are excluded. Source: COMPUSTAT and CRSP. Coverage: January 1952 - June 2018.

- **Cash-flow-to-price ratio,** CF/P: the firm-level CF/P is calculated on a monthly basis, where the 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, and the market value is updated at the end of each month. The market CF/P in month t is the average of firm-level CF/P, winsorized at 1% and 99%. Firms with negative CF/P are excluded. Source: COMPUSTAT and CRSP. Coverage: January 1952 - June 2018.

- **Market** B/M**,** E/P**,** CF/P: The market B/M (E/P, CF/P) in month t is the average B/M (E/P, CF/P) of firms listed in NYSE, NASDAQ, and AMEX, winsorized at 1% and 99%. Firms with negative B/M (E/P, CF/P) are excluded. Financial and utilities firms are excluded. Source: COMPUSTAT and CRSP. Coverage: January 1952 - June 2018.

[1] ↑Kenneth French's website mentions "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.

- **Market-Wide Misvaluation,** RMV **and** RMV^{mwz}: RMV is calculated by using the same method on B/M, E/P or CF/P. The method is illustrated by using B/M. At the end of month t, we calculate market-wide B/M, and we obtain the past 10 years or market-wide B/M from $t-119$ to $t-1$. We rank the past B/M ratios from smallest to largest, then find the relative standing of the B/M in the historical time-series. RMV is the relative standing scaled by 120. For example, if the most recent market-wide B/M is the highest during the past 10 years, then the relative standing is the 120^{th} and $RMV = 1$. Coverage: January 1962 - June 2018.

  RMV^{mwz} is calculated using B/M, E/P or CF/P. At the end of month t, we obtain the cross-section of firm-level B/M (or E/P, CF/P) ratios as the current distribution in month t. The cross-section of firms include common stocks (share code in CRSP is 10 or 11) listed on NYSE, NASDAQ, and AMEX. Financials and utilities are excluded. We form the historical benchmark distribution by pooling all cross-sections of B/M (or E/P, CF/P) from $t-121$ to $t-1$. We extract the 99 percentiles (from 1^{st} to 99^{th}) from the current distribution to form an approximate current distribution, and we extract the 99 percentiles from the historical benchmark distribution to form an approximate benchmark distribution. We use the two approximate distribution to conduct Mann-Whitney U-tests. Since we use normal approximation to obtain the test statistics, the final statistics are z-statistics. Large negative z-statistics indicate that the current distribution of firm-level B/M ratios deviates significantly to the left of the historical distribution and, therefore, correspond to market-wide overvaluation states. For example, $RMV_{0.01}^{mwz-}$ denotes a case in which the current distribution of firm-level B/M ratios deviates significantly to the left of the historical distribution (p-value = 0.01). Similarly, large positive z-statistics indicate that the current distribution of firm-level B/M ratios deviates significantly to the right of the historical distribution and, therefore, correspond to market-wide undervaluation states. For example, $RMV_{0.01}^{mwz+}$ denotes a case in which the current distribution of firm-level B/M ratios deviates significantly to the right of the historical distribution (p-value = 0.01).

- **Value spread**: following Cohen, Polk, and Vuolteenaho (2003), the value spread is $log(B/M)^H - log(B/M)^L$, the difference between the natural logarithm of B/M (or E/P, CF/P) of the top quintile group and the bottom quintile group, sorted by firm-level B/M (or E/P, CF/P). Coverage: January 1962 - June 2018.

- **3-day CAR of earnings announcement**: the cumulative abnormal return, CAR, of the 3-day event window $[-1, 1]$ around earnings announcement is estimated by using the market model on the returns from $t-390$ to $t-30$. For each stock at the end month t (portfolio formation time), we sum up the CARs of the earnings announcements that happened from $t+1$ to $t+12$, to obtain the annual CAR of earnings announcement. Coverage: January 1963 - June 2018.

