ESSAYS ON THE RISKINESS OF VALUE STOCKS

by

CIARÁN JOHN O'NEILL

A dissertation submitted in partial fulfillment
Of the requirements for the degree of

Doctor of Philosophy
EDHEC Business School

January, 2023

Dissertation Committee:

Enrique Schroth, PhD
John Campbell, PhD
Laurent Calvet, PhD
Emmanuel Jurczenko, PhD

EDHEC BUSINESS SCHOOL

APPROVAL FORM

CANDIDATE'S NAME: Ciaran John O'NEILL

TITLE OF DISSERTATION: **"Essays on the Riskiness of Value Stocks"**

APPROVAL:

Enrique Schroth		*Chair*
John Y. Campbell		*External Examiner*
Laurent Calvet		*Member*
Emmanuel Jurczenko	Saisissez du texte ici	~~*Member*~~

☐ with minor revisions

☐ with major revisions

DATE: 10 January 2023

Abstract

In Paper 1 of this dissertation, I propose a risk-based explanation of the value premium with two equity risk premia; a larger premium for near-term systematic cashflow risk and a smaller one for distant cashflow risks. I contend that value stocks have higher sensitivity to near-term risks, and are duly discounted. I show that an Epstein-Zin representative agent prices innovations in both near-term consumption growth and anticipated future consumption growth (or wealth). I hypothesize that negative near-term cashflow shocks adversely impact value stocks through both a *price* and a *cashflow* channel, while growth stocks have a hedging quality that makes them less sensitive to shocks. To test these ideas, I develop an exactly-solved linear present value model of the price-dividend ratio which disentangles near-term and future cashflows with two time-varying risk premia, and I use an Unscented Kalman Filter to estimate the model on US market data historically. I find evidence of a dual risk premium structure in asset prices, with the dividend-level premium being larger. I then measure the sensitivity of sorted-portfolio returns to the estimated premia and find that (a) expected returns of value stocks have higher loadings on the larger premium, and (b) unexpected value returns are more sensitive to dividend-level shocks. Thus, value stocks are found to be more prone to cashflow and price declines in recessionary times when they become riskiest and discount rates are high, while growth stocks are less risky during recessions but become most sensitive to shocks during booms, when discount rates are low.

In Paper 2, I seek to identify the decisive factors causing value stocks to be especially threatened by near-term cashflow shocks. I argue that value stocks possess intrinsic attributes which induce high sensitivity of firm cashflows (and prices) to shocks. First, I relate the risk premium for near-term shocks to an original asset risk measure, the *Cashflow Shock Elasticity of Price*, and I measure components of this elasticity for sorted portfolios historically. I find that value stocks have a significantly larger elasticity than growth stocks, due primarily to the sensitivity of asset *cashflows* to shocks. Second, I present a comparative static model of the firm which pinpoints the fundamental determinants of cashflow shock elasticity (i.e., revenue beta, operating & financial leverage, and low profit margins) and I measure these attributes in sorted portfolios historically. I find compelling evidence that these characteristics are far more abundant in value firms than growth firms. Value stocks are shown to possess inherent fundamental traits that cause them to be highly sensitive to aggregate cashflow events, rendering them poor economic hedges at inopportune times, and therefore riskier and more discounted.

Contents

Acknowledgements

I would like to express my sincere gratitude to my thesis advisor, Professor Laurent E. Calvet, EDHEC Business School, for his scholarly advice, encouragement and thoughtful supervision of my thesis work. I also wish to thank the other members of my PhD Dissertation Committee, Professor Enrique Schroth, Director of the PhD in Finance Program EDHEC Business School, Professor John Y. Campbell, Harvard University, and Professor Emmanuel Jurczenko, EDHEC Business School. Their comments and suggestions, especially those of the External Examiner, Prof. Campbell, were immensely helpful.

I am also grateful to Professors Raman Uppal & Abraham Lioui, EDHEC Business School, for their contributions to the direction of my dissertation research and comments on my early drafts. Indeed, I would like to acknowledge all of the Finance faculty members at EDHEC Business School, and my fellow PhD classmates, who generously shared their time and insights at the PhD in Finance Forums and elsewhere.

Finally, I would like to extend a special thanks to Brigitte Bogaerts-Chevillotte and Mathilde Legrand of the PhD in Finance Programme at EDHEC for their unwavering support and help.

List of Tables

List of Figures

Value Stocks Are Riskier - Paper 1

by

Ciarán John O'Neill

EDHEC PhD in Finance

Keywords: value premium, equity risk premium, two risk premia, value stocks, equity duration, value portfolio sorts, long horizon value returns, excess return persistence, cashflow shocks, dividend shocks, cash flow shocks, cash flow elasticity, cash flow sensitivity, cash flow beta, revenue beta, time variability, time varying risk, long run risks, linear present value model, price dividend ratio, dividend yield, book to price, price to book, market to book, book to market, earnings yield, cashflow yield, Epstein Zin Weil, unscented kalman filter, linearity generating processes

Abstract

I propose a risk-based explanation of the value premium in which there are two components of the equity risk premium; a larger premium for *near-term* systematic cashflow risk and a smaller one for *distant* risks. I hypothesize that value stocks have higher sensitivity to near-term cashflows, and are duly discounted. I show how a representative agent with Epstein Zin preferences prices risky assets based on their exposures to innovations in both near-term consumption growth and anticipated future consumption growth (or wealth).[1] In this economy, the SDF is high when near-term consumption is shocked negatively, and also when wealth is negatively shocked for other reasons. I hypothesize that negative near-term cashflow shocks bring low payoffs for value stocks due to their high *cash flow elasticity of price* (i.e., both their cashflows and market-to-cashflow ratio can decline in response to the aggregate shock).[2] In contrast, the cashflows and multiples of growth stocks have a hedging quality that makes them less sensitive to near-term aggregate shocks.

To test these ideas, I develop an exactly-solved linear present value model of the price-dividend ratio which disentangles near-term cash flows from expected future cash flow growth with two time-varying risk premia. I use an Unscented Kalman Filter to estimate the model on US market data. I find strong evidence of the existence of two different risk premia, with the premium for near-term cashflow risks being larger. I measure the sensitivity of value and growth stocks to the estimated premia and find that (a) the expected returns of value stocks have higher loadings on the larger risk premium, and (b) unexpected value returns are more sensitive to near-term cashflow shocks. In this sense, value stocks are more prone to cashflow, and price, declines during (and in anticipation of) recessions when they are riskiest and discount rates are high. Growth stocks are less risky during recessions but become most sensitive to shocks during booms, when discount rates are low.

[1] It is also be possible to derive this result with time-additive utility - see *Appendix*.

[2] The positive correlation between cashflow shocks and market-to-cashflow multiples for value stocks may derive from their excess operating leverage, financial leverage, industry maturity, obsolescence risk, implied equity duration, and earnings reinvestment risk. These ideas are explored in O'Neill (2022) *Paper 2*.

1.1 Introduction

For close to a century, there has been compelling evidence of an equity value premium (the tendency of high book to market stocks to earn higher average returns than stocks with low ratios). From the early writings of Benjamin Graham in 1934 and 1949, strong empirical support of the value effect has been found in numerous studies using data from many different time periods and countries.[3] Examples of this empirical research include Fama & French (1992, 1998, 2012), Lakonishok, Schleifer & Vishny (1994), Daniel & Titman (1997), Lettau & Wachter (2007) and Asness, Moskowitz, & Pedersen (2013). From 1926 to 2018, the decile of US equities with the highest book-to-market ratio outperformed the decile with the lowest ratio by a statistically significant 5% to 14% per year on average.[4] These premium returns were earned without proportionately higher return volatility or *CAPM* beta.[5]

Given these long-term average returns, many investors have embraced value strategies as a cornerstone of their long-term investment policies. However, value stocks have also had prolonged periods when they underperformed the broad market and growth stocks, including the decade ending in the internet bubble in 2000 and the decade following the Financial Crisis in 2009. From 2009 to 2019, for example, large growth stocks returned 308% including reinvested dividends, while large value stocks returned 202%. In the same period, small growth stocks (a notorious underperformer historically) returned 236% compared to 169% for small value stocks.[6]

While these recent perverse returns have caused some to question the persistence of the value premium, there have been at least four other occasions since 1926 when the premium

[3] Security Analysis, with David Dodd (1934) and The Intelligent Investor (1949).

[4] Depending on portfolio weighting method. Data from Ken French, univariate book-to-market sorts.

[5] See Lettau & Wachter (2007), Fama & French (1992, 1993) and O'Neill (2022).

[6] Total value-weighted returns, 12/31/2009 through 12/31/2019. Source FTSE Russell (indexcalculator.ftserussell.com). Russell style indices, Russell 1000 for large stocks and Russell 2000 for small, are industry standard benchmarks for value and growth funds.

has been negative over a decade.[7] In fact any serious investigation of the value premium must address not only long-term average excess returns to value stocks, but also the long cycles of relative returns between value and growth stocks that we see in the data.

Despite its longevity, the cause of the observed value premium in long-term average returns is disputed. There are two competing theories; *risk-based* theories argue that value stocks possess systematic risks which rational investors must be compensated for, while *behavioral theories* point to irrational investors and temporary mis-pricing as the explanation.[8] Whatever the explanation for the value premium in the cross-section of returns, history also suggests that it is time-varying and the underlying mechanisms for this time-variability are also disputed. Research on time variability has focused mainly on aggregate market risk premia.[9]

This paper is not intended to arbitrate between these competing theories of the source of the value premium. Instead, I propose an explanation of the premium in which value stocks are fundamentally more risky than growth stocks, and their relative riskiness can be time varying. Although behavioral theories have intuitive appeal (because people are prone to judgement errors) and are likely to be at least a part of the story, I do not study them here. I emphasize risk-based explanations because I find them more convincing and enduring. The value effect is well known and has been an investible strategy since at least Graham & Dodd (1934), so the fact that the premium has not been competed away, suggests that it has rational underpinnings. The premium must represent compensation for some unwanted risks of value stocks; otherwise, intelligent investors in pursuit of higher returns would exploit repeating patterns of mis-pricing and the value premium would disappear.

---

[7] See Fama & French (2020) for a discussion of the persistence of the value premium. See O'Neill (2022) for some additional historical empirical perspectives on the value premium.

[8] For examples of *risk-based* research, see Fama & French (1992, 1993, 1995, 1996, 1998, 2006, 2012), Carlson, Fisher & Giammarino (2004), Zhang (2005), Lettau & Wachter (2007). For examples of *behavioral* research, see DeBondt & Thaler (1985, 1987), Lakonishok, Shleifer & Vishny (1994) and Daniel & Titman (1997, 1998).

[9] Bansal & Yaron (2004) and Campbell & Cochrane (1999) propose competing mechanisms for time-varying risk premia, though neither focuses on the value premium *per se*.

In my model, unexpected equity returns are driven by near-term cashflow shocks, shocks to expected future cashflow growth and shocks to risk premia. The elasticity of an asset's price to cashflow shocks depends on the sensitivity of its cashflow to aggregate cashflow shocks, its proximity to financial distress, and the market-implied duration of its cash flows. Value stocks are intrinsically riskier than growth stocks because they are more sensitive to near-term aggregate cash flow shocks for which investors require a large risk premium. (Growth stocks may be more sensitive to shocks to expected future aggregate cashflow growth, but such shocks require a smaller risk premium.) My results suggest that value stocks earn a premium return over growth stocks because they are more prone to cashflow and stock price declines during (and in anticipation of) cashflow recessions when they become riskiest and discount rates are high. Growth stocks are less risky during recessions but become most sensitive to future growth expectation shocks and risk premium shocks during booms, when discount rates are low.

This paper is organized as follows. In the next section, I provide updated summary data on the history of the value premium and a brief review of some prior research.[10] In *Section 1.3* (and also in the *Appendix*), I derive a stochastic discount factor (SDF) with two risk premia from a model of preferences for a representative agent who prices both shocks to current consumption and shocks to wealth (future consumption). This SDF provides the theoretical underpinning for the having two risk premia in my exactly-solved linear present value model of the price-dividend (PD) ratio in *Section 1.4*. *Section 1.5* describes the Unscented Kalman Filter I use to estimate the model as well as the tests of the relative riskiness of value and growth stocks, and discusses key results. *Section 1.6* concludes.

[10]See O'Neill (2022) for a more thorough empirical treatment of the history of the value premium including some non-standard perspectives.

1.2 History of Value Premium & Prior Research

1.2.1 Summary Statistics

In this section, I present data on the long-term history of the value premium in US stock prices since 1952. *Table 1.1* shows summary return statistics for capitalization-weighted univariate sorted-decile portfolios of US equities for the period from January 1952 to December 2019.[11] On average, for the period from 1952 to 2019, capitalization-weighted excess returns to US value stocks have exceeded the returns to growth stocks by approximately 4-5% per annum, which is an amount that is both economically and statistically meaningful.[12] All portfolio return data for univariate sorts on earnings-to-price (E/P), cashflow-to-price (C/P), dividend-to-price (D/P) and book-to-market (B/M) in *Table 1.1* are taken from Ken French's website,[13] which in turn takes its fundamental data from Compustat and its pricing data from CRSP, covering most NYSE, AMEX and NASDAQ stocks.[14] Panel A shows that mean excess returns are consistently increasing in deciles as we move from growth (Decile 1) to value (Decile 10). Depending on the univariate ratio used for the portfolio sorts, the value-minus-growth excess return spread ranges between 4 and 5% per year over this period.[15] The value premium over this long period is economically large and statistically significant (as shown by the standard errors in Panel C). The Sharpe ratios in Panel D of *Table 1.1* are also generally increasing in deciles, indicating that value stocks

---

[11] This is an updated and expanded version of *Table 1* in Lettau & Wachter (2007).

[12] Excess returns are defined as equity returns in excess of the risk-free rate.

[13] See $https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\_library.html$

[14] Except book value data which is hand collected from Moody's Manuals and is available back to 1926. Also, although I include statistics for D/P for comparison to *Table 1.1* in Lettau & Wachter (2007), this ratio is less useful than the others as a measure of value since a high dividend yield can just reflect a firm's dividend payout policy, rather than indicating a discounted stock.

[15] It is notable that the average annual excess return spread that I observe is 1 - 3% *lower* than the observations reported in Lettau & Wachter (2007). This decline is fully explained by the perverse value-growth portfolio return spread for US equities over the period 2010 to 2019. This is shown in the right-hand column *Table 1.1*. See O'Neill (2022) for an elaboration of this point and other aspects of the history and time-variability of the value premium.

have delivered larger excess returns *per unit of standard deviation*. *Table 1.2* presents similar summary statistics for equal-weighted portfolios. In general, equal-weighted returns are larger than capitalization-weighted returns across all deciles and for the value-minus-growth spread, which averages 7 to 10% per year depending on the univariate sorting ratio used. The standard deviations are also higher but the standard errors in Panel C indicate high levels of statistical significance and the Sharpe ratio for the equal-weighted value-minus-growth portfolio is 0.75, which is twice as large as for the comparable capitalization-weighted portfolio.

At least two factors explain the higher observed value premium using equal-weighting versus capitalization-weighting. First, equal-weighted portfolios have larger weightings in stocks with smaller market capitalizations, and small cap equities had higher returns than large cap equities over this time period.[16] Second, the monthly equal-weighted return calculation used in Ken French's data library (and in many of the Fama & French papers) reapplies equal weighting to the portfolio every month, not just at the annual June sorted portfolio rebalancing. Such a return calculation will benefit from the implicit buying and selling that the portfolio does each month to re-equalize the weights: each month it will (costlessly) sell down stocks that were up the most during the previous month and buy stocks that were down the most, thereby benefitting from any short-term price reversal effects.[17]

Table 1.1 & *Table 1.2* lend strong support to the existence of a value premium in the

[16]From January 1952 to December 2019, the annualized capitalization-weighted monthly average return to a portfolio of the smallest 30% of US stocks, by market cap, exceeded returns for the largest 30% by 2.5% per annum, according to data from Ken French's website.

[17]There is strong evidence of profitability of short-term price reversal strategies in US equities over this period. See, for example, Nagel (2011) and de Groot, Huij & Zhou (2012). Furthermore, comparing equal-weighted to capitalization-weighted returns, it is worth noting that these two factors add 300 basis points to mean value returns (Decile 10) while mean growth returns (Decile 1) are little changed. I believe that a price momentum effect partly explains why growth portfolios benefit less from the change in weighting method. The growth portfolios, in general, have larger weightings in stocks with positive price momentum, a factor that produced positive excess returns in this period. As a result, re-equalizing the weights each month requires selling stocks with positive momentum and buying stocks with negative momentum, which likely lowers portfolio returns compared to a buy-and-hold portfolio.

pricing of US equities. The excess return premium earned by value stocks is economically and statistically large and is not explained by either the volatility of their returns or a small cap effect. This paper addresses this observed anomaly by proposing a framework in which value stocks earn premium returns because they are riskier than growth stocks in ways that investors care about.

It bears noting, however, that in the decade following the Great Recession in 2007-2009, value stocks materially underperformed the market averages, and growth stocks in particular. During this period, capitalization-weighted returns on value stocks were more than 5% less *per year* than growth stock returns.[18] This ”lost decade” in the profitability of value strategies has raised questions about the persistence of the value premium and even whether it has ever existed (see, for example, Lev & Svristava (2019) and Fama & French (2020)). I do not address this issue directly in this paper. Given the long-term evidence in *Table 1.1* & *Table 1.2*, I take it as given that the value premium exists, albeit with time-variability, and that its existence requires an explanation. However, O’Neill (2022) offers a more comprehensive perspective on the recent challenging performance of value stocks and the persistence of the value premium. In the context of a risk-based explanation of the value premium, I also point out that the chronic negative returns to value stocks after 2008 coincided with two extreme contractionary shocks to the US economy (the Great Recession and the Coronavirus pandemic and related lockdowns). If these shocks are the types of unanticipated negative risk events that value stocks are more exposed to and are discounted for, then a decade of negative relative returns for value strategies can be entirely consistent with risk-discounting of value stocks and above-average expected returns for (risky) value stocks going forward.[19]

[18]Data from Ken French’s website for the period 12/31/2009-12/31/2019 using univariate sorts on market-book ratios and simple annualization, taking 12 times the monthly average return of growth decile minus the value decile.

[19]To use an insurance analogy, a similar phenomenon occurs in the property & casualty insurance market when, after a large natural catastrophe like a hurricane or an earthquake, prior written insurance policies turn out to be unprofitable for the insurers and lead to in a ”hard-pricing” cycle of higher insurance premiums.

1.2.2 Risk versus Behavior: A Brief Literature Review

There is not enough space in this paper for a comprehensive review of all prior research on the value premium. Beginning with the early exposition on fundamental value investing in Graham & Dodd (1934), many studies have documented the value effect. It has been observed in many geographies, across many time periods and within many asset classes.[20] This section provides a summary of the salient strands of research that have been proposed to explain the effect. Broadly speaking, explanations of the value premium have sought to identify either the systematic risks that value stocks possess or the systematic pricing errors that investors make. Basu (1977 &1983) were early papers to document the positive association between measures of cheapness (earnings yield in this case) and subsequent excess returns. This work suggested that the existing asset pricing models could not account for the returns generated by cheap stocks.

1.2.3 Systematic Risks

Fama & French (1992) is regarded as a seminal paper for risk-based explanations of the value premium. They identify large value (and size) premia in the pricing of US equities which cannot be easily explained by the capital asset pricing model (*CAPM*). Subsequent work in Fama & French (1993, 1995, 1996, 1998, 2006, 2012) show the robustness of these pricing anomalies across time periods and countries and have spawned a series of factor-pricing models which have become alternative lenses to *CAPM* to view the pricing of equities. An important underlying theme in this work is that the value premium represents compensation for priced risks (e.g., distress risk). In fact, a recent paper by Kapadia (2011) argues that the premium to the Fama & French HML factor can be explained by exposure to an aggregate distress risk factor linked to business failures.

Zhang (2005) takes the risk explanation of the value premium in a different direction.

[20] See Asness, Moskowitz, & Pedersen (2013) for a recent discussion of the ubiquity of the effect.

He shows how the premium can emerge in a neoclassical, rational expectations framework where asset-heavy value stocks face capital reversibility costs, particularly in bad times when risk is priced high. Subsequent work by Xing (2008) and Zhang (2017) and Hou et al. (2017) incorporate contemporary Q-theory into asset pricing. Zhang's *Investment CAPM* derives asset-pricing relationships (including equilibrium expected risk premia) from real investment decisions of individual firms. Related work in this area by Lettau & Wachter (2007), Campbell & Vuolteenaho (2004) and Carlson, Fisher & Giammarino (2004) also emphasizes the role of cash flow characteristics of firms in risk-based explanations of the value premium. I build on this work to develop of my present-value cashflow model in *Section 1.4*.

1.2.4 Systematic Mispricing

Early work by DeBondt & Thaler (1985, 1987) takes issue with the risk-based explanation of the value premium. They find evidence, instead, that investor over-reaction and under-reaction to earnings and price news, caused by common psychological biases, are consistent with observed anomalies in returns. One of the most prominent papers in behavioral explanations of the value premium, Lakonishok, Shleifer & Vishny (1994), argues that portfolios of value stocks outperform glamor (growth) portfolios because they exploit cognitive biases of investors and not because the portfolios are riskier. Subsequent work in Shleifer & Vishny (1997) and LaPorta, Lakonishok, Shleifer & Vishny (1997) provide further theoretical and empirical support for a 'persistent mispricing' explanation of the value effect.

Daniel & Titman (1997, 1998) also take issue with the Fama-French risk-based and factor-based explanations. They find no evidence that value stocks have a separate distress risk factor and, instead, introduce a characteristics model of mispricing (i.e., the shared common characteristics of cheap stocks, not their risk, explains the value premium). Davis, Fama & French (2000) offer a counter argument and rebuttal. Daniel, Hirshleifer & Subrahmanyam (1998) develop an influential model of asset pricing in which psychological biases of investors lead directly to observed patterns of under and over-reaction in prices while a paper by the same authors in 2001 introduces a framework for security pricing in which covariance risks and mis-valuation can coexist in equilibrium.

In terms of theory, this paper draws on all of this prior work. The papers of Fama & French laid the important groundwork for thinking about the value premium as a compensation for risk. For the specific risk framework I propose in this paper, the papers on equity duration by Cornell (1999) and Lettau & Wachter (2007) are important building blocks, as is the work on 'cash flow beta' in Campbell & Vuolteenaho (2004) and Cohen, Polk & Vuolteenaho (2002). My model is closely related to the Linearity Generating (LG) model class proposed by Gabaix (2007, 2009) and also draws on the present-value models in van Binsbergen & Koijen (2011). This paper is also consistent with recent literature arguing that claims to near-term dividends are riskier than claims to distant future dividends (see, for example, van Binsbergen, Brandt & Koijen (2012), Giglio, Maggiori & Stroebel (2015), and Gormsen & Lazarus (2021)).

For now, I turn my attention to the preferences of a representative investor who consumes the aggregate dividend, in order to derive an SDF that prices shocks to near term consumption and cashflow separately from shocks to long-term consumption and cashflow growth.

1.3 A Stochastic Discount Factor with Two Risk Premia

In this section, I propose a model of preferences for a representative agent who consumes the aggregate dividend, in which the stochastic discount factor covaries with near-term aggregate consumption and also with anticipated future aggregate consumption growth. The agent fears, and prices, near-term consumption shocks to the extent that they disrupt his optimal current lifestyle, while he fears (and prices) shocks to expected future consumption growth to the extent that they disrupt his preferences to sustain and grow his desired lifestyle in the future. This framework provides a theoretical foundation for using two time-varying risk premia in my linear present value model of the price-to-dividend (PD) ratio derived in *Section 1.4* and tested in *Section 1.5*.

The dual-premium SDF that I derive below assumes that the representative agent has Epstein-Zin preferences. However, it is also possible to derive a similar two-factor SDF assuming time-additive utility where felicity in any period derives from consumption in that period *and* from post-consumption wealth. With time-additive utility, the inclusion of wealth in the periodic utility function captures the idea that the agent cares about his anticipated future consumption and that fluctuations in wealth (caused, for example, by changes in long-term expected consumption growth in the economy) can affect his utility today, even if his current consumption does not change.[21] See *Appendix* for this alternative derivation.

I begin by assuming there is a representative investor with recursive Epstein-Zin-Weil (EZW) recursive preferences, as proposed in Epstein & Zin (1989, 1991) and Weil (1990). Specifically, the agent's utility at time t is given by *equation (1)*,

$$U_t = [(1-\alpha)C_t^{\frac{1-\gamma}{\theta}} + \alpha E_t[U_{t+1}^{1-\gamma}]^{\frac{1}{\theta}}]^{\frac{\theta}{1-\gamma}} \tag{1}$$

where γ is risk aversion, α is the elasticity of intertemporal substitution, and $\theta = \frac{1-\gamma}{1-\frac{1}{\alpha}}$. Under these preferences, the SDF can be written as follows.

$$M_{t+1} = \alpha(\frac{C_{t+1}}{C_t})^{\frac{-1}{\alpha}}(\frac{U_{t+1}}{E_t[U_{t+1}^{1-\gamma}]^{\frac{1}{1-\gamma}}})^{-\gamma+\frac{1}{\alpha}} \tag{2}$$

[21] This model of felicity is also consistent with the ”spirit of capitalism” framework of Bakshi & Chen (1996) in which agents care about wealth as a measure of social status. However, the agent in my model cares about the information that current wealth conveys about his future consumption plans, rather than his social standing.

Epstein & Zin (1989, 1991) then showed that when the agent satisfies the intertemporal budget constraint in *(3)*, the unobservable continuation utility in SDF *(2)* can be replaced with the return on wealth and consumption growth, leading to the restated SDF in *(4)*.

$$W_{t+1} = (W_t - C_t)(1 + R_{w,t+1}) \tag{3}$$

where W_{t+1} and $R_{w,t+1}$ represent the time *t+1* wealth and return on wealth respectively.

$$M_{t+1} = (\alpha(\frac{C_{t+1}}{C_t})^{\frac{-1}{\alpha}})^{\theta}(\frac{1}{1 + R_{w,t+1}})^{1-\theta} \tag{4}$$

According to this SDF, marginal utility is a function both of current consumption growth and the return on wealth. It follows that the covariance of asset returns with shocks to either of these factors will be priced. Taking logs of *(4)*, the innovations in the log SDF can be written as

$$\hat{m}_{t+1} = -\theta(\frac{\hat{c}_{t+1}}{\alpha}) - (1-\theta)\hat{r}_{w,t+1} \tag{5}$$

where $c_{t+1} = log(\frac{C_{t+1}}{C_t})$, $\hat{c}_{t+1} = c_{t+1} - E_t[c_{t+1}]$, $r_{w,t+1} = log(1 + R_{w,t+1})$ and $\hat{r}_{w,t+1} = r_{w,t+1} - E_t[r_{w,t+1}]$.

Then, if I assume that consumption growth rates and returns on wealth (and other assets) are lognormal, the premium on an arbitrary risky asset i is given by *(6)* and the premium on the wealth return specifically is given in *(7)*.

$$E_t[r_{i,t+1}] - r_{f,t+1} + \frac{\sigma_i^2}{2} = \frac{\theta}{\alpha}\sigma_{i,c} + (1-\theta)\sigma_{i,w} \tag{6}$$

$$E_t[r_{w,t+1}] - r_{f,t+1} + \frac{\sigma_w^2}{2} = \frac{\theta}{\alpha}\sigma_{w,c} + (1-\theta)\sigma_w^2 \tag{7}$$

where $\sigma_{i,j}$ is a covariance between innovations in log quantities *i* and *j*.

I can also use the SDF in *(4)* and *(5)*, together with my lognormality assumption, to write the log risk free rate in this economy, as shown in *(8)*.

$$r_{f,t+1} = -\theta log(\alpha) + \frac{\theta}{\alpha}E_t[c_{t+1}] + (1-\theta)E_t[r_{w,t+1}] - (\frac{\theta}{\alpha})^2\frac{{\sigma_c}^2}{2} - (1-\theta)^2\frac{{\sigma_w}^2}{2} - \frac{\theta(1-\theta)}{\alpha}\sigma_{c,w} \tag{8}$$

Then, using *(7)* to substitute for $E_t[r_{w,t+1}]$ in *(8)* and simplifying, I can express the risk free rate as a function of expected log consumption growth and several constants.

$$r_{f,t+1} = -log(\alpha) + \frac{1}{\alpha}E_t[c_{t+1}] - (\frac{\theta}{\alpha^2})\frac{{\sigma_c}^2}{2} - (1-\theta)\frac{{\sigma_w}^2}{2} \tag{9}$$

If I take this expression for the risk-free rate and substitute it back into *(7)*, I can show that the expected log return on wealth can also be expressed as a constant plus $\frac{1}{\alpha}$ times expected consumption growth. Then, when this insight is combined with a Campbell-Shiller log-linearization of returns and decomposition of returns into cashflow news and discount rate news, as in Campbell & Shiller (1988a) and Campbell (1991), I can show that the premium on risky assets depends on the covariance of the asset's returns with current consumption growth and changes in anticipated future consumer growth, which is what I want.

Equation (10) uses the Campbell-Shiller loglinearization and the return decomposition to write surprises in the (log) return on wealth as

$$\hat{r}_{w,t+1} = (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j d_{w,t+j+1} - (E_{t+1} - E_t)\sum_{j=1}^{\infty}\rho^j r_{w,t+j+1} \tag{10}$$

where d_w is log dividend growth and ρ can be interpreted as a discount factor. In this representative agent setting, the dividend on the wealth portfolio is also equal to aggregate consumption. Combining this fact with the observation above that the expected log return on wealth can also be expressed as a constant plus $\frac{1}{\alpha}$ times expected consumption growth, I can rewrite *(10)* as

$$\hat{r}_{w,t+1} = \hat{c}_{t+1} + (1 - \frac{1}{\alpha})(E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j c_{t+j+1} \tag{11}$$

$$\hat{r}_{w,t+1} = \hat{c}_{t+1} + (1 - \frac{1}{\alpha})\hat{g}_{t+1} \tag{12}$$

where $\hat{g}_{t+1}$ reflects revisions in expectations of future consumption growth. Armed with this expression, it is straightforward to rewrite the log SDF in *(5)* and the premium on an arbitrary risky asset i as follows.

$$\hat{m}_{t+1} = -\gamma \hat{c}_{t+1} - (\gamma - \frac{1}{\alpha})\hat{g}_{t+1} \tag{13}$$

$$E_t[r_{i,t+1}] - r_{f,t+1} + \frac{\sigma_i^2}{2} = \gamma \sigma_{i,c} + (\gamma - \frac{1}{\alpha})\sigma_{i,g} \tag{14}$$

Equations (13) and *(14)* show that in a lognormal model for a representative agent with EZW preferences, risky assets are priced in a two-factor model where the factors are innovations in near-term consumption growth and innovations in anticipated future consumption growth. Such a model represents a hybrid of the *Capital Asset Pricing Model* (*CAPM*) and the *Consumption CAPM* (*CCAPM*) in that marginal utility varies with shocks to current consumption and also shocks to wealth (and in particular the wealth shocks that are driven by revisions to future growth expectations).

For the remainder of this paper, I assume the existence of an SDF with this dual-risk premium structure in order to derive a testable, linear present value model of asset prices.

1.4 A Closed-Form Linear Present Value Model of Asset Prices with Two Time-Varying Risk Premia

In this section I develop an exactly-solved, affine model of the price-to-dividend (PD) ratio. The great advantage of having a closed-form model is that it can be estimated and tested against real historical data, without any need for approximations or simulations. My model is in the class of Linearity Generating (LG) processes introduced in Gabaix (2007, 2009), with some modified linearity-generating *twists* in the spirit of those used in Van Binsbergen & Koijen (2011) and elsewhere. Unlike those papers, my model has risk premiums for *both* innovations in near-term dividends (cashflows) and innovations in expected future dividend growth. Specifically, the PD ratio is shown to be a function of time-varying expected growth rates and two time-varying risk premia. Together with the simple return decomposition in *Section 1.4.1* below, this will allow for an exact decomposition of unexpected returns into dividend shocks, shocks to expected growth, and shocks to risk premia. The sensitivity of value stocks and growth stocks to these components of unexpected returns can then be measured.

1.4.1 Return Decomposition and Present Value Relation

I begin with a simple decomposition of next period's gross return, R_{t+1}, and a rearrangement of terms.

$$
\begin{aligned}
R_{t+1} &= \frac{D_{t+1}}{P_t} + \frac{P_{t+1}}{P_t} \\
&= \frac{D_{t+1}}{P_t} + (\frac{D_{t+1}}{P_t})(\frac{P_{t+1}}{D_{t+1}}) \\
&= \frac{D_{t+1}}{P_t}(1 + \frac{P_{t+1}}{D_{t+1}})
\end{aligned} \tag{15}
$$

Equation (15) says that realized returns can be expressed as the product of the realized dividend yield and the terminal PD ratio plus one.

Equation (16) takes conditional expectations of *(15)* and then *(17)* rewrites the covariance component of *(16)* in terms of deviations from expected values.

$$
E_t[R_{t+1}] = E_t[\frac{D_{t+1}}{P_t}]E_t[1 + \frac{P_{t+1}}{D_{t+1}}] + Cov_t[\frac{D_{t+1}}{P_t}, \frac{P_{t+1}}{D_{t+1}}] \tag{16}
$$

$$
E_t[R_{t+1}] = E_t[\frac{D_{t+1}}{P_t}]E_t[1 + \frac{P_{t+1}}{D_{t+1}}] + Cov_t[\frac{D_{t+1}}{P_t} - E_t[\frac{D_{t+1}}{P_t}], \frac{P_{t+1}}{D_{t+1}} - E_t[\frac{P_{t+1}}{D_{t+1}}]] \tag{17}
$$

Equation (17) says that conditional expected returns can be expressed as a sum of two components: a *predicted component* based on the expected dividend and (one plus) the expected PD ratio, and a *covariance adjustment component* based on the comovement of unanticipated dividends with unanticipated PD ratios.[22] If shocks to dividends and shocks to PD ratios are uncorrelated, we only need to know expected dividends and the expected PD ratio to calculate expected returns (let us call this expected return $\mu_{\rho=0}$). However, assets for which dividend and PD shocks are negatively correlated have a hedging quality that lowers expected returns below $\mu_{\rho=0}$, ceteris paribus, while a positive correlation between dividend and PD shocks raises expected returns above $\mu_{\rho=0}$. These are not risk-based asset-pricing

[22]When next period's PD ratio is expected to be unchanged from this period, the predicted component of returns is given by the expected dividend yield plus the expected dividend growth rate.

results; these claims derive only from the statistical properties of expectations and covariances.[23] The covariance adjustment component of expected returns may be particularly pertinent to the value premium. If the dividends of value stocks are highly sensitive to aggregate dividend shocks and also positively correlated with innovations in PD ratios (i.e., they have a high *cashflow elasticity of price*), then the covariance adjustment component of expected returns for value stocks will be positive.[24] I will return to this point later in this paper.

In order to develop my model of the PD ratio, I will also employ a commonly-used result that takes conditional expectations of *equation (15)*, rearranged to derive another present value relation. This relation expresses the current period's PD ratio as a function of expectations of next period's PD ratio.

$$\frac{P_t}{D_t} = \frac{E_t[\frac{D_{t+1}}{D_t}(1 + \frac{P_{t+1}}{D_{t+1}})]}{E_t[R_{t+1}]} \tag{18}$$

1.4.2 Processes and Linearity-Inducing Devices

Throughout *Section 1.4*, my goal is to develop a time-varying, affine model of the PD ratio that will have the following structure.

$$\frac{P_t}{D_t} = \alpha + \beta' X_t \tag{19}$$

Here, X_t is a vector of state variables, α is a constant, and β is a vector of parameter values.

[23] If investors believe that positive dividend shocks will be magnified by higher unanticipated PD ratios (and vice versa) for certain assets, then expectations of returns on those assets (i.e., $E_t[(\frac{D_{t+1}}{P_t})(1 + \frac{P_{t+1}}{D_{t+1}})]$), must be higher than the product of the expectations of $\frac{D_{t+1}}{P_t}$ and $1 + \frac{P_{t+1}}{D_{t+1}}$.

[24] The elasticity of an asset's price to an aggregate cashflow shock depends on (a) the response of the asset's cashflow to aggregate cashflows and (b) the response of the asset's price-to-cashflow multiple to the shock. Assets with high elasticity will experience large price declines after a negative aggregate cashflow shock, attributable to a disproportionate decline in the asset's cashflows, exacerbated by a decline in the price-to-cashflow ratio.

The simple Gordon growth model (which does not allow for time-variability) provides the intuition for the choice of state variables in my model. In the Gordon model, the PD ratio is a positive function of the expected dividend growth rate, g, and a negative function of the discount rate (or expected return), μ.

$$\frac{P}{D} = \frac{1+g}{\mu - g} \tag{20}$$

For my model, I conjecture that the PD ratio is an affine function of time-varying expected dividend growth rates and time-varying discount rates. I assume, for now, that the risk-free rate, r_f, is constant. I also assume that there are two risk premia embedded in discount rates (expected returns); θ^d is a premium on innovations in current dividends and θ^g is a premium on innovations in expected future dividend growth.

$$\textit{Discount Rate} = r_f + \theta_t^d + \theta_t^g \tag{21}$$

My model is different than the *good beta-bad beta* framework in Campbell & Vuolteenaho (2004) in that different types of ”cashflow news” (e.g, news about current cashflows, and news about future expected cashflow growth) can have different effects on asset prices.
Using this conjecture, the time-varying affine PD ratio in my model can be written as follows (noting that I now define the state variables as deviations from their unconditional mean values, the magnitude of which is captured in the α term).

$$\frac{P_t}{D_t} = \alpha + \beta_1 \hat{g}_t + \beta_2 \hat{\theta}_t^d + \beta_3 \hat{\theta}_t^g \tag{22}$$

where $\hat{g}_t$, $\hat{\theta}_t^d$ and $\hat{\theta}_t^g$ are time-varying deviations of expected growth rates and risk premia from long-term average values ($\bar{g}, \bar{\theta}^d, \bar{\theta}^g$). (Not surprisingly, α, representing a long run average PD ratio, is expected to be positive and I also expect $\beta_1 > 0$, $\beta_2 < 0$, and $\beta_3 < 0$.) Substituting this into the present value relation in *equation (18)*, I get

$$\alpha + \beta_1 \hat{g}_t + \beta_2 \hat{\theta}_t^d + \beta_3 \hat{\theta}_t^g = \frac{E_t[\frac{D_{t+1}}{D_t}(1 + \alpha + \beta_1 \hat{g}_{t+1} + \beta_2 \hat{\theta}_{t+1}^d + \beta_3 \hat{\theta}_{t+1}^g)]}{E_t[R_{t+1}]} \tag{23}$$

To solve *equation (23)* for α, β_1, β_2, and β_3, I will need to take the expectation on the right hand side. For this, I will need to define the processes for dividends, expected growth rates and risk premia. The essence of the LG class of models in Gabaix (2007, 2009) is to introduce some devices or ”tricks” into otherwise standard *AR(1)* processes in order to induce linearity and a closed-form solution. I use these techniques here to derive an exactly-solved affine function of the PD ratio.