- **Fund flows to Domestic Equity**: following Ben-Rephael, Kandel and Wohl (2012), we construct domestic equity dollar flows by aggregating dollar flows of five equity fund types: growth, aggressive growth, income&growth, income equity, and sector. Dollar flows are "new sales" minus "redemption" plus "exchanges in" minus "exchanges out", which are obtained from the Investment Company Institute (ICI). The total net asset value (TNA) of domestic equity is obtained similarly by summing the value of assets under management across the five aforementioned categories. Following prior literature (e.g., and Sirri and Tufano (1998)), percentage flows to domestic equity are calculated as the ratio of dollar flows divided by lagged TNA. Coverage: January 1991 - December 2015.[2]

- **Fund flows to Bonds**: Following the procedure outlined for the construction of domestic equity flows, we begin by calculating dollar flows to bond funds by aggregating dollar flows of the following fund types: corporate bonds, global bonds, high yield bonds, MBS, national municipal bonds, state municipal bonds, stratified income bonds, national non-taxable money market funds, state non-taxable money market funds, taxable money market (government) and non-taxable money-market (non-government). Dollar flows are "new sales" minus "redemption" plus "exchanges in" minus "exchanges out", which are obtained from the Investment Company Institute (ICI). The total net asset value (TNA) of bond funds is obtained similarly, by summing the value of asset under management across the aforementioned fund types. Following prior literature (e.g., and Sirri and Tufano (1998)), percentage flows to bond funds are calculated as the ratio of dollar flows divided by the lagged TNA. Coverage: January 1991 - December 2015.

- **Change in analysts' price target,** ΔPTG: the change in analyst price target at the end of month t is the difference between the consensus price target in month t and the past 12-month average consensus in price target, scaled by the past 12-month average consensus in price target. Source: I/B/E/S. Coverage: January 2000 - June 2018.

- **Fund flows to value and growth funds**: following Chevalier and Ellison (1997), the fund flow is calculated as $flow_{\mathrm{i},t} = \frac{TNA_{\mathrm{i},t} - TNA_{\mathrm{i},t-1} \times (1+RET_{\mathrm{i},t})}{TNA_{\mathrm{i},t-1}}$. We obtain the fund TNA and returns from CRSP Survivor-Bias-Free U.S. Mutual Fund Database. Our sample of funds excludes balanced, bond, money market, international, sector funds, as well as funds not invested primarily in equity. To identify value and growth funds, we rely on fund names. For example, if a fund's name contains the words "Value Fund", "Value Strategy", "Value Portfolio", or some other combination of these words, we classify it as a value fund. A similar identification is used for growth funds. Coverage: January 1980 - June 2018.

[2]↑The population of the funds covered by ICI was enlarged in January 1991 to include TIAA-CREF funds, so our sample starts in January 1991.

- **Net flows to bond and equity funds**: following Ben-Rephael, Kandel and Wohl (2012), the net flows are calculated as: "new sales" minus "redemption" plus "exchanges in" minus "exchanges out", which are obtained from the Investment Company Institute (ICI). Coverage: January 1991 - December 2015.[3]

- **NEIO**: following Ben-Rephael, Kandel and Wohl (2012), *NEIO* is the normalized aggregate net exchanges ("exchanges in" minus "exchanges out") of the equity funds. Coverage: January 1991 - December 2015.

- **Market beta of value and growth stocks**: following Daniel and Moskowitz (2016), the market betas for value and growth stocks are estimated using 126-day rolling market model regressions. We use 10 daily lags of the market return in estimating the market betas, $r_{\mathrm{i},t} = \beta_0 r_{m,t} + ... + \beta_{10} r_{m,t-10} + \epsilon_{\mathrm{i},t}$, where $r_{\mathrm{i},t}$ is the return of value (or growth) stocks. The daily beta is the sum of the estimated coefficients $\hat{\beta}_0 + ... + \hat{\beta}_{10}$. The market beta of month t is the average daily market beta in month t. The alpha of month t is the sum of daily alpha in month t. Coverage: January 1962 - June 2018.

[3]↑The population of the funds covered by ICI was enlarged in January 1991 to include TIAA-CREF funds, so our sample starts from January 1991.

B. ADDITIONAL TABLES

Table B.1. Momentum and Value Premium Conditional on Extrapolation, Value-weighted, 1968-2018