My model proposes the following process for dividends.

$$\frac{D_{t+1}}{D_t} = (1 + g_t)(1 + \epsilon_{t+1}^d) \tag{24}$$

where $g_t = \bar{g} + \hat{g}_t$ and ϵ_{t+1}^d is an innovation with zero mean and standard deviation σ_d. This multiplicative structural form is not essential but is helpful for producing a clean closed-form solution. For now, I make no assumptions about ϵ_{t+1}^d except that the innovations have a zero expected value. As in Van Binsbergen & Koijen (2011), I also introduce a slightly twisted definition of expected returns that will help to induce linearity in the PD ratio more easily. Specifically, I define another expected return, μ_t', such that

$$\frac{1 + g_t}{E_t[R_{t+1}]} \equiv 1 + g_t - \mu_t' \tag{25}$$

In most circumstances, $E_t[R_{t+1}]$ and μ_t' are very similar and either can be referred to as *expected return*.[25] Using this definition, the unconditional mean expected return and the conditional expected return can be decomposed as

$$\bar{\mu'} = r_f + \bar{\theta^d} + \bar{\theta^g} \tag{26}$$

$$\mu'_t = r_f + \theta^d_t + \theta^g_t \tag{27}$$

The final trick required to produce an affine PD ratio is to gently *twist* the processes for the de-meaned expected growth rates and risk premia away from a traditional $AR(1)$ structure. Specifically, I introduce a time-varying parameter, Φ_t, such that

$$\begin{aligned}
\hat{g}_{t+1} &= \rho^g \Phi_t \hat{g}_t + \epsilon^g_{t+1} \\
\hat{\theta}^d_{t+1} &= \rho^{\theta^d} \Phi_t \hat{\theta}^d_{t+1} + \epsilon^{\theta^d}_{t+1} \\
\hat{\theta}^g_{t+1} &= \rho^{\theta^g} \Phi_t \hat{\theta}^g_{t+1} + \epsilon^{\theta^g}_{t+1}
\end{aligned} \tag{28}$$

where Φ_t is given by

$$\Phi_t = \frac{1 + \bar{g} - \bar{\mu'}}{1 + g_t - \mu'_t} \tag{29}$$

and $|\rho^i| < 1, E_t[\epsilon^i{}_{t+1}] = 0, (i = g, \theta^d, \theta^g)$. Standard deviations of the noises are given by $\sigma_g, \sigma_{\theta^d}, \sigma_{\theta^g}$. In most situations involving growth rates and expected returns, which are typically close to zero, Φ_t will be close to 1 and the processes in *(28)* will behave like *AR(1)* processes up to second order terms.[26]

Substituting the process for dividends into *(23)* and using definition *(25)* for expected returns, I can now write

[25] Van Binsbergen & Koijen (2011) measure the empirical correlation of the the two definitions at 0.998.

[26] The online appendix for Gabaix (2009) provides simulation results that support the claim that, in practice, the *twist* introduced by Φ_t is small. In my own estimation work described in *Section 1.5*, I find that the average value of Φ_t is 0.99 with a standard deviation of 0.03.

$$\alpha + \beta_1 \hat{g}_t + \beta_2 \hat{\theta}^d_t + \beta_3 \hat{\theta}^g_t = (1 + g_t - \mu'_t) E_t[(1 + \epsilon^d_{t+1})(1 + \alpha + \beta_1 \hat{g}_{t+1} + \beta_2 \hat{\theta}^d_{t+1} + \beta_3 \hat{\theta}^g_{t+1})] \tag{30}$$

In order to expand the expectation on the right hand side of *equation (30)*, the covariance structure between shocks to dividends and shocks to expected growth rates and risk premia must be specified. While it is often assumed (e.g., in Lettau & Wachter (2007) and Van Binsbergen & Koijen (2011)) that near-term dividend shocks and expected future dividend growth shocks are uncorrelated (i.e., $Cov(\epsilon^d_{t+1}, \epsilon^g_{t+1}) \equiv \sigma_{dg} = 0$), I do not make this assumption in my model. I do not have an *a priori* belief about this covariance and I prefer to let the data speak for themselves.[27] Similarly, the covariance between dividend shocks and shocks to risk premia ($\sigma_{d\theta^d}$ and $\sigma_{d\theta^g}$ respectively) are allowed to enter the model. There is ample evidence in macro finance literature (return predicability literature in particular) that asset returns correlate with the business cycle so the inclusion of these covariances will enhance the model's ability to explain important asset pricing dynamics.

Using this assumed covariance structure and the processes defined in *(28)* (and recalling that $E_t[\epsilon^i_{t+1}] = 0$, $(i = d, g, \theta^d, \theta^g)$), *equation (30)* is expanded as follows.

$$\alpha + \beta_1 \hat{g}_t + \beta_2 \hat{\theta}^d_t + \beta_3 \hat{\theta}^g_t = \frac{\pi}{\Phi_t}[1 + \alpha + \beta_1(\rho^g \Phi_t \hat{g}_t + \sigma_{dg}) + \beta_2(\rho^{\theta^d} \Phi_t \hat{\theta}^d_t + \sigma_{d\theta^d}) + \beta_3(\rho^{\theta^g} \Phi_t \hat{\theta}^g_t + \sigma_{d\theta^g})] \tag{31}$$

I note that, in *equation (31)*, $\pi \equiv 1 + \bar{g} - \bar{\mu'}$. I also note the following relation.

$$\begin{aligned} \frac{\pi}{\Phi_t} &= 1 + g_t - \mu'_t \\ &= 1 + \bar{g} - \bar{\mu'} + (g_t - \bar{g}) - (\mu'_t - \bar{\mu'}) \\ &= \pi + \hat{g}_t - \hat{\theta}^d_t - \hat{\theta}^g_t \end{aligned} \tag{32}$$

[27] It will be possible later to explore the implications of alternative assumptions for this covariance.

Combining *(31)* and *(32)*, I get

$$\begin{aligned}\alpha + \beta_1 \hat{g}_t + \beta_2 \hat{\theta}^d_t + \beta_3 \hat{\theta}^g_t =& (\pi + \hat{g}_t - \hat{\theta}^d_t - \hat{\theta}^g_t)(1 + \alpha + \beta_1 \sigma_{dg} + \beta_2 \sigma_{d\theta^d} + \beta_3 \sigma_{d\theta^g}) \\ &+ \pi(\beta_1 \rho^g \hat{g}_t + \beta_2 \rho^{\theta^d} \hat{\theta}^d_t + \beta_3 \rho^{\theta^g} \hat{\theta}^g_t)\end{aligned} \tag{33}$$

Now I can gather terms in $\hat{g}_t$, $\hat{\theta}_{dt}$ and $\hat{\theta}_{g_t}$ and then I can solve for α, β_1, β_2, and β_3.

$$\begin{aligned}\alpha &= \pi(1 + \alpha + \beta_1 \sigma_{dg} + \beta_2 \sigma_{d\theta^d} + \beta_3 \sigma_{d\theta^g}) \\ \beta_1 &= 1 + \alpha + \beta_1 \sigma_{dg} + \beta_2 \sigma_{d\theta^d} + \beta_3 \sigma_{d\theta^g} + \pi \beta_1 \rho^g \\ \beta_2 &= -(1 + \alpha + \beta_1 \sigma_{dg} + \beta_2 \sigma_{d\theta^d} + \beta_3 \sigma_{d\theta^g} - \pi \beta_2 \rho^{\theta^d}) \\ \beta_3 &= -(1 + \alpha + \beta_1 \sigma_{dg} + \beta_2 \sigma_{d\theta^d} + \beta_3 \sigma_{d\theta^g} - \pi \beta_3 \rho^{\theta^g})\end{aligned} \tag{34}$$

Following some straightforward algebra, the coefficient values are identified as follows.

$$\begin{aligned}\alpha &= \frac{\pi}{1 - \pi - \frac{\sigma_{dg}}{1-\pi\rho^g} + \frac{\sigma_{d\theta d}}{1-\pi\rho^{\theta^d}} + \frac{\sigma_{d\theta g}}{1-\pi\rho^{\theta g}}} \\ \beta_1 &= \frac{\alpha}{\pi(1 - \pi\rho^g)} \\ \beta_2 &= \frac{-\alpha}{\pi(1 - \pi\rho^{\theta^d})} \\ \beta_3 &= \frac{-\alpha}{\pi(1 - \pi\rho^{\theta g})}\end{aligned} \tag{35}$$

Finally, I can write the PD ratio, as an affine function of expected growth and the components of expected returns, in the following way.

$$\frac{P_t}{D_t} = \frac{1}{1 - \pi - \delta}(\pi + \frac{\hat{g}_t}{1 - \pi\rho^g} - \frac{\hat{\theta}^d_t}{1 - \pi\rho^{\theta^d}} - \frac{\hat{\theta}^g_t}{1 - \pi\rho^{\theta g}}) \tag{36}$$

where $\delta(\equiv \frac{\sigma_{dg}}{1-\pi\rho^g} - \frac{\sigma_{d\theta d}}{1-\pi\rho^{\theta^d}} - \frac{\sigma_{d\theta g}}{1-\pi\rho^{\theta g}})$ is a covariance adjustment factor.

Despite the algebra and LG twists required to get to this point, the interpretation of *(36)* is quite straightforward. In general, the PD ratio will be an increasing function of expected growth rates and a decreasing function of risk premia. The degree to which a current deviation of expected growth (or risk premia) from its long term average impacts the PD ratio is controlled by the persistence factor of shocks, ρ^g (or ρ^{θ^d} or ρ^{θ^g}). When expected growth and risk premia are not allowed to be time varying, the PD ratio is given by $\frac{\pi}{1-\pi}$ which is essentially the Gordon growth model. When expected growth and risk premia *can* vary over time, but their values are currently resting at their long-term average, the PD ratio becomes $\frac{\pi}{1-\pi-\delta}$ where δ is a covariance adjustment factor. If dividend shocks covary positively with innovations in the PD ratio (via shocks to expected growth and risk premia), δ will be positive. The degree of the covariance adjustment will, again, be controlled by the persistence of the shocks to expected growth and risk premia. Importantly, for a given observed PD ratio and average expected growth rate ($\bar{g}$), the larger is δ, the larger must be $1 - \pi(\equiv \bar{\mu} - \bar{g})$. This implies that the more positive the covariance between dividend shocks and PD ratio shocks, the higher expected returns, $\bar{\mu}$, must be. This is the analog to the *covariance adjustment component* of expected returns that was discussed in *Section 1.4.1*.

The linear closed-form model of the PD ratio in *equation (36)* is the primary target of the model estimation techniques described in the next section. There, I use a long history of US market data to estimate both the model parameters and the unobservable variables. These estimated values will, in turn, be used to test the central idea of the paper that value stocks earn higher returns than growth stocks because they are riskier.

1.5 Model Estimation, Testing & Results

In this section, I estimate the closed-form model of the PD ratio in *equation (36)* and use the estimated parameter values and latent variables (i.e., expected future growth and risk premia) to test the relative riskiness of value and growth stocks in the context of the model's shocks.

My estimation and testing strategy is done in two parts. First, I use an *Unscented Kalman Filter* to estimate the unobservable time series of expected growth rates and the two risk premia (and to estimate the model parameters) on a deep history of aggregate US stock market data. This will reveal the degree to which the market prices near-term cashflow shocks differently from expected future cashflow growth shocks. It will also estimate, by maximum likelihood, the persistence of each shock in the data and the covariance between them. The behavior of estimated expected growth and risk premia at important moments in US stock market history (e.g., the internet bubble in 1999 & 2000 and the financial crisis in 2008 & 2009) will also be instructive. Given that my present value model is exactly solved, these estimation results can be used to generate an exact decomposition of realized market returns into expected and unexpected returns, and the latter can be further decomposed into each of the model's shocks. Second, I test the relative riskiness of value stocks and growth stocks by running standard *Ordinary Least Squares* time series regressions of sorted-portfolio returns against the components expected market returns (i.e., the two risk premia). If value stocks earn premium returns because they are more risky than growth stocks, this should be evident in the loadings of expected value returns on the risk premia (e.g., value stocks should have a higher loading on the higher risk premium). In addition, unexpected returns to value stocks (calculated as realized returns minus expected returns from the aforementioned regression) should demonstrate higher sensitivity to shocks in factors that carry a higher risk premium.

1.5.1 The Unscented Kalman Filter

While the price-to-dividend ratio and actual realized dividend growth are observable, the other key state variables in my model (g_t, θ_t^d, and θ_t^g) are not observed and must be estimated. In a completely linear system of transition and measurement equations, the standard Kalman filter would be optimal. However, given the multiplicative measurement equation for dividends in my model (*equation (24)*) and the time-varying LG *twists* to the transition equations (*equation (28)*), non-linear filtering techniques are required to estimate my model. It is possible to use an *Extended Kalman Filter* for this non-linear problem, but that approach has some well-documented weaknesses (see, for example, Wan & Merwe (2002)) and is only first-order accurate. Instead, I use the Unscented Kalman Filter (*UKF*) as proposed in Julier & Uhlman (1997) and described in Wan & Merwe (2002), which achieves third order accuracy for any non-linearity without burdensome additional computational effort.[28] Specifically, I use a UKF with *scaled unscented transform* and also an *augmented state vector* (to handle the non-additive noise in the dividend measurement equation).[29]

1.5.1.1 Data

The model described in *Section 1.4* has two primary observables; the price-to-dividend ratio (P_t/D_t) and the realized gross dividend growth rate (D_t/D_{t-1}). All other time series and parameters must be estimated from these observables. In this study, which is based on US equity prices, the observable data are taken from Prof. Robert Shiller's website.[30] Prof. Shiller's data has been widely vetted and is both high in quality and deep in history. The data

[28] Fernandez-Villaverde & Rubio-Ramırez (2004, 2006) and van Binsbergen & Koijen (2011) demonstrate that a *particle filter* could also be used for this estimation problem.

[29] The scaled unscented transform was intially proposed in Julier (2000) who found this algorithm to be superior to the unscaled version "in all respects". The use of the augmented state (to include the process and measurement noises in the state vector) is in line with the original formulation of the unscented Kalman filter in Wan & Merwe (2002).

[30] See http://www.econ.yale.edu/ shiller/data.htm and, in particular, U.S. Stock Markets 1871-Present and CAPE Ratio.

are available monthly (interpolated where necessary) with a history back to 1871. U.S. stock market average prices are represented by the value-weighted *S&P Composite*. Monthly composite prices reflect the average of daily closing levels each month and dividends reflect rolling four-quarter totals for the composite. The UKF is estimated on annual (December) data for the period from 1950 to 2019, largely mirroring the time period and data frequency for the value premium summary statistics in *Table 1.1* & *Table 1.2*. The choice of annual frequency for this study reflects a balance of competing considerations; I would like to have a large enough sample of data points to estimate the model efficiently while also leaving sufficient time between data points for aggregate fundamentals and expectations to evolve and for prices to react.

Definition of Dividends/Cashflow: This study uses actual paid-out cash dividends for the S&P Composite to represent aggregate equity cashflows, although other definitions of cashflow were also considered. Some studies include share repurchases in corporate payouts (e.g., 'total payout yields' as in Boudoukh, Michaely, Richardson, and Roberts (2007)). As noted by van Binsbergen & Koijen (2011), there "is an increasing amount of evidence that firms prefer stock repurchases over dividend payments" such that they "consider total payout data to be the relevant source of data".[31]

While share repurchases are important for shareholder returns and total shareholder payouts may be a more accurate measure of corporate cashflows, I use simple dividend payouts in this study because my model, as written in *Section 1.4*, does not include non-dividend corporate outlays in payout yields. Instead, the effect of these expenditures (including share buybacks) is intended to be captured in price changes rather than dividend yields. Mine is a present value model whose foundation is the definition of a gross return (*return = dividend yield + capital appreciation*, as in *equation (15)*). Thus, if I included share repurchases in paid-out cashflows, I would be double counting their contributions to returns because they

[31] van Binsbergen & Koijen (2011), *Section 2.2*.

would be included in the dividend yield and in the price changes they induce.[32]

1.5.1.2 The Non-Linear Dynamic System & Filter Setup

To initiate the recursions of the UKF, the measurement (i.e., observation) equations, transition (i.e., process) equations, augmented state covariances, and the initial state means and covariances must be specified. This is done in this section. *Table 1.3* shows the measurement and transition equations, as well as the covariance matrix of the augmented state. The augmented state covariance matrix, Σ_t^a, concatenates the covariance matrix of the measurement equation noises (ϵ_d) and the transition equation noises (ϵ^g, ϵ^{θ^d}, ϵ^{θ^g}) to the filtered state covariance, Σ_t.[33]

Table 1.4 shows the values for the state means and covariances that I use to initiate the UKF. Given that the state variables are defined as deviations from long-term average values, it is reasonable to set the initial values of $\hat{g}_0$, $\hat{\theta}_0^d$, and $\hat{\theta}_0^g$ to zero. Likewise, the state covariance is initialized with a diagonal matrix with the parameterized state variances on the diagonal.[34]

1.5.1.3 Parameter Estimation: Maximum Likelihood

In order for the UKF to generate a series of filtered values for the unobserved expected growth rates and risk premia, all of the parameters in the model (including the unconditional

[32]Broader definitions of corporate payouts can be used, although I do not do so here. Companies often set payout policies with a view to sustaining and growing dividends over time, even in adverse circumstances. As a result, paid-out dividends may not fluctuate as freely with the economy as corporate operating cashflows do. It is possible to define a hybrid payout measure that applies an average payout ratio to actual operating earnings in order to create a time series of pseudo *distributable cashflow* that fluctuates with the economy. Even in this case, however, the model may need to be re-specified since the definition of a return in *equation (15)* would not be satisfied.

[33]Note that there is no noise in the observation of the PD ratio, so only ϵ_d is included in the measurement noise.

[34]For any run of the UKF, the exact values for the variances on the diagonal are provided by the optimization algorithm that drives the maximum likelihood estimation of the model's parameters. This is described in more detail later.

means of the latent variables as well as variances, correlations and persistence terms) must be specified. *Table 1.5* lists all of the model's parameters. Of course the *true* parameter values are unknown and so they must be estimated. The only exception to this is the risk-free rate, r_f, which in this study is assumed to be constant at 4.17% per year, reflecting the average observed t-bill rate over the study period.[35]

The parameters in my model are estimated by *maximum likelihood*. I use an optimization algorithm which estimates the filtered states of my model for a wide range of candidate parameter values and selects an optimum based on maximizing the likelihood of the observed data, given those selected parameter values and estimated filtered states. Specifically, I use the *Differential Evolution* (*DE*) metaheuristic search and optimization algorithm attributed to Storn & Price (1997). This is a global, derivative-free, black-box optimization technique for multi-dimensional real-valued functions, such as mine. Unlike gradient-based optimizers, it uses an evolutionary process to iteratively search for and improve candidate solutions over wide spaces. *DE* is a leading state-of-the-art optimization technique that is used widely in various fields including machine learning and electrical engineering. Further details of the algorithm's implementation and applications can be found in Storn & Price (1997) and Das & Suganthan (2011).[36]

From among the wide universe of candidate solutions considered by the *DE* algorithm, the set of parameter values which generates filtered states estimates that maximize the (log)likelihood of observing the observed price-to-dividend ratio (P_t/D_t) and the realized gross dividend growth rate (D_t/D_{t-1}), is considered optimal. As in the standard Kalman Filter the log likelihood is constructed from a multivariate normal log probability density of a particular observation vector given the filtered state mean vector and covariance matrix.

---

[35] 4.17% is the arithmetic average of the annual t-bill rate from 1950-2019 in Prof. Aswath Damodaran's *Historical Returns on Stocks, Bonds and Bills - United States* (see *www.damodaran.com*). In a subsequent study, I hope to estimate a variant of my price-dividend model with stochastic short rates, which may enable the model to capture other pricing dynamics.

[36] I implemented the Differential Evolution algorithm using the SciPy *Optimize* module in Python. The reference guide for this implementation is available at *https://docs.scipy.org*.

1.5.2 Estimation & Testing Results

Table 1.6 shows the values of the UKF parameters that maximize the likelihood of the observed data using the Differential Evolution optimization algorithm (together with the standard errors in parentheses). Using these parameter values, *Figure 1.1* charts the time series of the filtered latent variables, g_t, θ_t^d, and θ_t^g.