This table reports the average value-weighted returns of momentum (Panel A), and value premium (Panel B), conditional on the level of over-extrapolation (DOX). In Panel A, the momentum strategy is constructed at end of each month by sorting stocks into decile portfolios based on their cumulative 12-month returns, and then track them for 12 months. The value/growth decile portfolios are formed at the end of each month and tracked for 12 months. In the last column, I report the performance of the long-short portfolios (Winners-Losers for momentum, and Value-Growth for value premium). In Panel B, the value premium is calculated using B/M, E/P, and C/P, respectively. Stocks with price less than $1 are excluded at the time of portfolio formation. For each decile portfolio and the long-short portfolio, I report the following statistics: the average monthly returns of the 12-month holding period ($\bar{R}$), the t-statistics of $\bar{R}$ ($t(\bar{R})$), Jensen's alpha (α), and its corresponding t-statistics ($t(\alpha)$), the average excess returns over the 1-month T-bill rate ($\bar{R} - R_f$), the standard deviation of the excess returns (σ), and the Sharpe ratio (SR). *High DOX* is defined as the states where DOX is greater than the 70^{th} percentile, and *Low DOX* is defined as the states where DOX is less than the 30^{th} percentile. *Mid DOX* represents the states where DOX is in between the 30^{th} and 70^{th} percentiles. The difference between *High DOX* and *Low DOX* is reported in the last column, and the corresponding p-values are reported in parenthesis. The sample covers from Jan 1968 to November 2018.

Panel A. Momentum (12-0-12)

Statistics	*All*	*High DOX*	*Mid DOX*	*Low DOX*	*High - Low*
$\bar{R}$	0.67	-0.01	0.91	1.04	-1.05
$t(\bar{R})$	[3.42]	[-0.02]	[4.36]	[3.70]	(0.01)
α	0.68	-0.01	0.93	1.05	-1.06
$t\alpha$	[3.42]	[-0.02]	[4.45]	[3.74]	(0.01)
σ	2.00	2.60	1.62	1.58	1.02
SR	0.14	-0.15	0.35	0.39	-0.99

Panel B. Value Premium

Panel B.1. B/M					
Statistics	*All*	*High DOX*	*Mid DOX*	*Low DOX*	*High - Low*
$\bar{R}$	0.36	0.84	0.44	-0.22	1.06
$t(\bar{R})$	[1.49]	[1.66]	[1.51]	[-0.69]	(0.01)
α	0.36	0.84	0.44	-0.22	1.06
$t\alpha$	[1.49]	[1.66]	[1.50]	[-0.70]	(0.01)
σ	2.08	2.58	1.81	1.69	0.90
SR	-0.01	0.17	0.05	-0.38	1.22
Panel B.2. E/P					
Statistics	*All*	*High DOX*	*Mid DOX*	*Low DOX*	*High - Low*
$\bar{R}$	0.19	0.67	-0.01	-0.01	0.68
$t(\bar{R})$	[0.96]	[1.78]	[-0.02]	[-0.04]	(0.04)
α	0.21	0.67	0.01	0.00	0.67
$t\alpha$	[1.01]	[1.80]	[0.02]	[0.01]	(0.04)
σ	1.77	1.96	1.75	1.50	0.46
SR	-0.11	0.14	-0.21	-0.29	1.55
Panel B.3. C/P					
Statistics	*All*	*High DOX*	*Mid DOX*	*Low DOX*	*High - Low*
$\bar{R}$	0.31	0.70	0.23	0.04	0.66
$t(\bar{R})$	[1.67]	[2.22]	[0.79]	[0.14]	(0.03)
α	0.32	0.70	0.23	0.04	0.66
$t\alpha$	[1.70]	[2.22]	[0.81]	[0.16]	(0.03)
σ	1.61	1.70	1.64	1.41	0.29
SR	-0.05	0.18	-0.08	-0.28	2.43

Table B.2. Predicting Momentum/Value Premium, Value-weighted, 1968-2018

This table reports the equal-weighted returns of momentum (Panel A), and value premium (Panel B), conditional on the degree of over-extrapolation (DOX). The following regression specifications are estimated:

$$R^{MOM}_{t+1,t+12}(or\ R^{VAL}_{t+1,t+12}) = a_0 + \Gamma X_t + \epsilon_{t+1}, \tag{B.1}$$

$$R^{MOM}_{t+1,t+12}(or\ R^{VAL}_{t+1,t+12}) = a_1 DOX\ High + a_2 DOX\ Mid + a_3 DOX\ Low + \Gamma X_t + \epsilon_{t+1}, \tag{B.2}$$

$$R^{MOM}_{t+1,t+12}(or\ R^{VAL}_{t+1,t+12}) = a_0 + bDOX_t + \Gamma X_t + \epsilon_{t+1}, \tag{B.3}$$

The dependent variables are the average future 12-month "12-0-12" momentum (Panel A) and different value premium (Panel B). *DOX High*, *DOX Mid* and *DOX Low* are dummy variables equal to 1 if DOX is greater than its sample 70^{th} percentile, in between the 30^{th} and 70^{th} percentiles, and below the 30^{th} percentile, respectively. Following **CG(2018)**, DOX is the DOX extracted from II during the period from December 1967 to May 1992, the DOX extracted from the principal component time-series of II and AA from June 1992 to October 2018. X are vectors of the other control variables corresponding to momentum and value premium. The control variables X for dependent variable $R^{MOM}_{t+1,t+12}$ include market volatility (Wang and Xu, 2015), market illiquidity (Avramov, Cheng, and Hameed, 2016), momentum gap (Huang, 2015), and the investor sentiment index in Baker and Wurgler (2006). The control variables for value premium $R^{VAL}_{t+1,t+12}$ 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. Model (1), (3) and (5) estimate Eq(B.1), Eq(B.2) and Eq(B.3) without the control variables X, whereas Model (2), (4) and (6) include the control variables. The t-statistics are adjusted for serial correlation and heteroskedasticity and reported in brackets. The bottom of each panel reports the following statistics and tests: $\hat{a1} - \hat{a3}$ is the in-sample momentum/value premium wedge between high DOX and low DOX, and $p - Value(H_0 : \hat{a1} = \hat{a3})$ is the in-sample p-value of a test of the null-hypothesis that there is no difference in momentum/value following high versus low DOX. The sample covers from Jan 1968 to November 2019.

Panel A. Momentum 12-0-12

parameter	(1)	(2)	(3)	(4)	(5)	(6)
Int	0.007	0.026			0.015	0.031
	[3.42]	[2.15]			[3.75]	[2.35]
DOX High			0.000	0.011		
			[-0.04]	[1.40]		
DOX Mid			0.009	0.019		
			[4.37]	[2.38]		
DOX Low			0.010	0.019		
			[3.69]	[2.49]		
DOX					-0.020	-0.017
					[-1.91]	[-1.86]
Macro controls	N	Y	N	Y	N	Y
N	611	611	611	611	611	611
Adj. R^2	0.099	0.150	0.141	0.183	0.039	0.081
$\hat{a1} - \hat{a3}$			-0.010	-0.008		
$p - Value(H_0 : \hat{a1} = \hat{a3})$			(0.010)	(0.023)		

Table B.2. Predicting Momentum/Value Premium, Equal-weighted, 1968-2018 (continued)

Panel B. Value Premium

Panel B.1. B/M

parameter	(1)	(2)	(3)	(4)	(5)	(6)
Int	0.004	-0.034			-0.006	-0.039
	[1.49]	[-4.44]			[-1.10]	[-4.64]
DOX High			0.008	-0.025		
			[1.68]	[-2.94]		
DOX Mid			0.005	-0.028		
			[1.55]	[-3.56]		
DOX Low			-0.002	-0.034		
			[-0.58]	[-4.48]		
DOX					0.021	0.017
					[1.77]	[1.64]
N	611	611	611	611	611	611
Adj. R^2	0.028	0.262	0.063	0.274	0.043	0.265
$\hat{a1} - \hat{a3}$			0.010	0.009		
$p - Value(H_0 : \hat{a1} = \hat{a3})$			(0.014)	(0.023)		

Panel B.2. E/P

parameter	(1)	(2)	(3)	(4)	(5)	(6)
Int	0.002	-0.022			-0.006	-0.026
	[0.96]	[-3.08]			[-1.25]	[-3.30]
DOX High			0.006	-0.014		
			[1.73]	[-2.78]		
DOX Mid			0.000	-0.019		
			[-0.00]	[-3.32]		
DOX Low			0.000	-0.019		
			[0.04]	[-3.35]		
DOX					0.018	0.013
					[1.79]	[1.53]
N	611	611	611	611	611	611
Adj. R^2	0.011	0.124	0.039	0.142	0.041	0.135
$\hat{a1} - \hat{a3}$			0.006	0.005		
$p - Value(H_0 : \hat{a1} = \hat{a3})$			(0.039)	(0.095)		

Panel B.3. C/P

parameter	(1)	(2)	(3)	(4)	(5)	(6)
Int	0.003	-0.024			-0.003	-0.029
	[1.67]	[-3.84]			[-0.83]	[-4.61]
DOX High			0.007	-0.017		
			[2.15]	[-3.00]		
DOX Mid			0.002	-0.021		
			[0.73]	[-3.53]		
DOX Low			0.000	-0.024		
			[0.13]	[-4.45]		
DOX					0.015	0.014
					[1.82]	[1.71]
N	611	611	611	611	611	611
Adj. R^2	0.034	0.198	0.058	0.217	0.035	0.195
$\hat{a1} - \hat{a3}$			0.007	0.007		
$p - Value(H_0 : \hat{a1} = \hat{a3})$			(0.029)	(0.017)		