(It must be noted that since the two risk premia in *equation (36)* enter my model symmetrically, and since no additional information is provided to the Unscented Kalman Filter to specifically link the less persistent risk premium component with near-term cashflow shocks (as opposed to distant shocks), when interpreting my estimation results, I must choose which component to label as the near-term cashflow risk premium and which to label as the distant cashflow risk premium. Despite this model limitation, my decision to label the less persistent component (which has a larger average premium) as the dividend-level premium is not arbitrary. Using an equity duration argument, if the larger risk premium compensates, instead, for future dividend growth shocks, then I would expect growth stocks to be *more* sensitive to this premium than I found, and that growth stocks would have higher average returns than value stocks. My labeling decision is also supported by (a) my overarching thesis about value stock risk (that it derives from cashflow shock sensitivity), (b) the OLS regression results in *Tables 1.7 & 1.8* of this paper, and (c) the results in *Tables 2.2, 2.3, 2.4, 2.5, 2.6, 2.7 & 2.8* (from O'Neill (2022), Paper 2) which clearly show that value stock prices and cashflows are more sensitive to near-term aggregate cashflow shocks than growth stock prices and cashflows.)

Unconditional Means

The estimated value of the unconditional mean expected growth rate parameter is 7.9%. This compares to a mean realized dividend growth rate of 6% over this period. While there is no requirement that average expected growth equals realized growth, the average value of the filtered time series of expect growth rates (i.e., $\bar{g}$ plus the average of $\hat{g}_t$) is 6.5% which is rather close to the realized growth rate over this time period (and was estimated without any data calibration efforts). More pertinently, the unconditional mean risk premia, $\bar{\theta}^d$ and $\bar{\theta}^g$, are estimated at 5.8% and 0.5% respectively, indicating a significant difference between the pricing of near-term cashflow risk and distant cashflow risk. The averages of the time series of filtered values of θ_t^d and θ_t^g , 4.7% and 1.7% respectively, offer a similar result. Together with the unconditional expected growth rate, the unconditional risk premia imply an estimated unconditional mean PD ratio of 36.1 which compares favorably to the mean observed PD ratio of 37.4 in this period.

Persistence of Shocks

The model has three persistence terms; ρ^g, ρ^{θ_d}, and ρ^{θ_g}. Shocks to expected growth are found to have a persistence of 0.395. This somewhat surprising result suggests that expected growth shocks, while impactful, do not have a long memory. If such shocks wear off after only a few years, it is possible that they can be more impactful to stocks with a low implied duration of cashflows (i.e., value stocks) than stocks with high duration (i.e., growth stocks). The persistence of shocks to ρ^{θ_d}, estimated at 0.255, is also low. When economic events or news cause investors to become more or less fearful of near-term cash flows, such changes of opinion appear to be short-lived. This is consistent with the estimated standard deviation of θ_d shocks of 8.9% which is twice the estimated volatility of θ_g shocks (4.5%). Shocks to the risk premium for expected future growth are the most persistent at 0.871. Investors fears about distant cashflow growth are slow to change but when they do, they are long-lasting.

Correlation of Shocks

The estimated correlation parameters in the model are also revealing. Near-term cash flow shocks are found to be negatively correlated with the risk premium for near-term cashflows ($\rho^{d\theta^d}$ = -44%). This result is entirely consistent with evidence in macro finance literature that investors become more fearful during recessions and more courageous during economic booms. The correlation of near-term cash flow shocks with θ_g is found to be *positive* at 72%. At first glance, this result appears to contradict the observation that investors become more cautious in bad economic times. However, it is also evident *Table 1.6* that θ^d and θ^g are negatively correlated ($\rho^{\theta^d\theta^g}$ = -0.680). Thus, the overall comovement of risk premia with economic events depends on the relative magnitude of the innovations in the two risk premia and how those are weighted by investors in market prices. This result also allows for the impact of near-term cashflow shocks to be offset to some degree by opposite revisions to long-term expected growth, an effect that will be more pronounced for assets that have low exposure to near-term cashflow risk but high exposure to distant cashflow risk.[37] Shocks to expected growth rates are found to be positively correlated with near-term cashflow shocks (ρ^{dg} = 0.374), suggesting, perhaps unsurprisingly, that investors tend to extrapolate good (and bad) near-term economic times to long-term growth expectations. I also find that shocks to expected growth are positively correlated with both risk premia ($\rho^{g\theta^d} \approx \rho^{g\theta^g} \approx$ 0.4).

Gathering all of these parameter estimates together, I can write the following estimated equation for the PD ratio in *Equations (22)* and *(36)*.

$$\frac{P_t}{D_t} = 36.1 + (60.1 \times \hat{g}_t) - (246.9 \times \hat{\theta}_t^d) - (49.2 \times \hat{\theta}_t^g) \tag{37}$$

Equation (37) says that when g_t, θ_t^d, and θ_t^g are sitting at their unconditional means, the value of the PD ratio is 36.1 based on the data used in this study. Deviations of g_t above $\bar{g}$ lead to higher PD ratios while deviations of risk premia above their unconditional means lead to lower PD ratios, as one would expect. Importantly, the coefficient on $\hat{\theta}_t^d$, at -246.9,

[37] This is precisely the ”hedging quality” of growth stocks that gives them a lower cashflow elasticity of price than value stocks, as discussed in *Section 1.4.1*.

is five times larger than the coefficient on $\hat{\theta}_t^g$, at -49.2. Thus, even though shocks to θ_t^d are negatively correlated θ_t^g, the former will dominate in terms of their effect on market prices.

Figure 1.1 charts the filtered values for g_t, θ_t^d, and θ_t^g for the time period of this study, 1950 - 2019. Much of the discussion above concerning the relative magnitude of each factor and the correlations between them are evident in the chart. Some additional observations are worth making. From 1950 to 1995, all three filtered series have markedly lower volatility than 1996 - 2019. Beginning in the late 1990's, θ^g becomes increasingly smaller while θ^d becomes larger and expected growth, g, is revised upwards. This divergence coincides with the divergence between the returns to growth and value stocks during the *internet bubble* period that reached a peak in March 2000. The sharp rise in θ^g and fall in θ^d following that peak also mirror the selloff in growth stocks and resurgence in value stocks that occurred during that period. The financial crisis in 2008 & 2009 is notable in the chart for the sharp decline in expected growth rates followed by a sharp increase in θ^d, likely reflecting ongoing elevated fear of recession. Following the financial crisis, expected growth returns to its normal range but θ^g remains below its long-term average and θ^d remains above its long-term average, which is consistent with the positive relative returns of growth versus stocks in the decade following the Great Recession.

1.5.3 Relative Riskiness of Value & Growth Stocks

These estimation results support the idea that the market prices near-term cashflow risk differently than distant cashflow risk and that shocks to the former carry a higher risk premium than shocks to the latter. These results were estimated from the time series of PD ratios and realized dividend growth rates for the *aggregate* market, represented by the *S&P Composite* in Prof. Robert Shiller's data. However, if value stocks earn premium returns over growth stocks because they are riskier, it must be the case that the discount rates (i.e., expected returns) of value stocks have a higher loading on θ^d than θ^g.

To test this, I ran OLS regressions of the annual realized returns (at time t+1) of each of the ten decile B/M-sorted portfolios from Prof. Ken French's website (in excess of the risk-free rate) against the filtered values (at time t) for θ^d than θ^g from the UKF (as in *equation (37)*).

$$R^i_{t+1} - r_f = (\beta^d_i \times \theta^d_t) + (\beta^g_i \times \theta^g_t) + \epsilon^i_{t+1} \; (i = 1, ..., 10) \tag{38}$$

The predicted values from this regression represent the expected returns/discount rates for each of the ten sorted portfolios and the estimated regression coefficients represent the loadings on the two aggregate risk premia. *Table 1.7* summarizes the results from these regressions for both value-weighted and equal-weighted portfolio returns.

A number of results are evident in *Table 1.7*. First, for most portfolios, the loading on θ^d exceeds the loading on θ^g. This is consistent with the finding that investors are more fearful of near-term cashflow risk than expected future growth risk. Second, the loading on θ^d for value portfolios is economically and statistically much larger than for growth portfolios. For both value-weighted and equal-weighted returns, the coefficient on θ^d for the deepest value portfolios (Decile 10) is about twice the loading for the growth portfolios (Decile 1). This result offers strong support for the idea that value stocks have higher expected returns because they are riskier, in that they have a higher exposure to near-term cashflow risk which command a high risk premium. It may also be the case that value portfolios have a marginally higher coefficient on θ^g than growth stocks but this is ambiguous; it is somewhat true for value-weighted portfolios, but is not true for equal-weighted portfolios.

To investigate further, I subtracted the predicted returns from each of the regressions in *Table 1.7* from the realized return for the ten B/M-sorted portfolios to create a time series on *unexpected* portfolio returns, $\tilde{R}^i$ (see *equation (39)*). Then I conducted univariate regressions of the unexpected portfolio returns on the four shocks from the UKF model, ϵ^d, ϵ^g, ϵ^{θ^d} and ϵ^{θ^g} (see *equation (40)*). The slope coefficients from these univariate regressions are shown in *Table 1.8*.[38]

$$\tilde{R}^i_{t+1} - r_f = (R^i_{t+1} - r_f) - (\hat{\beta}^d_i \times \theta^d_t + \hat{\beta}^g_i \times \theta^g_t) \tag{39}$$

$$\tilde{R}^i_{t+1} = \tilde{\beta}^j_i \times \epsilon^j_{t+1} + \tilde{\epsilon}^j_{t+1}, \ (i = 1, ..., 10; \ j = d, g, \theta^d, \theta^g) \tag{40}$$

The results support the primary finding from *Table 1.7*. Unexpected returns to value portfolios are significantly more sensitive to near-term cash flow shocks than growth portfolio returns. For both value-weighted and equal-weighted returns, the coefficient on ϵ^d is higher for higher B/M portfolios. This result is precisely what would be expected if value stocks have a higher cashflow elasticity of price than growth stocks; when near-term cashflow shocks occur, value stock prices move in the same direction as the shock (and growth stock prices move less and/or in the opposite direction), even though value stocks were already discounted for the possibility. Once again, I find that shocks to expected growth have an ambiguous, and not statistically significant, effect on growth and value returns. (The fact that there is no discernible pattern to the coefficients on ϵ^{θ^d} and ϵ^{θ^g} in *Table 1.8* is somewhat surprising and may merit a further, multivariate empirical analysis of the relationship between unexpected portfolio returns and the four model shocks which contemplates the covariance structure between the shocks.)

1.6 Conclusion

In this paper, I proposed a risk-based explanation of the value premium in which there are two components of the equity risk premium; a larger premium to compensate for near-

[38]Given the covariance structure between the four shocks, the absolute value of the coefficients in these univariate regressions is of less interest here. Rather, I am interested in the difference in the coefficients between growth and value portfolios.

term systematic cashflow risk and a smaller one for distant cashflow risks. I justified this dual-risk-premium SDF by showing how a representative agent (either with Epstein-Zin preferences or time-additive utility with wealth in the utility function) will price assets based on their exposures to innovations in near-term consumption growth and also innovations in anticipated future consumption growth (or wealth). To test these ideas, I developed an exactly-solved linear present value model of the price-dividend ratio which disentangles near-term cash flows from expected future cash flow growth with two time-varying risk premia and I used an Unscented Kalman Filter and Maximum Likelihood optimization to estimate the model on a long history of US market data.

I found evidence that strongly supports the existence of two different risk premia in the pricing of US stocks, with the premium for near-term cashflow risks being meaningfully larger than the premium for risks to expected future cash flow growth. I also measured the relative riskiness of value and growth stocks in this framework by running regressions of value-sorted portfolio returns on the filtered risk premia. These regressions revealed that expected returns for value stocks have a significantly higher loading on the risk premium for near-term cash flows, than growth stocks. I also found that unexpected returns for value stocks are more sensitive to near-term cashflow shocks than growth stocks. Taken together, these results support the idea that value stocks earn higher returns than growth stocks because they are riskier in ways that investors care about.

1.7 References

Asness, C., Liew, J., Pedersen, L.H., and Thapar, A., 2018. Deep Value. *CEPR Discussion Paper No. DP12685*

Asness, C., Moskowitz, T. and Pedersen, L.H., 2013. Value and Momentum Everywhere. *Journal of Finance* 68, 929-985

Bansal, R., Dittmar R.F., and Lundblad, C.T., 2005. Consumption, dividends, and the cross-section of equity returns, *Journal of Finance* 60, 1639-1672

Bansal, R. and Yaron, A., 2004. Risks for The Long Run: A Potential Resolution of Asset Pricing Puzzles. *Journal of Finance* 59, 1481-1509

Basu, S., 1977. Investment Performance of Common Stocks in Relation to their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis. *Journal of Finance* 32, 663-682

Basu, S., 1983. The Relationship Between Earnings Yield, Market Value and Return for NYSE Common Stocks: Further Evidence. *Journal of Financial Economics* 12, 129-156

Buffett, W.E., 1984. The Superinvestors of Graham and Doddsville. *Hermes*, Columbia Business School

Campbell, J.Y. and Cochrane, J.H., 1999. By Force of Habit: A ConsumptionBased Explanation of Aggregate Stock Market Behavior. *Journal of Political Economy* 107, 205-251

Campbell., J.Y. and Vuolteenaho, T., 2004. Bad Beta, Good Beta. *American Economic Review* 94, 1249-1275

Carlson, M., Fisher, A., and Giammarino, R., 2004. Corporate investment and asset price dynamics: Implications for the cross section of returns. *Journal of Finance* 59, 2577-2603

Chen, A., 2018. A General Equilibrium Model of the Value Premium with Time-Varying Risk Premia. *The Review of Asset Pricing Studies* 8, 337-374

Choi, J., 2013. What Drives the Value Premium?: The Role of Asset Risk and Leverage. *Review of Financial Studies* 26, 2845-2875

Cohen, R.B., Polk, C., and Vuolteenaho, T., 2003. The Price is (Almost) Right. EFA 2005 Moscow Meetings Paper.

Cohen, R.B., Polk, C. and Vuolteenaho, T., 2003. The Value Spread. *Journal of Finance* 58, 609-642

Cornell, B., 1999. Risk, duration, and capital budgeting: New evidence on some old questions *Journal of Business* 72, 183–200.

Daniel, K. and Hirshleifer, D. and Subrahmanyam, A., 1998. Investor Psychology and Security Market Under-and Overreactions. *Journal of Finance* 53, 1839-1885

Daniel, K.D., Hirshleifer, D. and Subrahmanyam, A., 2001. Overconfidence, Arbitrage, and Equilibrium Asset Pricing. *Journal of Finance*, 56, 921-965

Daniel, K., and Titman, S., 1997. Evidence on the Characteristics of Cross Sectional Variation in Stock Returns. *Journal of Finance* 52, 1-33

Daniel, K., and Titman, S., 1998. Characteristics or Covariances? *The Journal of Portfolio Management* 24, 24-33

Das, S., and Suganthan P.N., 2011. Differential Evolution: A Survey of the State of the Art. IEEE Trans. on Evolutionary Computation, Vol. 15, No. 1, pp. 4-31, February

Davis, J.L., Fama, E.F. and French, K.R., 2000. Characteristics, Covariances, and Average Returns: 1929 to 1997. *Journal of Finance* 55, 389-406

DeBondt, W.F.M., Thaler, R., 1985. Does the Stock Market Overreact? *Journal of Finance* 40, 793-805

DeBondt, W.F.M., Thaler, R., 1987. Further Evidence on Investor Overreaction and Stock Market Seasonality. *Journal of Finance* 42, 557-581

de Groot, W., Joop Huij and Weili Zhou, 2012. Another look at trading costs and short-term reversal profits. *Journal of Banking & Finance*, 2012, vol. 36, issue 2, 371-382

Epstein, Larry G., and and Zin, Stanley E, 1989. Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework. *Econometrica* Vol. 57, No. 4 (Jul., 1989), pp. 937-969

Epstein, Larry G., and and Zin, Stanley E, 1991. Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: An Empirical Analysis. *Journal of Political Economy* Vol. 99, issue 2, 263-86

Fama, E.F. and French, K.R., 1992. The Cross-section of Expected Stock Returns. *Journal of Finance* 42, 427-465

Fama, E.F. and French, K.R., 1993. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics* 33, 3-56

Fama, E.F. and French, K.R., 1995. Size and Book-to-Market Factors in Earnings and Returns. *Journal of Finance* 50, 131-155

Fama, E.F. and French, K.R., 1996. Multifactor Explanations of Asset Pricing Anomalies. *Journal of Finance* 51, 55-84

Fama, E.F. and French, K.R., 1998. Value Versus Growth: The International Evidence. *Journal of Finance* 53, 1975-1999

Fama, E.F. and French, K.R., 2006. The Value Premium and the *CAPM*. *Journal of Finance* 61, 2163-2185

Fama, E.F. and French, K.R., 2012. Size, Value and Momentum in International Stock Returns. *Journal of Financial Economics* 105, 457-472

Fama, E.F. and French, K.R., 2020. The Value Premium. Fama-Miller Working Paper No. 20-01

Gabaix, X., 2007. Linearity-Generating Processes: A Modelling Tool Yielding Closed Forms for Asset Prices, NBER Working Paper No. 13430

Gabaix, X., 2009. Linearity-Generating Processes: A Modelling Tool Yielding Closed Forms for Asset Prices, NYU, CEPR & NBER Working Paper

Giglio, Stefano, Maggiori, M., and Stroebel, J., 2015. Very Long-Run Discount Rates. *Quarterly Journal of Economics* 130, 1-53

Gordon, Myron J., 1962. The Investment, Financing, and Valuation of the Corporation, Irwin, Homewood

Gormsen, N.J., and Lazarus, E., 2021. Duration-Driven Returns. Unpublished paper

Graham, B., and Dodd, D., 1934. Security Analysis. *New York, McGraw-Hill*

Graham, B., 1949. The Intelligent Investor. *Harper & Row*

Gulen, H., Xing, Y., and Zhang, L., 2011. Value versus Growth: Time-Varying Expected Stock Returns. *Financial Management* 40, 381-407

Guo, H., Savickas, R., Wang, Z., and Yang, J., 2009. Is the Value Premium a Proxy for

Time-Varying Investment Opportunities? Some Time-Series Evidence. *Journal of Financial and Quantitative Analysis* 44, 133-154

Hou., K., Mo, H., Xue, C., and Zhang, L., 2017. The Economics of Value Investing. NBER Working Paper No. 23563

Kapadia., N, 2011. Tracking down distress risk. *Journal of Financial Economics*, Volume 102, Issue 1, Pages 167-182

Lakonishok, J., Shleifer, A., and Vishny, R.W., 1994. Contrarian Investment, Extrapolation, and Risk. *Journal of Finance* 49, 1541-1578

La Porta, R., Lakonishok, J., Shleifer, A. and Vishny, R.W., 1997. Good News for Value Stocks: Further Evidence on Market Efficiency. *Journal of Finance* 52, 859-874

Lettau, M. and Wachter, J.A., 2007. Why is Long-Horizon Equity Less Risky? A Duration-Based Explanation of the Value Premium. *Journal of Finance* 62, 55-92

Lev., B., & Srivastava, A., 2019. Explaining the Recent Failure of Value Investing. NYU Stern School of Business.

Li, X., Brooks, C. and Miffre, J., 2009. The Value Premium and Time-Varying Volatility. *Journal of Business Finance and Accounting* 36, 1252-1272

Li, Y., Ng, D.T., and Saminathan, B., 2014. Predicting Time-varying Value Premium Using the Implied Cost of Capital: Implications for Countercyclical Risk, Mispricing and Style Investing. *Available at SSRN*

Kirby, C., 2018. The Value Premium and Expected Business Conditions. *Available at SSRN*

Merton, R.C., 1973. An Intertemporal Capital Asset Pricing Model. *Econometrica* 41, 867-887

Nagel, Stefan, 2011. Evaporating Liquidity. *NBER Working Paper* No. w17653, *Available at SSRN*

O'Neill, Ciarán, 2022. Value Stocks are Riskier - *Paper 2*. PhD. Dissertation, EDHEC PhD. in Finance

Petkova, R., and Zhang, L., 2005. Is Value Riskier Than Growth? *Journal of Financial Economics* 78, 187-202

Rosenberg, B., Reid, K., & Lanstein, R. 1985. Persuasive Evidence of Market Inefficiency. *The Journal of Portfolio Management* 11 (3) 9-16.