Table B.3. Market-wide Misvaluation (calculated by E/P, CF/P) and the Value Premium (equal-weighted), 1968-2018

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 and RMV^{mwz}). The definitions of variables are described in Appendix A. At the end of each month, we calculate E/P and CF/P and sort the 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. In each panel, we report the number of months under different scenarios of RMV (RMV^{mwz}), the market E/P or CF/P, the value spread, the previous-12-month average returns of V, G, and VmG, the next-month returns of V, G and VmG, and the next-12-month average returns of V, G and VmG. Newey-West t-statistics are reported in brackets. Panel A reports results for using E/P to calculate RMV (RMV^{mwz}) and identify value and growth stocks. Panel B reports results for using CF/P to calculate RMV (RMV^{mwz}) and identify value and growth stocks.

Panel A. RMV calculated using E/P

Panel A1. Using RMV misvaluation measure

				Previous 12 months, %			Next 1 month, %			Next 12 months, %		
condition	N	Market E/P	Value spread	V	G	VmG	V	G	VmG	V	G	VmG
Overvalued ($RMV_{0.05}$)	66	0.06	1.88	0.24	4.83	-4.59	0.67	-0.65	1.32	0.34	-0.39	0.73
				[0.65]	[11.01]	[-16.16]	[1.04]	[-1.01]	[5.01]	[1.18]	[-0.97]	[2.31]
Overvalued ($RMV_{0.10}$)	109	0.06	1.88	-0.11	4.14	-4.25	0.86	0.15	0.71	0.52	-0.06	0.58
				[-0.39]	[11.37]	[-16.08]	[2.09]	[0.31]	[2.65]	[1.91]	[-0.16]	[2.52]
Overvalued ($RMV_{0.20}$)	158	0.06	1.87	-0.41	3.77	-4.18	1.23	0.56	0.67	0.77	0.27	0.50
				[-1.59]	[9.75]	[-16.23]	[3.56]	[1.36]	[2.71]	[2.94]	[0.92]	[2.67]
Normal (RMV_{normal})	316	0.08	1.87	-1.04	3.11	-4.15	0.83	0.91	-0.08	1.11	1.04	0.07
				[-3.7]	[11.65]	[-17.48]	[2.12]	[2.56]	[-0.36]	[3.60]	[3.43]	[0.42]
Undervalued ($RMV_{0.80}$)	126	0.11	2.03	-3.09	2.33	-5.42	3.07	1.25	1.82	2.76	1.32	1.44
				[-5.26]	[3.11]	[-8.43]	[3.47]	[1.59]	[2.84]	[4.44]	[2.74]	[4.00]
Undervalued ($RMV_{0.90}$)	72	0.12	2.02	-3.92	1.53	-5.44	3.20	0.61	2.58	3.08	1.14	1.95
				[-5.10]	[1.83]	[-8.60]	[2.52]	[0.68]	[3.46]	[3.22]	[1.79]	[3.75]
Undervalued ($RMV_{0.95}$)	46	0.13	1.97	-5.12	0.03	-5.16	4.06	1.12	2.95	3.51	1.40	2.11
				[-9.42]	[0.06]	[-10.27]	[2.19]	[0.93]	[2.76]	[2.51]	[1.69]	[2.68]

Panel A2. Using RMV^{mwz} misvaluation measure

				Previous 12 months, %			Next 1 month, %			Next 12 months, %		
condition	N	Market E/P	Value spread	V	G	VmG	V	G	VmG	V	G	VmG
Overvalued ($RMV_{0.01}^{mwz-}$)	105	0.06	1.79	-0.58	3.45	-4.03	1.07	-0.13	1.20	0.64	-0.13	0.77
				[-1.89]	[6.34]	[-12.53]	[2.24]	[-0.26]	[4.57]	[1.95]	[-0.39]	[3.82]
Overvalued ($RMV_{0.05}^{mwz-}$)	183	0.06	1.87	-0.60	3.48	-4.08	1.22	0.60	0.62	0.71	0.24	0.47
				[-3.69]	[13.05]	[-20.75]	[2.61]	[1.64]	[1.37]	[2.99]	[1.91]	[2.03]
Overvalued ($RMV_{0.10}^{mwz-}$)	242	0.06	1.88	-0.60	3.49	-4.10	0.96	0.54	0.42	0.67	0.34	0.33
				[-2.78]	[11.65]	[-19.44]	[3.21]	[1.61]	[1.63]	[3.02]	[1.49]	[1.92]
Normal (RMV_{normal}^{mwz})	216	0.08	1.94	-1.46	3.23	-4.69	0.84	1.03	-0.19	1.17	1.06	0.11
				[-4.56]	[8.78]	[-12.83]	[1.86]	[2.27]	[-0.73]	[3.02]	[2.81]	[0.59]
Undervalued ($RMV_{0.10}^{mwz+}$)	142	0.11	1.87	-2.27	2.30	-4.57	3.02	1.27	1.75	2.84	1.58	1.26
				[-3.27]	[4.22]	[-10.55]	[4]	[1.91]	[3.36]	[5.45]	[3.74]	[3.64]
Undervalued ($RMV_{0.05}^{mwz+}$)	105	0.12	1.84	-2.42	1.99	-4.41	3.29	1.18	2.11	2.93	1.53	1.41
				[-4.36]	[5.87]	[-10.93]	[4.04]	[2.45]	[1.91]	[6.15]	[4.45]	[2.38]
Undervalued ($RMV_{0.01}^{mwz+}$)	77	0.13	1.77	-2.63	1.64	-4.28	3.66	1.38	2.28	3.24	1.67	1.57
				[-2.48]	[2.01]	[-11.17]	[2.89]	[1.75]	[2.96]	[3.76]	[3.02]	[3.08]

Panel B. RMV calculated using CF/P

Panel B1. Using RMV misvaluation measure

condition	N	Market CF/P	Value spread	Previous 12 months, %			Next 1 month, %			Next 12 months, %		
				V	G	VmG	V	G	VmG	V	G	VmG
Overvalued ($RMV_{0.05}$)	79	0.13	2.25	0.31	4.37	-4.05	1.06	-0.48	1.54	0.37	-0.40	0.77
				[1.29]	[10.85]	[-15.00]	[1.96]	[-0.72]	[4.46]	[1.16]	[-1.34]	[2.47]
Overvalued ($RMV_{0.10}$)	121	0.13	2.24	0.13	4.07	-3.94	0.93	-0.32	1.25	0.66	0.01	0.66
				[0.63]	[12.53]	[-15.60]	[2.41]	[-0.71]	[3.69]	[2.06]	[0.03]	[2.52]
Overvalued ($RMV_{0.20}$)	172	0.14	2.24	-0.16	3.64	-3.79	1.10	0.19	0.91	0.90	0.32	0.58
				[-0.63]	[9.95]	[-14.05]	[3.47]	[0.48]	[3.28]	[3.34]	[1.19]	[2.59]
Normal (RMV_{normal})	279	0.18	2.22	-0.79	3.42	-4.21	1.15	1.34	-0.19	1.15	1.05	0.10
				[-2.29]	[11.08]	[-12.19]	[2.53]	[3.42]	[-0.61]	[3.27]	[3.35]	[0.43]
Undervalued ($RMV_{0.80}$)	149	0.24	2.37	-2.55	2.14	-4.69	2.36	0.49	1.87	2.71	1.05	1.66
				[-4.40]	[4.17]	[-10.23]	[3.29]	[0.78]	[4.03]	[4.24]	[2.22]	[4.70]
Undervalued ($RMV_{0.90}$)	92	0.26	2.41	-3.63	1.32	-4.95	3.22	0.31	2.91	3.15	1.02	2.13
				[-5.53]	[2.32]	[-10.77]	[3.03]	[0.34]	[4.74]	[3.57]	[1.73]	[4.35]
Undervalued ($RMV_{0.95}$)	53	0.28	2.39	-4.77	0.29	-5.06	3.49	0.67	2.82	3.54	1.20	2.34
				[-7.24]	[0.60]	[-7.68]	[2.19]	[0.53]	[2.66]	[2.71]	[1.40]	[3.00]