Santos, T., and Veronesi, P., 2005. Cash-Flow Risk, Discount Risk, and the Value Premium. *NBER Working Paper No. 11816*

Shleifer, A., and Vishny, R.W., 1997. The Limits of Arbitrage. *Journal of Finance* 52, 35-55

Storn, R and Price, K, 1997. Differential Evolution - a Simple and Efficient Heuristic for Global Optimization over Continuous Spaces, *Journal of Global Optimization*, 11, 341 - 359

van Binsbergen, J.H., Brandt, M, and Koijen, R.S.J., 2012. "On the Timing and Pricing of Dividends", *American Economic Review* 102, 1596-1618gi

van Binsbergen, J.H., and Koijen, R.S.J., 2011. Likelihood-Based Estimation of Exactly-Solved Present-Value Models. *Available at SSRN*

Weil, P., 1990. Nonexpected Utility in Macroeconomics. *The Quarterly Journal of Economics* Vol. 105, No. 1 (Feb., 1990), pp. 29-42

Xing, Y., 2008. Interpreting the Value Effect Through the Q-Theory: An Empirical Investigation. *The Review of Financial Studies* 21, 1767-1795
Zhang, L., 2005. The Value Premium *Journal of Finance* 60, 67-103
Zhang, L., 2017. The Investment *CAPM*. *European Financial Management* 23, 545-603

1.8 Appendix: Alternative Derivation of SDF with Two Risk Premia

In this appendix, I derive an SDF with two risk premia similar to that in *Section 1.3* above, but without assuming the representative agent has EZW preferences. I begin with an agent whose utility in any period derives from consumption in that period *and* from post-consumption wealth in that period. As before, the inclusion of wealth in periodic utility means that this agent cares about his anticipated future consumption and that fluctuations in wealth (e.g., caused by changes in long-term consumption growth in the economy) can affect his utility today, even if his current consumption does not change. Specifically, the agent's felicity in any period is represented as follows.[39]

$$u_t = (\frac{{C_t}^{1-\gamma}}{1-\gamma}){W_t}^{\alpha} \tag{41}$$

where γ is risk aversion and α measures how much the agent cares about wealth. Utility is also time additive and the agent seeks to maximize lifetime utility *(42)* subject to his intertemporal budget constraint for post-consumption wealth *(43)*.

$$\max_{C_t} U_t = \sum_{t=0}^{\infty} \delta^t u_t \tag{42}$$

$$W_{t+1} = W_t R_{w,t+1} - C_{t+1} \tag{43}$$

Importantly, the growth rate of post-consumption wealth is different from the return on

[39] This model of felicity is also consistent with the "spirit of capitalism" framework of Bakshi & Chen (1996) in which agents care about wealth as a measure of social status. However, the agent in my model cares about the information that current wealth conveys about his future consumption plans, rather than his social standing.

wealth in this model. That is, the return on wealth is the growth rate of wealth *plus* the propensity to consume.

$$R_{w,t+1} = \frac{W_{t+1}}{W_t} + \frac{C_{t+1}}{W_t} \tag{44}$$

Because the agent's utility is time additive, we can use a simple variational argument to derive the Euler equation. Assume the agent has an optimal consumption and investment path. Now consider a deviation from that optimum that reduces current consumption by one unit, which is then invested for one period at rate $R_{w,t+1}$ before being consumed in the next period. Given that we are at an optimum, such a deviation will have a zero effect on the agent's lifetime utility. That is

$$0 = -U_{c,t} + U_{w,t} + E_t(U_{c,t+1}R_{w,t+1}) \tag{45}$$

where U_c and U_w are marginal utilities. Rewriting this condition with the utility function in *(41)* and *(42)*, the Euler equation is given by

$$1 = E_t(\frac{C_{t+1}{}^{-\gamma}W_{t+1}{}^{-\alpha}R_{w,t+1}}{C_t{}^{-\gamma}W_t{}^{-\alpha} + \alpha(\frac{C_t{}^{1-\gamma}}{1-\gamma})W_t{}^{-\alpha-1}}) \tag{46}$$

Simplifying the ratio of marginal utilities on the right hand side of the Euler equation, the stochastic discount factor, M_{t+1}, in this economy shows that the agent cares about the growth rate of consumption *and* the growth rate of wealth. That is

$$M_{t+1} = (\frac{C_{t+1}}{C_t})^{\gamma}(\frac{W_{t+1}}{W_t})^{\alpha}(1 + \frac{\alpha}{1-\gamma}\frac{C_t}{W_t}) \tag{47}$$

Indeed, taking logs of *(47)* and expressing the result in terms of innovations (i.e., $\hat{m}_{t+1} = m_{t+1} - E_t(m_{t+1})$), the log SDF simplifies to

$$\hat{m}_{t+1} = -\gamma \hat{c}_{t+1} - \alpha \hat{w}_{t+1} \tag{48}$$

where $\hat{c}_{t+1}$ and $\hat{w}_{t+1}$ represent innovations in $log(\frac{C_{t+1}}{C_t})$ and $log(\frac{W_{t+1}}{W_t})$ respectively. Furthermore, if I assume now that growth rates and returns are lognormal, I can write the log risk premium for any arbitrary asset, i, as in *(49)*.

$$E_t(r_{i,t+1}) - r_{f,t+1} + \frac{\sigma_i^2}{2} = \gamma \sigma_{r_i,c} + \alpha \sigma_{r_i,w} \tag{49}$$

where $\sigma_{r_i,c}$ and $\sigma_{r_i,w}$ are the covariances between log asset returns and innovations in log consumption growth and log wealth growth respectively. Importantly, *equation (49)* can be applied directly to the wealth portfolio also. In this case, I will make use of a multiplicative decomposition of wealth returns by rewriting *equation (44)* above.

$$R_{w,t+1} = (1 + \frac{C_{t+1}}{W_{t+1}})\frac{W_{t+1}}{W_t} \tag{50}$$

Taking logs of *(50)* and using $z_{t+1} = log(1 + \frac{C_{t+1}}{W_{t+1}})$ and $g_{wt+1} = log(\frac{W_{t+1}}{W_t})$

$$r_{w,t+1} = z_{t+1} + g_{wt+1} \tag{51}$$

Now I can rewrite *(49)* specifically for the wealth asset, using the decomposition in *(51)*.

$$[E_t(g_{wt+1}) + E_t(z_{t+1})] - r_{f,t+1} + \frac{\sigma_{r_w}^2}{2} = \gamma\sigma_{r_w,c} + \alpha\sigma_{r_w,w} \tag{52}$$

I use the SDF in *(47)* and the rule for taking logs of expected values of lognormal variables to find the risk-free rate in this economy (i.e., $r_{f,t+1} = -log(E_t(M_{t+1}))$).

$$r_{f,t+1} = \gamma E_t(g_{ct+1}) + \alpha E_t(g_{wt+1}) + q_t - \frac{\gamma^2{\sigma_{g_c}}^2}{2} - \frac{\alpha^2{\sigma_{g_w}}^2}{2} - \gamma\alpha\sigma_{g_c,g_w} \tag{53}$$

where $q_t = log(1 + \frac{\alpha}{1-\gamma}\frac{C_t}{W_t})$ and $g_{ct+1} = log(\frac{C_{t+1}}{C_t})$. *Equation (53)* says that the risk-free rate in this economy is a function of some constants and expectations of log consumption growth and log wealth growth.

Substituting for $E_t(g_{wt+1})$ from *(52)* into (*53)* and rearranging/simplfying, I derive an expression for the risk-free rate in terms of some known values as well as $E_t(g_{ct+1})$ and $E_t(z_{t+1})$.

$$r_{f,t+1} = \frac{\gamma}{1-\alpha}E_t(g_{ct+1}) - \frac{\alpha}{1-\alpha}E_t(z_{t+1}) + \textit{known values} \tag{54}$$

This is shown in *(54)*, which I can then substitute back into *(52)* to show that innovations in expected log returns on wealth are also a function of the same variables. When this insight is combined with a Campbell-Shiller loglinearization of returns (Campbell & Shiller, 1988a) and the decomposition of returns into cashflow news and discount rate news in Campbell (1991), I can show that the premium on risky assets depends on the covariance of the asset's returns with current consumption growth and changes in anticipated future consumer growth (and a third variable that is likely to be less significant).

Equation (55) uses the Campbell-Shiller loglinearization and the return decomposition to write surprises in the (log) return on wealth as

$$\hat{r}_{w,t+1} = (E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j d_{w,t+j+1} - (E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j r_{w,t+j+1} \tag{55}$$

where d_w is log dividend growth and ρ can be interpreted as a discount factor. In this representative agent setting, the dividend on the wealth portfolio is also equal to aggregate consumption. Combining this fact with the observation above that the expected log return on wealth can be written as a function of $E_t(g_{ct+1})$, $E_t(z_{t+1})$ and some known values, I can rewrite *(55)* as

$$\hat{r}_{w,t+1} = \hat{c}_{t+1} + (1 - \frac{\gamma}{1-\alpha})(E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j g_c t + j + 1 - (1 - \frac{\alpha}{1-\alpha})(E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j z_{t+j+1} \tag{56}$$

$$\hat{r}_{w,t+1} = \hat{c}_{t+1} + (1 - \frac{1}{\alpha})\hat{g}_{t+1} + (1 - \frac{\alpha}{1-\alpha})\hat{z}_{t+1} \tag{57}$$

where $\hat{g}_{t+1}$ reflects revisions in expectations of future consumption growth. In practice, $\hat{z}_{t+1}$ is likely to be close to zero.[40] Armed with this expression and ignoring the last term in *(57)*, it is straightforward to rewrite the log SDF in *(48)* and the premium on an arbitrary risky asset i in *(49)* as follows.

$$\hat{m}_{t+1} = -\gamma \hat{c}_{t+1} - (\gamma - \frac{1}{\alpha})\hat{g}_{t+1} \tag{58}$$

$$E_t(r_{i,t+1}) - r_{f,t+1} + \frac{\sigma_i^2}{2} = \gamma \sigma_{i,c} + (\gamma - \frac{1}{\alpha})\sigma_{i,g} \tag{59}$$

[40] $\hat{z}_{t+1} = log(1 + \frac{C_{t+1}}{W_{t+1}}) - E_t[log(1 + \frac{C_{t+1}}{W_{t+1}})]$ which equals $log(\frac{(1+\frac{C_{t+1}}{W_{t+1}})}{(1+E_t[\frac{C_{t+1}}{W_{t+1}}]})) - \frac{\sigma_z^2}{2}$.

1.9 Tables & Figures for Paper 1

This page intentionally left blank

Table 1.1: Value-Weighted Annualized Excess Returns for Sorted Value and Growth Portfolios, January 1952 to December 2019

All return data from Ken French's website. Stocks are sorted into decile portfolios in June of each year based on earnings-to-price (E/P), cashflow-to-price (C/P), dividend-to-price (D/P) or book-to-market ratio (B/M) using fiscal year-end fundamental data from the prior calendar year, and calendar year-end prices. Simple annualization is used (mean monthly returns are multiplied by 12, and standard deviations by the square root of 12. Risk free rate is the one-month treasury bill rate.

Metric	**Growth**				*Growth & Value Deciles*					**Value**	'52-'19	'10-'19
	1	2	3	4	5	6	7	8	9	10	V-G	V-G
					Panel A: Mean Excess Returns (% per year)							
E/P	6.90	6.01	7.46	7.24	7.57	9.01	9.81	10.41	11.35	11.98	5.08	-5.52
C/P	6.74	7.32	6.91	7.64	8.13	8.64	9.05	9.51	10.16	11.62	4.88	-6.40
D/P	7.25	6.92	7.50	8.33	7.21	8.24	8.37	9.22	8.57	7.74	0.48	2.34
B/M	6.78	7.62	7.81	7.46	8.17	8.82	7.44	9.70	10.53	10.81	4.02	-5.52
					Panel B: Standard Deviation (% per year)							
E/P	18.82	15.68	14.98	14.64	14.89	14.54	14.76	15.43	16.30	17.76	14.09	11.26
C/P	18.41	15.63	15.08	15.01	15.24	15.02	14.75	15.06	15.31	17.87	14.1	12.94
D/P	19.05	16.89	16.25	15.56	15.63	14.62	14.42	13.86	14.03	15.06	17.08	14.20
B/M	16.99	15.46	15.18	15.34	14.85	14.46	15.39	15.82	16.66	20.40	15.49	15.57
					Panel C: Standard Error of Mean Return							
E/P	0.65	0.54	0.52	0.51	0.52	0.51	0.51	0.54	0.57	0.62	0.49	0.98
C/P	0.64	0.54	0.52	0.52	0.53	0.52	0.51	0.52	0.53	0.62	0.49	1.13
D/P	0.66	0.59	0.56	0.54	0.54	0.51	0.50	0.48	0.49	0.52	0.59	1.24
B/M	0.59	0.54	0.53	0.53	0.52	0.50	0.54	0.55	0.58	0.71	0.54	1.36
					Panel D: Sharpe Ratio							
E/P	0.37	0.38	0.50	0.49	0.51	0.62	0.66	0.67	0.70	0.67	0.36	-0.49
C/P	0.37	0.47	0.46	0.51	0.53	0.51	0.61	0.63	0.66	0.65	0.35	-0.49
D/P	0.38	0.41	0.46	0.50	0.46	0.56	0.58	0.66	0.61	0.51	0.03	0.17
B/M	0.40	0.49	0.51	0.49	0.55	0.61	0.48	0.61	0.63	0.53	0.26	-0.35

Table 1.2: Equal-Weighted Annualized Excess Returns for Sorted Value and Growth Portfolios, January 1952 to December 2019

All return data from Ken French's website. Stocks are sorted into decile portfolios in June of each year based on earnings-to-price (E/P), cashflow-to-price (C/P), dividend-to-price (D/P) or book-to-market ratio (B/M) using fiscal year-end fundamental data from the prior calendar year, and calendar year-end prices. Simple annualization is used (mean monthly returns are multiplied by 12, and standard deviations by the square root of 12. Risk free rate is the one-month treasury bill rate.

Metric	**Growth** 1	2	3	4	*Growth & Value Deciles* 5	6	7	8	9	**Value** 10	'52-'19 V-G	'10-'19 V-G
					Panel A: Mean Excess Returns (% per year)							
E/P	7.21	8.89	9.06	9.69	10.19	10.84	11.52	12.24	13.37	14.53	7.32	-1.96
C/P	6.88	8.25	9.43	9.98	10.67	11.13	12.43	12.45	13.59	14.81	7.94	-4.37
D/P	9.23	10.49	10.15	10.76	10.89	10.75	11.10	11.31	10.31	8.97	-0.25	-1.53
B/M	4.79	7.41	8.83	9.77	10.23	10.55	11.94	12.02	13.59	14.90	10.11	-1.20
					Panel B: Standard Deviation (% per year)							
E/P	21.65	18.91	17.69	16.76	16.55	16.04	15.94	16.26	16.90	19.40	9.86	7.43
C/P	21.41	18.71	17.37	16.56	16.40	16.28	16.47	16.56	18.02	19.79	10.53	9.16
D/P	19.43	17.64	16.80	16.52	15.94	15.39	14.67	14.27	13.70	15.06	12.59	8.63
B/M	23.49	20.51	19.28	18.81	18.01	17.53	17.25	17.44	18.14	21.38	13.57	12.09
					Panel C: Standard Error of Mean Return							
E/P	0.75	0.66	0.61	0.58	0.58	0.56	0.55	0.57	0.59	0.67	0.34	0.62
C/P	0.74	0.65	0.60	0.58	0.57	0.57	0.57	0.58	0.63	0.59	0.37	0.76
D/P	0.68	0.61	0.58	0.57	0.55	0.53	0.51	050	0.48	0.52	0.44	0.72
B/M	0.82	0.71	0.67	0.65	0.63	0.61	0.60	0.61	0.63	0.74	0.47	1.01
					Panel D: Sharpe Ratio							
E/P	0.33	0.47	0.51	0.58	0.63	0.68	0.72	0.75	0.79	0.75	0.74	-0.26
C/P	0.32	0.44	0.54	0.60	0.65	0.68	0.75	0.75	0.75	0.75	0.75	-0.48
D/P	0.47	0.59	0.60	0.65	0.68	0.70	0.76	0.79	0.75	0.60	-0.02	-0.18
B/M	0.20	0.36	0.46	0.52	0.57	0.60	0.69	0.69	0.75	0.70	0.75	-0.10

Table 1.3: Unscented Kalman Filter Setup Equations

Measurement Equations	$\frac{P_t}{D_t} = \frac{1}{1-\pi-\delta}(\pi + \frac{\hat{g}_t}{1-\pi\rho^g} - \frac{\hat{\theta}_t^d}{1-\pi\rho^{\theta^d}} - \frac{\hat{\theta}_t^g}{1-\pi\rho^{\theta^g}})$ $\frac{D_{t+1}}{D_t} = (1+g_t)(1+\epsilon_{t+1}^d)$
Transition Equations	$\hat{g}_{t+1} = \rho^g \Phi_t \hat{g}_t + \epsilon_{t+1}^g$ $\hat{\theta}_{t+1}^d = \rho^{\theta^d} \Phi_t \hat{\theta}_{t+1}^d + \epsilon_{t+1}^{\theta^d}$ $\hat{\theta}_{t+1}^g = \rho^{\theta^g} \Phi_t \hat{\theta}_{t+1}^g + \epsilon_{t+1}^{\theta^g}$
Covariance Matrix	$\Sigma_t^a = \begin{bmatrix} \Sigma_t & 0 & 0 & 0 & 0 \\ 0 & \sigma_g^2 & \sigma_{g\theta^d} & \sigma_{g\theta^g} & \sigma_{dg} \\ 0 & \sigma_{g\theta^d} & \sigma_{\theta_d}^2 & \sigma_{\theta^d\theta^g} & \sigma_{d\theta^d} \\ 0 & \sigma_{g\theta^g} & \sigma_{\theta^d\theta^g} & \sigma_{\theta_g}^2 & \sigma_{d\theta^g} \\ 0 & \sigma_{dg} & \sigma_{d\theta^d} & \sigma_{d\theta^g} & \sigma_d^2 \end{bmatrix}$

Table 1.4: Unscented Kalman Filter Initial Values

Initial State Means	$\hat{g}_0 = 0$ $\hat{\theta}_0^d = 0$ $\hat{\theta}_0^g = 0$
Initial State Covariance	$\Sigma_0 = \begin{bmatrix} \sigma_g^2 & 0 & 0 \\ 0 & \sigma_{\theta_d}^2 & 0 \\ 0 & 0 & \sigma_{\theta_g}^2 \end{bmatrix}$

Table 1.5: Unscented Kalman Filter Pre-specified Paramaters

Risk-Free Rate	r_f
Unconditional mean expected growth	$\bar{g}$
Unconditional mean near-term cashflow risk premium	$\bar{\theta}^d$
Unconditional mean future cashflow growth risk premium	$\bar{\theta}^g$
Persistence of expected growth shocks	ρ^g
Persistence of θ^d shocks	ρ^{θ_d}
Persistence of θ^g shocks	ρ^{θ_g}
Variance of expected growth	σ_g^2
Variance of θ^d	$\sigma_{\theta^d}^2$
Variance of θ^g	$\sigma_{\theta^g}^2$
Variance of realized dividend growth	σ_d^2
Correlation of near-term dividend growth and θ^d	$\rho^{d\theta^d}$
Correlation of near-term dividend growth and θ^g	$\rho^{d\theta^g}$
Correlation of expected growth and θ^d	$\rho^{g\theta^d}$
Correlation of expected growth and θ^g	$\rho^{g\theta^g}$
Correlation of θ^d and θ^g	$\rho^{\theta^d\theta^g}$
Correlation of dividend growth and expected growth	ρ^{dg}

Table 1.6: UKF Optimal Paramater Values & Standard Errors

Risk-Free Rate	r_f	4.17%
Unconditional mean expected growth	$\bar{g}$	0.079 *(0.009)*
Unconditional mean near-term cashflow risk premium	$\bar{\theta}^d$	0.058 *(0.015)*
Unconditional mean future cashflow growth risk premium	$\bar{\theta}^g$	0.005 *(0.011)*
Persistence of expected growth shocks	ρ^g	0.395 *(0.132)*
Persistence of θ^d shocks	ρ^{θ_d}	0.255 *(0.176)*
Persistence of θ^g shocks	ρ^{θ_g}	0.871 *(0.096)*
Variance of expected growth	σ_g^2	0.013 *(0.006)*
Variance of θ^d	$\sigma_{\theta^d}^2$	0.008 *(0.010)*
Variance of θ^g	$\sigma_{\theta^g}^2$	0.002 *(0.005)*
Variance of realized dividend growth	σ_d^2	0.002 *(0.004)*
Correlation of near-term dividend growth and θ^d	$\rho^{d\theta^d}$	-0.437 *(0.229)*
Correlation of near-term dividend growth and θ^g	$\rho^{d\theta^g}$	0.719 *(0.204)*
Correlation of expected growth and θ^d	$\rho^{g\theta^d}$	0.413 *(0.320)*
Correlation of expected growth and θ^g	$\rho^{g\theta^g}$	0.376 *(0.175)*
Correlation of θ^d and θ^g	$\rho^{\theta^d\theta^g}$	-0.680 *(0.246)*
Correlation of dividend growth and expected growth	ρ^{dg}	0.374 *(0.118)*

Table 1.7: *Ordinary Least Squares* Regressions of Realized Portfolio Returns on Risk Premia, January 1950 to December 2019. Return data from Ken French's website. Stocks are sorted into decile portfolios based on book-to-market ratio (B/M) using fiscal year-end fundamental data from the prior calendar year, and calendar year-end prices.