Panel B2. Using RMV^{mwz} misvaluation measure

condition	N	CF/P	Value spread	Previous 12 months, %			Next 1 month, %			Next 12 months, %		
				V	G	VmG	V	G	VmG	V	G	VmG
Overvalued ($RMV_{0.01}^{mwz-}$)	78	0.15	2.20	-0.16	3.66	-3.82	0.62	-0.60	1.23	0.27	-0.56	0.84
				[-0.37]	[5.24]	[-8.85]	[1.17]	[-0.97]	[3.42]	[0.74]	[-1.55]	[2.59]
Overvalued ($RMV_{0.05}^{mwz-}$)	165	0.14	2.23	-0.23	3.67	-3.90	0.90	-0.03	0.92	0.69	0.09	0.60
				[-1.96]	[13.22]	[-18.76]	[2.73]	[1.51]	[1.71]	[2.54]	[1.98]	[1.47]
Overvalued ($RMV_{0.10}^{mwz-}$)	214	0.14	2.25	-0.21	3.64	-3.85	1.05	0.45	0.60	0.81	0.26	0.55
				[-0.93]	[11.42]	[-15.9]	[3.49]	[1.28]	[1.97]	[3.07]	[1.07]	[2.58]
Normal (RMV_{normal}^{mwz})	247	0.18	2.29	-1.14	3.46	-4.61	1.01	1.13	-0.12	1.13	1.00	0.13
				[-2.86]	[8.86]	[-10.52]	[2.22]	[2.57]	[-0.35]	[3.01]	[2.87]	[0.5]
Undervalued ($RMV_{0.10}^{mwz+}$)	139	0.25	2.25	-2.15	1.90	-4.06	2.79	0.74	2.05	3.07	1.45	1.62
				[-3.17]	[3.88]	[-12.07]	[3.47]	[1.2]	[4.06]	[4.83]	[3.13]	[4.31]
Undervalued ($RMV_{0.05}^{mwz+}$)	110	0.27	2.22	-2.33	1.74	-4.07	3.61	1.46	2.15	3.32	1.51	1.80
				[-3.94]	[6.46]	[-12.13]	[3.43]	[2.08]	[2.05]	[3.23]	[2.98]	[3.78]
Undervalued ($RMV_{0.01}^{mwz+}$)	76	0.29	2.17	-2.52	1.50	-4.02	3.41	1.02	2.38	3.51	1.38	2.13
				[-2.33]	[1.82]	[-9.38]	[2.8]	[1.14]	[3.18]	[3.63]	[2.18]	[3.64]

Table B.4. Market-wide Misvaluation and the Value Premium (value-weighted), 1968-2018

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 and RMV^{mwz}). The definitions of variables are described in Appendix A. 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. In each panel, we report the number of months under different scenarios of RMV (RMV^{mwz}), the market-wide B/M, the value spread, the previous-12-month average returns of V, G and VmG, the next-month returns of V, G, and VmG, and the next-12-month average returns of V, G, and VmG. Newey-West t-statistics are reported in brackets. Panel A reports the results for using RMV to identify misvaluation states. Panel B reports results for using RMV^{mwz} to identify misvaluation states. Both measures are based on the market-wide B/M ratio.

Panel A. Using RMV misvaluation measure

				Previous 12 months, %			Next 1 month, %			Next 12 months, %		
condition	N	Market B/M	Value spread	V	G	VmG	V	G	VmG	V	G	VmG
Overvalued ($RMV_{0.05}$)	85	0.54	2.05	-0.02	2.76	-2.78	1.27	-0.47	1.73	0.73	0.49	0.23
				[-0.06]	[6.74]	[-7.87]	[2.68]	[-0.97]	[3.03]	[2.32]	[1.38]	[0.45]
Overvalued ($RMV_{0.10}$)	129	0.55	2.07	-0.27	2.51	-2.78	1.20	0.05	1.15	0.93	0.79	0.15
				[-0.89]	[7.59]	[-7.68]	[3.11]	[0.12]	[2.43]	[3.22]	[2.52]	[0.36]
Overvalued ($RMV_{0.20}$)	195	0.59	2.06	-0.39	2.41	-2.79	1.25	0.62	0.63	0.96	0.93	0.03
				[-1.59]	[8.21]	[-8.55]	[4.18]	[1.85]	[1.61]	[3.82]	[3.34]	[0.10]
Normal (RMV_{normal})	285	0.79	2.12	-1.54	2.00	-3.54	1.03	1.37	-0.34	1.11	1.03	0.08
				[-4.38]	[9.16]	[-8.15]	[2.44]	[4.70]	[-0.89]	[3.44]	[4.22]	[0.29]
Undervalued ($RMV_{0.80}$)	120	1.18	2.41	-4.57	0.31	-4.88	2.17	0.01	2.16	2.24	0.40	1.84
				[-4.25]	[0.72]	[-5.40]	[1.99]	[0.01]	[2.53]	[3.27]	[0.78]	[3.66]
Undervalued ($RMV_{0.90}$)	91	1.26	2.43	-5.37	-0.24	-5.13	2.65	0.03	2.62	2.37	0.33	2.04
				[-4.44]	[-0.65]	[-4.68]	[2.18]	[0.04]	[2.70]	[2.78]	[0.56]	[3.69]
Undervalued ($RMV_{0.95}$)	67	1.29	2.44	-6.42	-0.79	-5.63	3.49	0.29	3.20	2.48	0.34	2.14
				[-5.10]	[-2.45]	[-4.52]	[2.52]	[0.35]	[2.99]	[2.51]	[0.48]	[3.40]

Panel B. Using RMV^{mwz} misvaluation measure

				Previous 12 months, %			Next 1 month, %			Next 12 months, %		
condition	N	Market B/M	Value spread	V	G	VmG	V	G	VmG	V	G	VmG
Overvalued ($RMV^{mwz-}_{0.01}$)	86	0.64	2.05	0.52	2.94	-2.43	1.19	-0.40	1.59	0.77	0.26	0.50
				[2.40]	[5.97]	[-5.18]	[2.39]	[-0.85]	[3.04]	[1.93]	[0.64]	[1.06]
Overvalued ($RMV^{mwz-}_{0.05}$)	179	0.63	2.06	-0.85	2.30	-3.15	0.98	0.88	0.10	0.95	0.98	-0.03
				[-3.77]	[11.27]	[-11.69]	[2.88]	[3.38]	[0.28]	[3.61]	[4.57]	[-0.11]
Overvalued ($RMV^{mwz-}_{0.10}$)	234	0.62	2.07	-0.50	2.48	-2.98	0.88	0.77	0.10	0.86	1.01	-0.15
				[-2.33]	[9.22]	[-10.10]	[2.34]	[2.23]	[0.25]	[3.04]	[3.85]	[-0.50]
Normal (RMV^{mwz}_{normal})	233	0.75	2.18	-1.96	2.07	-4.03	1.36	1.34	0.02	1.30	0.98	0.32
				[-4.55]	[10.80]	[-8.24]	[3.17]	[3.76]	[0.05]	[3.96]	[3.47]	[0.89]
Undervalued ($RMV^{mwz+}_{0.10}$)	133	1.20	2.27	-3.70	0.11	-3.80	2.09	0.16	1.93	2.03	0.44	1.59
				[-3.29]	[0.29]	[-4.10]	[1.99]	[0.29]	[2.51]	[3.24]	[1.01]	[3.60]
Undervalued ($RMV^{mwz+}_{0.05}$)	118	1.23	2.29	-3.32	0.95	-4.26	1.93	0.82	1.11	1.86	0.69	1.17
				[-4.40]	[2.97]	[-6.37]	[2.92]	[1.66]	[1.89]	[4.70]	[2.04]	[3.30]
Undervalued ($RMV^{mwz+}_{0.01}$)	78	1.32	2.28	-4.10	-0.35	-3.75	3.36	0.26	3.10	2.83	0.50	2.33
				[-3.33]	[-0.83]	[-3.80]	[2.99]	[0.39]	[4.15]	[3.47]	[0.89]	[4.39]

Table B.5. Market-wide Misvaluation and Predictability of Value Premium (value-weighted), 1968-2018

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 either $(RMV - 0.5)^2$ (Panel A) or $|RMV^{mwz}|$ (Panel B). $Value\,spread$ is defined as 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. Detailed variable definitions are in Appendix A. Newey-West t-statistics are reported in brackets.

Panel A. $DOM = (RMV - 0.5)^2$

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]	[-3.3]	[-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

Panel B. $DOM = |RMV^{mwz}|$

Coefficient	h=3			h=6			h=12		
a0	-1.09	-7.28	-10.13	-0.82	-7.29	-10.17	-0.32	-6.95	-11.28
	[-2.46]	[-2.46]	[-3.15]	[-2.16]	[-3.14]	[-3.92]	[-1.12]	[-4.53]	[-5.67]
a1	0.79	0.80	0.62	0.64	0.66	0.47	0.40	0.42	0.23
	[3.6]	[3.86]	[3.43]	[3.64]	[4.16]	[3.37]	[3.19]	[4]	[2.55]
a2		2.86	2.58		2.98	2.61		3.06	3.62
		[2.07]	[1.84]		[2.74]	[2.22]		[4.24]	[4.03]
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

Table B.6. 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. 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]	