	Growth				*Growth & Value Deciles*					**Value**
	1	2	3	4	5	6	7	8	9	10
					Value-Weighted Portfolios					
β^d	1.29	1.45	1.35	1.38	1.56	1.63	1.47	1.87	1.96	2.02
t-stat	*3.29*	*4.32*	*4.17*	*4.12*	*4.57*	*4.93*	*3.98*	*4.56*	*4.77*	*4.22*
β^g	0.93	0.79	0.87	0.95	0.92	0.83	1.04	1.13	1.16	1.20
t-stat	*2.40*	*2.36*	*2.70*	*2.85*	*2.70*	*2.54*	*2.82*	*2.77*	*2.86*	*2.52*
R-squared	17%	23%	23%	23%	26%	28%	22%	26%	27%	23%
					Equal-Weighted Portfolios					
β^d	0.93	1.38	1.52	1.79	1.78	1.95	2.13	2.19	2.40	2.72
t-stat	*1.65*	*2.8*	*3.28*	*3.82*	*3.77*	*4.27*	*4.37*	*4.39*	*4.51*	*4.11*
β^g	1.24	1.16	1.09	1.27	1.16	1.14	1.07	1.24	1.28	1.39
t-stat	*2.21*	*2.37*	*2.36*	*2.72*	*2.48*	*2.51*	*2.20*	*2.5*	*2.41*	*2.13*
R-squared	8%	14%	16%	21%	20%	23%	23%	24%	25%	21%

Table 1.8: Slope Coefficients from Univariate Regressions of Unexpected Portfolio Returns on Model Shocks, January 1950 to 2019.. Return data from Ken French's website. Stocks are sorted into decile portfolios based on book-to-market ratio (B/M) using fiscal year-end fundamental data from the prior calendar year, and calendar year-end prices.

Shocks	**Growth**				*Growth & Value Deciles*					**Value**
	1	2	3	4	5	6	7	8	9	10
					Value-Weighted Portfolios					
ϵ^d	-0.34	-0.23	-0.05	0.00	0.22	0.27	0.35	0.33	0.22	0.81
ϵ^g	1.61	1.49	1.70	1.59	1.47	1.49	1.69	1.56	1.47	2.05
ϵ^{θ^d}	2.27	2.06	1.87	1.79	1.68	1.73	1.92	2.03	2.06	2.24
ϵ^{θ^g}	-3.62	-3.24	-2.95	-2.79	-2.53	-2.57	-2.84	-3.00	-3.06	-3.15
					Equal-Weighted Portfolios					
ϵ^d	-0.14	-0.23	-0.22	-0.30	-0.16	0.07	0.11	0.25	0.55	0.45
ϵ^g	2.45	2.15	1.97	1.87	1.78	1.75	1.90	1.93	2.18	2.29
ϵ^{θ^d}	2.79	2.52	2.36	2.36	2.37	2.25	2.26	2.44	2.34	3.07
ϵ^{θ^g}	-4.38	-3.98	-3.74	-3.77	-3.71	-3.44	-3.46	-3.36	-3.42	-4.49

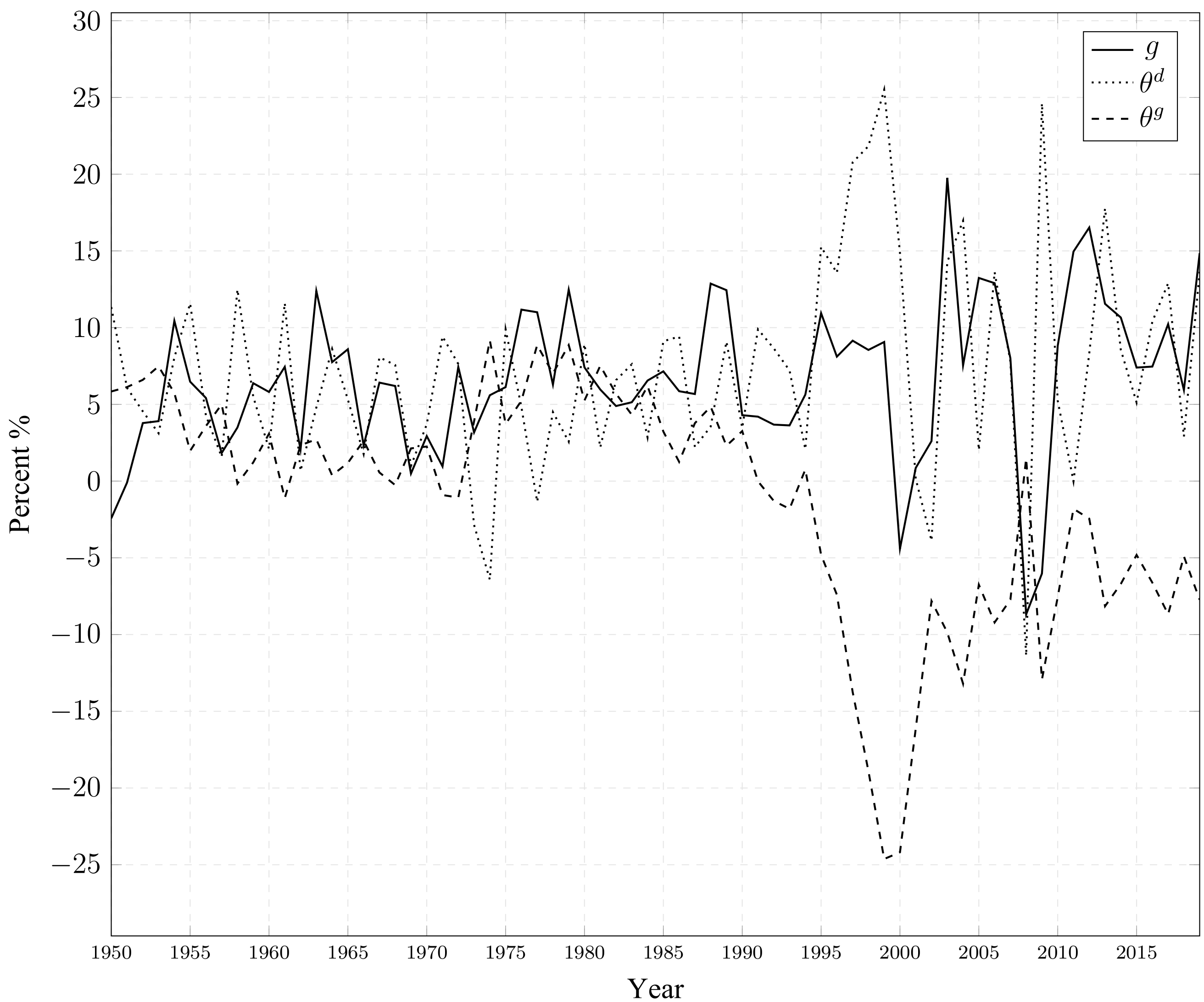

Figure 1.1: Filtered Values of Expected Growth and Risk Premia from UKF, 1950 to 2019

Value Stocks Are Riskier - Paper 2

by

Ciarán John O'Neill

EDHEC PhD in Finance

Keywords: value premium, equity risk premium, two risk premia, value stocks, equity duration, value portfolio sorts, long horizon value returns, excess return persistence, cashflow shocks, dividend shocks, cash flow shocks, cash flow elasticity, cash flow sensitivity, cash flow beta, revenue beta, time variability, time varying risk, long run risks, linear present value model, price dividend ratio, dividend yield, book to price, price to book, market to book, book to market, earnings yield, cashflow yield, Epstein Zin Weil, unscented kalman filter, linearity generating processes

Abstract

In O'Neill (2022) *Paper 1*, I proposed a risk-based explanation of the value premium in which there are two components of the equity risk premium; a large premium to compensate for near-term systematic cashflow risk and a smaller one for distant cashflow risks. I found evidence of this dual risk premium structure in historical aggregate stock prices, and that value stocks are more highly sensitive to near-term cashflow risks than growth stocks and are discounted accordingly. In this paper, I cultivate this risk-based explanation by parsing the principal reasons that near-term cashflow shocks are especially threatening to value stocks. In particular, I argue that value stocks *cashflows* (as well as prices) have high shock sensitivity, which can be attributed to specific innate firm characteristics. First, I relate the risk premium for near-term cashflow shocks to an original asset risk measure, the *Cashflow Shock Elasticity of Price*, and I show that portfolios of value stocks have a larger shock elasticity than growth stock portfolios (mainly due to the outsized response of portfolio *cashflows* to aggregate shocks). Second, using a comparative static model of the firm, I identify the firm-level fundamental determinants of outsized shock elasticity (i.e., revenue beta, operating & financial leverage, and low profit margins) and I show that these attributes are more abundant in value firms than growth firms. Together with the findings in O'Neill (2022), the results here show that value stocks possess inherent fundamental traits that cause them to be highly sensitive to aggregate cashflow events, which renders them poor economic hedges for investors at inopportune times and therefore riskier, and more discounted.

2.1 Introduction

The value premium (the propensity of high book-to-market stocks to earn higher average returns than stocks with low ratios) has both enthralled and confounded investors for almost a century. Advocated by Benjamin Graham as a cornerstone of serious, considered *investing* (as opposed to *speculation*) as far back as 1934, the value effect has been observed over multiple time periods, across many asset classes, in many studies and in practice.[41] Over the years, value strategies have become a bedrock of long-term investment policies for many large and small investors, providing superior risk-adjusted investment performance for some.[42] However, many other investors have eschewed value investing because (a) the securities that are assigned to value portfolios are often unglamorous and unpopular, with poor growth prospects and negative news headlines, and (b) portfolios of value stocks have frequently experienced long periods of subpar total returns, some longer than the typical tenure of a professional investment manager.[43]

The evidence that value stocks have higher long-term average returns, but with an undesirable inconsistency as well as an 'out of favor' quality at their moment of maximum opportunity, has inspired two primary hypotheses for why the value premium exists. The *behavioral hypothesis* theorizes that repeating patterns of irrational human behavior (overexhuberance at some times or for some assets, excessive pessimism at other times

[41] Security Analysis, with David Dodd (1934) and The Intelligent Investor (1949). For Graham, "An investment operation is one which, upon thorough analysis, promises safety of principal and a satisfactory return. Operations not meeting these requirements are speculative.". Some notable examples of prior empirical studies Fama & French (1992, 1998, 2012), Lakonishok, Schleifer & Vishny (1994), Daniel & Titman (1997), Lettau & Wachter (2007) and Asness, Moskowitz, & Pedersen (2013).

[42] From 1926 to 2018, the decile of US equities with the highest book-to-market ratio outperformed the decile with the lowest ratio by a statistically significant 5% to 14% per year on average, depending on portfolio weighting method (data from Ken French, univariate book-to-market sorts). See also *The Superinvestors of Graham-and-Doddsville*, Buffett (1984) for a practitioner study of a collection of successful investors with superior "value investing" track records.

[43] There have been at least six occasions since 1926 when the value premium has been negative for a decade or more (see *Figure 2.1* & *Figure 2.2*, and associated discussions in the Appendix). In the decade from 2009 to 2019 following the Great Recession, for example, large "growth" stocks returned 308% including reinvested dividends, while large "value" stocks returned 202% (source FTSE Russell, indexcalculator.ftserussell.com, total value-weighted returns, 12/31/2009 through 12/31/2019).

or for other assets) cause temporary asset-pricing errors which, when eventually fixed, produce the value premium. The *risk hypothesis* argues that value stocks possess several innate qualities that make them systematically riskier to investors, and these risks must be fairly compensated with higher expected returns.[44] As in O'Neill (2022), *Value Stocks are Riskier - Paper 1* (hereafter *Paper 1*), in this paper I favor a risk-based explanation of the value premium. Although I am confident that episodes of irrational behavior and mispricing do occur (perhaps frequently), and are at least a *part* of the value story, the fact that the value premium has (a) been widely-known and exploitable for a long time and (b) persisted rather than being competed away by greedy, excess-return-seeking investors with ample available capital, strongly suggests that it has rational, risk-based underpinnings.

In *Paper 1*, I advanced a risk-based explanation of the value premium in which there are two components of the equity risk premium; a larger premium to compensate for near-term systematic cashflow risk and a smaller one for distant cashflow risks. I showed how a representative agent with Epstein Zin preferences prices risky assets based on their exposures to innovations in near-term consumption growth and also innovations in anticipated future consumption growth (or wealth).[45] Using an Unscented Kalman Filter, I estimated my exactly-solved linear present value model of the price-dividend ratio (which disentangles near-term cash flows from expected future cash flow growth with two time-varying risk premia) on a long history of US stock prices and I found compelling evidence of the existence of two different risk premia. I also found that the premium for near-term cashflow risk is statistically and economically much larger than the premium for distant cash flow risks, and that value stock returns are far more responsive to near-term cashflow shocks and

[44] See DeBondt & Thaler (1985, 1987), Lakonishok, Shleifer & Vishny (1994) and Daniel & Titman (1997, 1998) for some notable examples of behavioral hypothesis research. For examples of risk hypothesis research, see Fama & French (1992, 1993, 1995, 1996, 1998, 2006, 2012, 2020), Carlson, Fisher & Giammarino (2004), Zhang (2005), Lettau & Wachter (2007).

[45] In this economy, the SDF is high when near-term consumption is shocked negatively, and also when wealth is negatively shocked even when near-term consumption is unchanged.

changes in the premium for near-term risks than growth stock returns.[46] These results are consistent with a world in which value stocks earn excess returns because they are riskier.

Nevertheless, by themselves, these results do not decisively rule in favor of a risk explanation of the value premium. They, and the framework from which they were estimated in *Paper 1*, offer only a one-sided risk explanation (i.e., the investor preference side) because they do not provide a firm-level rationale for why value stocks are especially threatened by near-term aggregate cashflow shocks.[47] Purely from a preference perspective, it is, of course, reasonable for consumer-investors to be fearful of near-term negative aggregate cashflow shocks (i.e., think recession, job losses, and drawdown of household savings), but why should value stocks, *in particular*, be expected to perform poorly at those times? Why not growth stocks? After all, it is also reasonable that long-term growth expectations, on which the high valuations of growth stocks rely, would also decline in bad economic times.

In *Paper 1*, I hypothesized that the answer may be found in the responses of an asset's cashflows (as well as prices) to aggregate shocks and that these responses may be governed by inherent firm attributes, such as operating leverage, financial leverage, industry maturity, growth opportunities and equity duration. If, as I supposed, value stocks are usually found in mature, slow-growing industries with pronounced macroeconomic cyclicality, and if they have high fixed costs and large debt burdens, then a negative aggregate shock can have an especially detrimental effect on firm cashflows, expected growth rates and perceived riskiness (the three ingredients of discounted present value), causing poor returns at those times. By corollary, if growth firms are found in newer industries with low macro sensitivity (as seems likely), and if they have low capital intensity and debt, then their cashflows,

[46]Over the time period 1950 to 2019, the risk premium for near-term cashflow shocks was estimated at 5.8% while the premium for distant risks was estimated at 0.5%, *Paper 1*. Over the same time period, the *beta* of value returns to the near-term cashflow premium was found to be 2 to 3 times that for growth returns. I also found that *unexpected returns* for value stocks (i.e., realized portfolio returns minus expected returns) were more sensitive to near-term cashflow shocks compared to growth stocks.

[47]Without this additional piece of the puzzle, for example, it may even be possible concoct a behavioral framework that can produce results which are similar to those found in *Paper 1*.

growth expectations, and discount rates can be more immune to shocks.[48]

But I did not explore these hypotheses in detail in *Paper 1*. This is the task I undertake here. Specifically, the goals of this paper are (1) to understand why value firms are especially vulnerable to negative cashflow shocks (which we know investors do not like) and (2) to relate the resulting discounting of value stock prices to inherent, measurable, fundamental firm attributes. If I succeed in these goals, then *Paper 1* and *Paper 2* (this paper) together offer a more complete risk-based explanation of the value premium than either paper alone. If *Paper 1* shows that investors *really* do not like negative near-term cashflow shocks and that value stock prices are especially discounted for this type of risk, and if *Paper 2* shows that the cashflows (as well as prices) of value firms have elevated sensitivity to shocks deriving from their inherent operating attributes, then, combined, these papers show that the value premium is the result of rational, considered investment decisions by risk-averse agents rather than occasional irrational behavior of an emotional investor crowd.

Importantly, even without an explicit risk model (such as the one I proposed in *Paper 1*, and which is further developed in this paper), the empirical history of the value premium provides some useful clues about the role of *risk* in explaining excess value-minus-growth returns. These empirical facts (which are mentioned here, but discussed in greater detail in the *Appendix*) lean more strongly in favor of a risk-based explanation than a behavioral one.

- **The value premium is large and has persisted for a long time.** In *Table 2.9* & *Table 2.10*, discussed in the *Appendix*, I show the mean returns, standard deviations, standard errors, and Sharpe ratios for univariate sorted-decile portfolios of US equi-

[48] I also noted in *Paper 1* that the cashflows and multiples of growth stocks may have a hedging quality related to the duration of their expected cashflows. Specifically, since the high valuations of growth stocks reflect rosy expectations of (and discount rates applied to) distant, rather than near-term, cashflows, their high *equity duration* can shield them from near-term shocks since current cashflows comprise only a small portion of their market value. In fact, growth firms can even be *beneficiaries* of negative shocks to the extent that their low macroeconomic sensitivity and unlevered balance sheets put them in a *relatively* strong financial position during economic downturns to acquire distressed assets ”on the cheap” while their financially-burdened competitors are retrenching.

ties from 1952 to December 2019 (both capitalization-weighted and equal-weighted). On average, capitalization-weighted excess returns for value stocks, exceeded the returns for growth stocks by 4-5% per year, while equal-weighted value-minus-growth returns averaged 7-10% per year (depending on the univariate sorting ratio). These excess returns are economically and statistically large and are not explained by either the volatility of returns or a small-cap effect. That these large excess returns have persisted for many decades, rather than being competed away by greedy investors, strongly hints at a risk-based underpinning.

- **The premium is not explained by the *Capital Asset Pricing Model* (*CAPM*).** In *Table 2.11*, discussed in the *Appendix*, I show the results of regressions of sorted portfolio excess returns against the value-weighted *CRSP* Index from 1952 to 2019. In general, the *alpha* coefficients from these regressions are increasing in deciles when moving from growth to value, and, at the extremes, are significantly negative for the growth portfolios and significantly positive for the value portfolios. In every case, the alpha on the portfolio that is long value and short growth is economically and statistically large (i.e., the premium return earned by value stocks cannot be solely attributed to higher *CAPM* betas). Even if *some* portion of the value premium can be attributed to *CAPM* betas, some other risk factor(s) has stronger explanatory power.

- **The value premium has been time varying and asymmetric.** *Figure 2.1*, discussed in the *Appendix*, plots the rolling 10-year mean capitalization-weighted value-minus-growth return from June 1936 through December 2019. On average, the mean 10-year value-minus-growth returns of 6.14% (per year) and the standard deviation is 5.50%. During this time period, there were at least 6 sub-periods when the 10-year mean annual value-minus-growth return was in excess of 15% and at least 6 sub-periods when the trailing 10-year mean was negative. This time variability of the value premium is more easily explained by time varying risks than behavioral pricing errors; if the value premium derives from irrational investor behavior that is rooted in *enduring* human flaws (e.g., short-sightedness, extrapolation, or excessive exhuberance/pessimism), then one might expect more stability in value-minus-growth return year after year. The value premium has also been asymmetric, deriving largely from the outperformance of value stocks rather than the underperformance of growth stocks. (See *Table 2.13* and associated discussion in the *Appendix*.) It is easier to explain this asymmetry by an asymmetric risk exposure, than it is to explain why investors are more irrational in the pricing of value stocks than they are in the pricing of growth stocks.

- **Excess returns for value portfolios endure for many years after formation.** In *Table 2.14* & *Table 2.15*, I present the results of an analysis of *buy-and-hold* returns for sorted portfolios of stocks over multiple holding periods (from 1 to 10 years after formation), using data from 1952 to 2019. Remarkably, *as the portfolio holding period is extended, the value premium remains strong in subsequent years*. In the second year after portfolio formation, for example, the value-minus-growth return is even larger than in the first year. Ditto for the third year. In fact, this pattern of sustained outperformance continues through the seventh year after portfolio formation, meaning that, in this long sample, it was possible to exploit the value effect using value portfolio sorts that were up to 72 months ”stale”. This result is consistent with a world in which stocks are discounted based on their exposures to slow-moving fundamental risks. It is difficult to reconcile this result with the behavioral hypothesis of the value premium.

Although none of these empirical facts are individually decisive in terms of explaining the value effect, as a group they are more supportive of a risk-explanation than a behavioral one. The particular risk explanation that I favor, as advanced in *Paper 1*, is rooted in the representative investor’s fear of near-term cashflow shocks. In the next section, I tie these fears to the cashflow shock elasticity of an asset. This elasticity, and its components, is a more practical measure of asset risk than the risk premium from the stochastic discount factor (*sdf*) in *Paper 1*, and underpins my empirical results in subsequent sections of this paper.

This paper is organized as follows. In *Section 2.2*, I introduce the conditional *Cashflow Shock Elasticity of Price* (η_t^{cp}) in order to explicitly relate an asset's discount rate to its cashflow shock sensitivity. (I also show how the components of η_t^{cp} relate to the time variability of the value premium.) *Section 2.3* then shows that value stocks have historically had a larger cashflow shock elasticity than growth stocks, as evidenced by the behavior of value-sorted portfolio prices, *and especially cashflows*, during past economic shocks. For robustness, I present results based on two different definitions of cashflow shocks. In *Section 2.4*, I show why and how value stocks have high cashflow sensitivity, first by using a comparative-static model of the firm to identify the asset-specific fundamental attributes that induce this sensitivity, and then by estimating those attributes for value-sorted portfolios of stocks historically. *Section 2.5* concludes.

2.2 The Cashflow Shock Elasticity of Price

I begin this section by introducing a quantity, the *Cashflow Shock Elasticity of Price*, or η^{cp}, which is the percentage change in the price of an asset for a given percentage exogenous shock to aggregate cashflows.[49] This is a tangible measure of the economic sensitivity of an asset's price, and is derived without reference to investor risk preferences. That is, in general,

$$\eta^{cp,i} = \frac{\%\Delta P^i}{\%\Delta C} \tag{60}$$

[49] For the purposes of this paper, shocks to aggregate cashflows are assumed to occur exogenously and the response of assets to those shocks is determined endogenously.

where P^i is the price of asset *i* and C is aggregate cashflow. This elasticity can also be represented as the slope of a linear regression of log prices (p) on log shocks ($\hat{c}$). That is, in conditional form,

$$p^i_{t+1} = \alpha^i_t + \beta^i_t \hat{c}_{t+1} + \epsilon_{t+1} \tag{61}$$

$$\eta^{cp,i}_t \equiv \beta^i_t = \frac{Cov_t(p^i_{t+1}, \hat{c}_{t+1})}{Var_t(\hat{c}_{t+1})} \tag{62}$$

where $\hat{c}_{t+1} = c_{t+1} - E_t[c_{t+1}]$ and ϵ_{t+1} is zero mean noise.

Importantly, with a simple decomposition of p^i_{t+1}, I can break down the covariance term in *(3)* into two parts: the covariance of the asset's *cashflows* with aggregate cashflows, and the covariance of the asset's *price-to-cashflow ratio* with aggregate cashflows.

$$\begin{aligned} p^i_{t+1} &\equiv log(P^i_{t+1}) = log(P^i_t(D^i_{t+1}/D^i_t)(PD^i_{t+1}/PD^i_t)) \\ &= p^i_t + d^i_{t+1} - d^i_t + pd^i_{t+1} - pd^i_t \end{aligned} \tag{63}$$

where PD^i is asset *i*'s price-to-cashflow ratio. Substituting p^i_{t+1} from *(4)* into *(3)*,

$$\begin{aligned} \eta^{cp,i}_t &= \frac{Cov_t(d^i_{t+1}, \hat{c}_{t+1}) + Cov_t(pd^i_{t+1}, \hat{c}_{t+1})}{Var_t(\hat{c}_{t+1})} \\ &= \frac{\mathbf{Cov_t(d^i_{t+1}, c_{t+1})} + \mathbf{Cov_t(pd^i_{t+1}, c_{t+1})}}{Var_t(\hat{c}_{t+1})} \end{aligned} \tag{64}$$

Equation (5) shows that assets whose cashflows, d^i, correlate highly with aggregate cashflows (i.e., economically sensitive assets) and whose *pd* ratio covaries highly and positively with shocks (i.e., asset discount rates and/or expected growth covary with shocks) will have a larger cashflow shock elasticity. Conversely, assets whose cashflows move inversely with aggregate cashflows and whose discount rates and/or expected growth rates are somehow hedged against shocks, will have a smaller $\eta_t^{cp,i}$.[50]

Although the quantity $\eta_t^{cp,i}$ is, in some sense, a measure of the riskiness of an asset, it is independent of investor risk preferences. This being the case, the role that cashflow elasticity plays in asset price discounting, if any, will depend on investor attitudes towards the risk characteristic it captures. This brings me to the main purpose of this section which is to show that *the factors that drive* $\eta_t^{cp,i}$ *are precisely the same factors driving the premium for near-term cashflow risk, as proposed in Paper 1*, and that, all else equal, assets with a large cashflow elasticity will be more discounted. Given that the premium for near-term cashflow risks accounts for the lion's share of the total risk premium (as shown in *Paper 1*), and that value stocks are especially sensitive to near-term cashflow shocks (also shown in *Paper 1*), $\eta_t^{cp,i}$ and its components are central to the value premium.

2.2.1 Relationship of Discount Rates to $\eta^{\mathbf{cp}}$

To show this, recall that in *Paper 1*, the representative agent (who consumes the aggregate dividend) fears and prices (a) near-term consumption/cashflow shocks which disrupt his optimal current lifestyle, and (b) shocks to expected future consumption/cashflow growth which disrupt the optimal lifestyle path in the future.[51] That is, the general form of the *sdf* in this economy, M_{t+1}, is a function of near-term aggregate cashflow, C_{t+1}, and expected future aggregate cashflow growth, G_{t+1}.

$$M_{t+1} = f(C_{t+1}, G_{t+1}) \tag{65}$$

The specific *sdf* in *Paper 1* (which assumes *Epstein-Zin-Weil (EZW)* recursive preferences

[50] I note that even if an asset's *pd* ratio is hedged against shocks, $Cov_t(d_{t+1}^i, c_{t+1})$ can still be sufficiently pro-cyclical that $\eta_t^{cp,i}$ remains positive.

[51] Note that since the representative agent consumes the aggregate dividend, I use the terms *aggregate consumption*, *aggregate dividend*, and *aggregate cashflow* interchangeably in this paper.

and lognormal cashflow growth and returns, and is expressed in log innovations) is given by *(7)* .[52]

$$\hat{m}_{t+1} = -\gamma \hat{c}_{t+1} - (\gamma - \frac{1}{\alpha})\hat{g}_{t+1} \tag{66}$$

where γ and α are the representative agent's risk aversion and elasticity of intertemporal substitution respectively, and $\hat{c}$ and $\hat{g}$ are log innovations in aggregate cashflow and expected cashflow growth.

As usual, in this economy the risk premium on any asset will depend on the covariance of its returns with the *sdf*. That is, for any asset *i*,

$$E_t[R^i_{t+1}] - R^f_{t+1} = -R^f_{t+1} Cov_t(M_{t+1}, R^i_{t+1}) \tag{67}$$

where R^i is the gross return on the asset and R^f is the gross risk-free rate. In log form, using the *sdf* in *(7)*, the *specific* risk premium in this economy is given by *(9)*.

$$\begin{aligned} E_t[r^i_{t+1}] - r^f_{t+1} + \frac{\sigma_i^2}{2} &= -Cov_t(m_{t+1}, r^i_{t+1}) \\ &= \gamma \sigma_t^{i,c} + (\gamma - \frac{1}{\alpha})\sigma_t^{i,g} \end{aligned} \tag{68}$$

where σ_i^2 is the variance of asset i's returns and $\sigma_t^{i,c}$ and $\sigma_t^{i,g}$ are the covariances of asset i's returns with near-term cashflow and expected cashflow growth, respectively.

Now, by decomposing next period's gross return into a component from dividend, D^i_{t+1}, and a component from changes in *pd* ratios, PD^i_{t+1}, I can expand the covariance terms in *(9)* and compare them directly to this in η^{cp} in *(5)*. That is,

[52] I also note that in the *Appendix* to *Paper 1*, I presented an alternative derivation of a similar dual-risk-premium *sdf* but without assuming *EZW* preferences.

$$R^i_{t+1} = \frac{D^i_{t+1}}{P^i_t}(1 + \frac{P^i_{t+1}}{D^i_{t+1}}) \tag{69}$$

which, in logs, writes as

$$r^i_{t+1} = d^i_{t+1} - p^i_t + log(1 + PD^i_{t+1}) \tag{70}$$

Then substituting r^i_{t+1} from *(11)* into *(9)*, the expanded covariance terms are

$$\sigma^{i,c}_t = \mathbf{Cov_t}(\mathbf{d^i_{t+1}}, \mathbf{c_{t+1}}) + \mathbf{Cov_t}(\mathbf{pd^i_{t+1}}, \mathbf{c_{t+1}}) \tag{71}$$

$$\sigma^{i,g}_t = \mathbf{Cov_t}(\mathbf{d^i_{t+1}}, \mathbf{g_{t+1}}) + \mathbf{Cov_t}(\mathbf{pd^i_{t+1}}, \mathbf{g_{t+1}}) \tag{72}$$

where $\bar{pd}^i = log(1 + PD^i_{t+1})$.

Comparing *(5)* and *(12)*, the close relationship between η^{cp} and risk premia is apparent; for all intents and purposes, the cashflow shock elasticity of an asset and the portion of the risk premium that compensates for near-term cashflow risk are driven by the same conditional covariances.[53] In other words, assets that have a large η^{cp} will be discounted more than other assets because they are exposed to the risks that investors fear. Moreover, as I found in *Paper 1*, the risk premium for near-term cashflow risk accounts for the lion's share of the overall equity risk premium.[54] Accordingly, η^{cp} is not merely a measure of asset risk;

[53] The reader will note that the covariance terms in *Equations (5) and (12)* are not exactly the same: *Equation (12)* uses $\bar{pd}^i_{t+1} \equiv log(1 + PD^i_{t+1})$ whereas *Equation (5)* uses $pd^i_{t+1} \equiv log(PD^i_{t+1})$. While not identical, these terms are perfectly correlated with each other and will have similar covariances with c_{t+1}.

[54] Over the time period 1950 to 2019, in *Paper 1*, I estimated the risk premium for near-term cashflow shocks at 5.8% while the premium for distant risks was estimated at 0.5%. The averages of the time series of filtered estimates of these two risk premia, 4.7% and 1.7% respectively, offer a similar result.

it captures the risk that investors fear most.[55]

With the connection between η^{cp} and risk premia established, it is straightforward then to relate η^{cp} to the value premium. To see this, recall that in *Paper 1*, I showed that value stock returns (both expected and unexpected) are significantly more sensitive to near-term cashflow shocks than growth stock returns.[56] This being the case, and given the relationship between η_t^{cp} and $\sigma_t^{i,c}$ just described, value stocks prices will be more elastic to cashflow shocks than growth stock prices because they are more exposed to the risk factor that investors care most about. I explore this supposition empirically in *Section 2.3* and I find strong supporting evidence.

2.2.2 $\eta^{\mathbf{cp}}$ and the Time Variability of the Value Premium

It is also possible to link η^{cp} to the *time variability* of the value premium. I will have more to say on this subject in *Section 2.4* (when I relate the conditional η^{cp} to inherent fundamental firm characteristics), but it is instructive to sketch out the link here, using a general framework and some examples. We know from the foregoing that there are two *principal* conditional covariances driving the equity risk premium.[57]

---

[55] This is not to suggest that the second component of the equity risk premium (i.e., that compensates for shocks to future cashflow growth) is unimportant, but it appears to play a lesser role in explaining the value premium. *Equation (13)* decomposes $\sigma_t^{i,g}$ (as I did for $\sigma_t^{i,c}$) and it is trivial to show that the pair of covariances in *(13)* directly compare to those in the conditional *Growth Shock Elasticity of Price*, η_t^{gp}. That is,

$$\begin{aligned}\eta_t^{gp} &= \frac{Cov_t(p_{t+1}^i, \hat{g}_{t+1})}{Var_t(\hat{g}_{t+1})} \\ &= \frac{\mathbf{Cov_t(d_{t+1}^i, g_{t+1}) + Cov_t(pd_{t+1}^i, g_{t+1})}}{Var_t(g_{t+1})}\end{aligned} \tag{73}$$

I hope to further investigate this quantity, and the role it plays in asset price discounting, in future research.

[56] For example, the beta of value returns to the near-term cashflow premium was found to be 2 to 3 times that for growth returns

[57] For the purposes of this illustration, $Cov_t(g_{t+1}, d_{t+1}^i) \equiv \sigma_t^{gd^i}$ and $Cov_t(g_{t+1}, pd_{t+1}^i) \equiv \sigma_t^{gpd^i}$ are relegated to secondary effects.

$$Cov_t(c_{t+1}, d^i_{t+1}) \equiv \sigma^{cd^i}_t$$
$$Cov_t(c_{t+1}, pd^i_{t+1}) \equiv \sigma^{cpd^i}_t \tag{74}$$

We also know that the larger is $\sigma^{cd^i}_t + \sigma^{cpd^i}_t$, the riskier, and more discounted, the asset will be. Now, arithmetically, $\sigma^{cd^i}_t + \sigma^{cpd^i}_t$ is likely to be larger if $sign(\sigma^{cd^i}_t) = sign(\sigma^{cpd^i}_t)$. This will occur if an asset's cashflow and price correlate with shocks in the same direction (i.e., when changes in asset cashflows are not offset by the changes those shocks induce in PD ratios).

The key point, as it relates to time variability, is to show that *an asset's fundamental characteristics (which, themselves, can be time varying) affect the relative sizes and signs of $\sigma^{cd^i}_t$ and $\sigma^{cpd^i}_t$*. To illustrate, consider how a cashflow shock affects two fundamentally different firms, (a) *Firm V*, which is highly economically cyclical and has high-debt, and (b) *Firm G*, which is low-cyclicality with low-debt. For *Firm V*, which is economically sensitive and financially distressed, positive shocks will lift firm cashflows, and also relieve financial duress (i.e., lower its discount rate/raise its PD ratio) while negative aggregate shocks have the opposite effect. Thus, *Firm V*'s fundamental characteristics induce a positive conditional correlation between its cashflow and its PD ratio.[58] This makes the asset riskier by raising its sensitivity to near-term cashflow shocks. For *Firm G*, economic shocks have a muted effect on firm cashflows (which are less cyclical by design), and also on firm riskiness and PD ratios (given its low debt). All else equal then, *Firm V* price will be more discounted than *Firm G*.

Although this example compares two firms at the same point in time, it can also represent the same firm at two different points in time, as long as firm fundamentals are time varying. For example, at one time *Firm V* may be pro-cyclical and indebted, resulting in a

[58] This conditional correlation may also be asymmetric. After an initial negative economic shock, for example, the consequences of a subsequent negative shock on an already strained and indebted firm would be more severe than the initial shock.

large risk discount in its price. At another time, perhaps because of strategic actions taken by the firm to reduce cyclicality or pay down debt, or because economic conditions improved, *Firm V* can evolve into *Firm G* and enjoy a smaller risk discount. The essential point is this: *if an asset's conditional covariances explain its risk discount, and if its covariances are linked to fundamental asset characteristics that can vary over time (e.g., with economic conditions, the aging of the firm, the firm's strategic choices), then asset risk and expected returns will be time varying too*. In this sense, the factors that explain the conditional value premium (i.e., the cashflow elasticity of price and its component covariances), can also explain why the premium has varied over time.[59]

In this section, I showed that an asset's cashflow elasticity of price is driven by the same principal covariances that drive the risk premium for near-term cash flow shocks. The empirical analysis in the next section investigates how the prices and cashflows of book-to-market sorted portfolios have responded to economic shocks in the past. I find strong evidence that value stock prices, and especially cashflows, have a more pronounced response to economic shocks than growth stocks, consistent with a risk explanation of the value premium which is based on cashflow shock elasticity.

[59]The stylized example using *Firm V* and *Firm G* can also illustrate how the value premium can expand in recessionary times and contract in boom times. Starting from a steady-state equilibrium, if a recession were to occur, *Firm V*'s cashflows, being procyclical, would decline sharply which, in turn, would stress the firm's ability to finance its debt (and invest for future growth) causing the firm to become riskier (i.e., closer to financial distress), and slower growing. Now, being a step closer to severe financial distress, *Firm V* is even more susceptible to a *subsequent* recessionary shock than it was in the steady state. That is, $\sigma_{t+1}^{cd^V} + \sigma_{t+1}^{cpd^V} > \sigma_t^{cd^V} + \sigma_t^{cpd^V}$, in tandem with a larger risk discount in its share price, and a lower PD ratio. Contrast this with *Firm G*. Following a recessionary shock, which has a muted impact on *Firm G*'s cashflow, the firm does not become riskier and, whether its absolute expected growth declines or not, its *relative* growth opportunities (compared to *Firm V*) improve. In this way, the expected return premium of *Firm V* (value) over *Firm G* (growth) can expand in recessionary economic times. (In boom times, *Firm V*, being less financially distressed, would be less impacted by shocks; positive shocks would not improve its risk profile much because the firm's coffers would already be full, and negative shocks would hurt less because the firm would have a larger buffer against financial distress at that time. Thus, the expected return premium of *Firm V* over *Firm G* (the value premium) can be lower at those times.)

2.3 Effect of Shocks on Portfolio Cashflows & Prices

In an ideal world, I would test the relationship between the conditional cashflow shock elasticity of price and the value premium by using a long panel of historical data to estimate η_t^{cp}, and its component parts, cross-sectionally at each point in time for sorted portfolios, and then comparing the mean estimates for value portfolios to those for growth portfolios. In reality, of course, the ”true” conditional distribution of the response of asset cashflows and prices to aggregate cashflow shocks is not observable. Instead, at each point in time, we observe only a single outcome for aggregate cashflows and prices, and a single outcome for portfolio cashflows and prices.

Given this data limitation, I employ *unconditional* historical analyses here to substitute, albeit imperfectly, for conditional observations. Such analyses can be instructive, particularly if conducted over long periods of time covering a broad range of macroeconomic events, as I do here. Two such analyses are presented in this section. The first uses *National Bureau of Economic Research (NBER)* official business cycle dating of economic expansions and contractions since the Great Depression to define aggregate cashflow shocks. The second defines shocks using the filtered estimates from *Paper 1*, for the period from 1950 to 2019. For each analysis, I measure the price and cashflow response of each book-to-market sorted portfolio to each shock at the time it occurred. The results of these analyses are consistent with each other and show that value stocks have a higher η^{cp} than growth stocks.

2.3.1 U.S. Business Cycle as Cashflow Shocks

Table 2.1 presents the chronology of economic contractions and expansions in the United States since the Great Depression, as assigned by the *NBER* Business Cycle Dating Committee.[60] Since 1929, there have been fifteen recessions (with the most recent being the

[60] See https://www.nber.org/research/business-cycle-dating for additional details on NBER methodology.

short, sharp COVID-induced contraction in early 2020) and fifteen expansions (including the most recent expansion that began in April 2020 and is still underway at the time of writing). The average contraction has lasted 12.5 months (or 10.4 months excluding the Great Depression) with average peak-to-trough decline in GDP of -6.8%. The average expansion has lasted 61.4 months with average annual real GDP growth of 4.7%.

To measure the behavior of value and growth stock prices around the dates of these events, I examine the price-only returns of book-to-market univariate sorted portfolios from Prof. Ken French's website.[61] These portfolio returns are available monthly back to 1926 and are calculated by sorting all NYSE, Nasdaq and AMEX stocks into deciles of book-to-market ratio in June of each year (using prior fiscal year book value and prior calendar year-end market values) and then calculating monthly portfolio returns though to the following June rebalance date, using *CRSP* pricing data. However, since the *NBER*'s choices of economic turning points reflects the dates when economic activity *actually* inflects, rather than the dates when stock prices begin to discount the ensuing economic inflection, those dates, by themselves, will not coincide with "shocks" in cashflow expectations. (For example, the *NBER* dates the Great Recession from December 2007 through June 2009, but the S&P500 index began declining six months before December 2007 and troughed four months before June 2009.) Therefore, in order to better capture the shocks associated with economic contractions and expansions, I measure price changes from the date of the peak of the market in the six months prior to a recession until the date of the market trough during the recession (and vice versa for expansions).[62] These dates are shown in *Table 2.2* and *Table 2.3*, along with the measured price change for each decile sorted portfolio and each economic event.

Table 2.2 shows the peak-to-trough mean monthly capitalization-weighted price-only

---

[61] See $https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\_library.html$

[62] To select these "shock" dates, market prices are represented by month-end prices for the S&P 500 Index. I also calculated sorted portfolio returns based on start dates within three months of the *NBER* expansions and contractions, with similar results.

returns for all ten book-to-market sorted portfolios during fourteen *NBER* economic contractions since the Great Depression.[63] Over this time period, value stocks have usually underperformed growth stocks during recessions. In ten of the fourteen contractions, average monthly returns were more negative for value portfolios than growth portfolios and, when averaged across all contractions, value portfolio (Decile 10) prices declined by 4.4% per month compared to a decline of 2.6% per month for growth portfolios (Decile 1).[64] The top 20% of growth stocks (i.e., Deciles 1 and 2 combined) outperform the cheapest 20% (i.e., Deciles 9 and 10 combined) by 1.3% *per month* on average during recessions. These are remarkable results, implying that in a typical recessionary year, value stocks underperform growth stocks by more than 20%, in stark contrast to their tendency to outperform growth stocks by 4%, or more, per year on average across all economic cycles (see *Table 2.9* & *Table 2.10*).

Table 2.3 shows the trough-to-peak mean monthly capitalization-weighted price-only returns for book-to-market sorted portfolios during fifteen *NBER* economic expansions since the Great Depression.[65] Value stocks have tended to outperform growth stocks during expansions over this time period. In eleven of the fifteen economic expansions, average monthly price returns were larger for value portfolios than for growth portfolios, and on average across all expansions, value prices increased by 0.5% more *per month* (or more than 6% annualized) than growth stock prices. Taken together, *Table 2.2* and *Table 2.3* show that value stocks have a larger cashflow shock elasticity of price than growth stocks; during unexpected economic contractions, value stock prices decline by more than growth stock prices and during booms, the reverse is true.

But within this overall price elasticity, what role is played by the near-term *cashflow*

[63] The *February, 1945 to October, 1945* contraction is excluded from this analysis since there was no associated peak to trough movement in market prices.

[64] When cumulative peak to trough monthly returns are used, rather than average monthly returns, value stocks decline by more than growth stocks in eleven of the fourteen recessionary periods.

[65] The most recent expansion began in April 2020 and is ongoing. Data in *Table 2.3* is shown through December 2021.

sensitivity of value and growth stocks, rather than the sensitivity of their PD ratios? The answer to this question can provide insights into the precise mechanisms that make value stocks riskier than growth stocks. I investigate this question by examining the behavior of realized dividend growth rates for book-to-market sorted portfolios during the *NBER* expansions and contractions listed in *Table 2.1*.

The results are shown in *Table 2.4*. Specifically, *Table 2.4* shows the mean year over year, capitalization-weighted percentage change in rolling three-month dividends paid by the constituents of each of the ten book-to-market sorted decile portfolios during the periods of expansions and contractions as identified by the *NBER*.[66] For each portfolio constituent in each month, the percentage growth in dividends is calculated as its rolling three-month total paid-out dividend divided by the prior year's comparable three-month dividend total. These three-month, year-over-year growth rates are then market-value weighted to produce the portfolio level dividend growth rate. Importantly, to conduct this analysis, I was required to build a custom data set that replicates the book-to-market sorting methodology used by Prof. Ken French (i.e., combining *Compustat* fundamental data and *CRSP* pricing data). The reason for this is that it is not possible to extract constituent-level dividend information from Prof. French's data and the year-over-year changes in portfolio-level dividends (which *can* be derived from Prof. French's data) do not accurately reflect the effect of the economic environment on the constituent cashflows.[67] Also, because the quality and availability of

[66]For this analysis, the start and end date of each expansion and contraction corresponds exactly with the *NBER* dates.

[67]This is a result of Prof. French's annual portfolio rebalancing methodology. When stocks are sorted by book-to-market ratio each June, they are also implicitly sorted by the dividend-to-market ratio because dividends are positively correlated with book values. Thus, the newly-formed *value* portfolio each June will usually have a higher dividend yield than the prior year's portfolio had at that same June month end. This will render any comparison of portfolio dividends in one year with dividends from the prior year meaningless as a representation of the dividend growth of the underlying consitituents. The more the portfolio constituents and their weights change each year as a result of the sorting methodology, the less the year-over-year comparisons of the portfolio-level fundamentals reflect the fundamentals of the constituent firms, which is the true barometer of the economic environment. I avoid this problem here by doing all year-over-year calculations at the constituent level and then grossing the constituent information back up to the portfolio level with the appropriate portfolio weights.

fundamental and pricing data prior to 1950 is markedly lower than the post 1950 data, *Table 2.4* only considers the eleven economic contractions and 10 economic expansions since 1950.[68]

The lower panel of *Table 2.4* (*NBER Expansions*) shows that on average during expansions, dividends for value portfolios (Decile 10) *decline* about 1.9% per year, while dividends for growth portfolios (Decile 1) grow at 13% per year, and dividend growth for all stocks (All Deciles) is 6.4%. (Based on this result alone, the cross-sectional book-to-market ratio is evidently a good predictor of realized dividend growth, as expected. It is also not surprising that in *every* economic expansion, all stocks, and growth stocks in particular, grew dividends faster than value stocks.) A similar pattern of relative dividend growth for value and growth portfolios occurs during *NBER Contractions*. As shown in the upper panel of *Table 2.4*, all stocks and growth stocks outgrow value stocks during recessionary periods, as expected. A more interesting and pertinent result, which can be seen by comparing the upper and lower panels of *Table 2.4*, is that the cashflows of growth stocks are far more resilient during economic downturns than value stock cashflows. That is, during contractions, growth stocks deliver *positive* dividend growth of 5.1% on average (compared to 13% in expansions) while mean dividend growth for value stocks is -17.8% (compared to -1.9% during expansions). In other words, when averaged across all contractions, growth stock dividends outgrow value stock dividends by almost 23% per year, while in expansionary periods their growth advantage is only 15% annually, approximately.

The conclusion from *Table 2.4* is that value stock cashflows are significantly more sensitive to the prevailing economic environment than growth stock cashflows. When read in conjunction with the results in *Table 2.2* and *Table 2.3*, the implication is that the excess cashflow shock elasticity of value stocks over growth stocks is, in large part, attributable to the excess sensitivity of their cashflows to aggregate shocks. In the next subsection, I ex-

[68]The most recent expansion that began in April 2020 and is still underway, is excluded here from this cashflow analysis but will be included at a later date once the data is available.

amine whether this finding, and the finding that value stocks have a larger shock elasticity than growth stocks, holds true when using an alternative definition of aggregate cashflow shocks. Specifically, I examine the price and cashflow responses of value and growth stocks to the filtered cashflow shocks that were estimated in *Paper 1*.

2.3.2 Filtered Cashflow Shocks from *Paper 1*

In *Paper 1*, I used an Unscented Kalman Filter and Maximum Likelihood optimization to estimate an exactly-solved linear present value model of the price-dividend ratio which disentangles near-term cashflows from expected future cashflow growth with two time-varying risk premia on aggregate US market data from 1950 to 2019. One of the outputs of this model and estimation methodology is *expected aggregate cashflows*, which can be compared to realized cashflows, by year, to generate *filtered aggregate cashflow shocks*. This provides an alternative definition of shocks with which to examine the price and cashflow sensitivity of value and growth stocks.

This approach to approximating the cashflow shock elasticity suffers from a number of limitations relative to the approach using NBER expansions and contractions. First, the filtered cashflow shocks are ”estimates” derived from a data-fitting exercise and do not necessarily correspond to actual observed aggregate cashflow events. In this sense, the shocks are only as good as the model, and no model captures reality perfectly.[69] Second, the model is estimated using calendar *annual* data only.[70] At this frequency, the model

[69]The model in *Paper 1* has two primary observable time series; the price-to-dividend ratio and the realized gross dividend growth rate. All other time series and parameter values are estimated from this data. The observable data are taken from Prof. Robert Shiller’s website (http://www.econ.yale.edu/ shiller/data.htm and, in particular, U.S. Stock Markets 1871-Present and CAPE Ratio). This study uses actual paid-out cash dividends for the S&P Composite to represent aggregate equity cashflows, although other definitions of cashflow were also considered.

[70]The Unscented Kalman Filter in *Paper 1* is estimated on annual data (year-end values) for the period from 1950 to 2019, largely mirroring the time period and data frequency for the value premium summary statistics in *Table 2.9*. The choice of annual frequency reflects a balance of competing considerations; I wanted to have a large enough sample of data points to estimate the model efficiently while also leaving sufficient time between data points for aggregate fundamentals and expectations to evolve and for prices to react.

is unable to identify important intra-year turning points in cashflow cycles, expectations and asset prices. The choice of annual frequency also limits the sample size to the seventy annual data points available since 1950. Despite these limitations, this approach offers a useful alternative perspective to the *NBER* expansion/contraction methodology, in that the shocks are measured not just by changes in observed cashflow growth, but also by changes in market prices and expectations in response to observed cashflows.

Table 2.5 shows the mean annual capitalization-weighted price-only returns for each book-to-market sorted portfolio, stratified by deciles of filtered cashflow shocks, for the period from 1952 to 2019.[71] (Thus, each of the cashflow shock deciles represented on the left hand side of the table, corresponds to a different sample of annual dates.) Our interest here is in how the price returns of value portfolios differ from growth portfolios for each decile of cashflow shock, and how this differential changes in periods of positive shocks versus negative shocks. This information is shown in the two columns on the right hand side of *Table 2.5*. For small cashflow shocks (Deciles 4 through 7), which may not be shocks at all, the pattern of *value minus growth* returns is ambiguous, but for extreme shocks (Decile 1 to 3, and 8 to 10) the pattern is clear; value stocks underperform growth stocks during large negative shocks and outperform during large positive shocks. For example, when cashflow shocks are extremely positive (Decile 10), mean returns for value-minus-growth (Decile 10 - Decile 1) are 6.5%, compared to mean relative returns of -4.3% when cashflow shocks are extremely negative (Decile 1). When cashflow shocks are in Decile 1, 2 or 3 (i.e., most extreme 30% positive shocks), mean value-minus-growth returns are 9.3%, compared to -3.8% during the 30% of the time when shocks are at their most negative. (A similar pattern of value-minus-growth returns is observed when value is defined as Deciles 9 & 10 (by book-to-market sorting) and growth as Deciles 1 & 2.). Importantly, these results echo the those shown in *Table 2.2* & *Table 2.3*: value stocks prices are more elastic to aggregate cashflow shocks than growth stock prices.

[71] Sorted portfolio returns come from Prof. Ken French.

In *Table 2.6*, I measure the responses of book-to-market sorted portfolio *cashflows* to the filtered cashflow shocks (similar to the analysis in *Table 2.4* for *NBER* shocks). Specifically, *Table 2.6* shows the mean year-over-year, capitalization-weighted percentage change in rolling three-month dividends paid by the constituents of each of the ten book-to-market sorted decile portfolios (as well as for *all stocks* as a group) stratified by deciles of filtered aggregate cashflow shocks. The column labeled *All Deciles* reveals that the Unscented Kalman Filter in *Paper 1* does a good job of identifying positive and negative cashflow shocks; there is a steady increase in the realized year-over-year dividend growth rate when moving from the most extreme negative shocks (Decile 1) through to the most positive (Decile 10), as one would hope and expect.[72]

Overall, the results in *Table 2.6*, which shows sorted portfolios stratified by filtered cashflow shocks, lead to similar conclusions to those in *Table 2.4*. In particular, the two columns on the right hand side show that portfolios of growth stocks outgrow portfolios of value stocks in *all* time periods, as expected, and *especially* during periods of the extremely negative cashflow shocks (when growth stock cashflows show resilience and value stock cashflows show pronounced vulnerability). During the most negative 10% of cashflow shocks, for example, growth stocks sustain positive dividend growth of 6.7%, while dividend growth for value stocks is -24.7%, on average. *Table 2.6* also shows that growth stocks grow 9.9% faster during the most positive cashflow events (Decile 10 of shocks) than during the most negative shocks (Decile 1), while value stocks experience 26.8% faster growth, which demonstrates, again, the extreme economic sensitivity of value stocks. The results in this table are not perfectly monotonic across cashflow shocks and book-to-market sorted portfolios, reflecting the imprecision and limitations of this second approach to measuring aggregate cashflow shocks. Nevertheless, *Table 2.6* provides further evidence that value stocks have excess cashflow sensitivity which can explain their discounted prices and their

[72]During the most positive estimated cashflow shocks, average year-over-year dividend growth for *All Stocks* is 8.2% compared to 0.2% during the most negative shocks, for example.

premium expected returns compared to growth stocks.

The evidence presented in this section asserts that (a) the prices of value stocks are more elastic to aggregate cashflow shocks than the prices of growth stocks and (b) the excess sensitivity of value stock *cashflows* to shocks, compared to growth stocks, is an essential explanation of (a). This being the case, the remaining element of my proposed risk explanation of the value premium is to identify the specific inherent fundamental qualities of value stocks that cause them to have elevated cashflow elasticity/sensitivity. This is the task I undertake in the next section.

2.4 Fundamental Determinants of Firm Cashflow Shock Sensitivity

I begin this penultimate section by proposing a simple comparative static model of the firm in order to identify the key fundamental determinants a firm's cashflow shock sensitivity. Specifically, this representative firm has both fixed and variable costs and its revenues depend in part on aggregate revenues.

In this general model, firm revenue growth, $\mathbb{R}^i_{t+1}/\mathbb{R}^i_t$, is a function of (a) long-term, firm-specific factors, $\alpha^i_{\mathbb{R}}$, (b) aggregate revenue growth, $\bar{\mathbb{R}}_{t+1}/\bar{\mathbb{R}}_t$, and (c) zero-mean noise, ϵ^i_{t+1}, as in *(16)*.

$$\frac{\mathbb{R}^i_{t+1}}{\mathbb{R}^i_t} = \alpha^i_{\mathbb{R}} + \beta^i_{\mathbb{R}} \frac{\bar{\mathbb{R}}_{t+1}}{\bar{\mathbb{R}}_t} + \epsilon^i_{t+1} \tag{75}$$

Cashflows for this firm, C^i_{t+1}, are simply revenues minus expenses, X^i_{t+1}, and the latter are comprised of variable costs (at a rate of l^i per unit of revenue) and conditionally fixed costs (at a rate of k^i per unit of assets at time t, A_t^i).[73]

$$C_{t+1}^i = \mathbb{R}_{t+1}^i - X_{t+1}^i \tag{76}$$

$$X_{t+1}^i = l^i \mathbb{R}_{t+1}^i - k^i A_t^i \tag{77}$$

In this framework, the cashflow growth of the firm at $t+1$ is given by *(19)*

$$\frac{C_{t+1}^i}{C_t^i} = (\frac{\mathbb{R}_{t+1}^i}{\mathbb{R}_t^i})(\frac{M_{t+1}^i}{M_t^i}) \tag{78}$$

where $M(\equiv 1 - X/S)$ represents cashflow margins.

For our purposes here, the derivative of *(19)* with respect to aggregate revenue growth reveals the fundamental drivers of the firm's cashflow shock sensitivity. That is,

$$\begin{aligned} \frac{d\frac{C_{t+1}^i}{C_t^i}}{d\frac{\bar{\mathbb{R}}_{t+1}}{\mathbb{R}_t}} &= (\frac{\mathbb{R}_{t+1}^i}{\mathbb{R}_t^i})(\frac{d\frac{M_{t+1}^i}{M_t^i}}{d\frac{\bar{\mathbb{R}}_{t+1}}{\mathbb{R}_t}}) + (\frac{M_{t+1}^i}{M_t^i})\beta_{\mathbb{R}}^i \\ &= \beta_{\mathbb{R}}^i \frac{(1-l^i)}{M_t^i} \\ &= \beta_{\mathbb{R}}^i \frac{(1-l^i)}{(1-l^i-\frac{k^i A_t^i}{\mathbb{R}_t^i})} \end{aligned} \tag{79}$$

Equation (20) says that that the sensitivity of the firm's cashflow growth to aggregate shocks depends on both the economic sensitivity of the firm's revenues ($\beta_{\mathbb{R}}^i$), and the fixed costs share (i.e., the magnitude of $\frac{k^i A_t^i}{\mathbb{R}_t^i}$ relative to the contribution margin, $1 - l^i$). If there are no fixed costs, then the beta of firm revenues to aggregate revenues (*revenue beta*) alone controls the response of firm cashflows to shocks, but if the fixed cost share is large (i.e., if the firm's operating leverage is large) then the revenue beta effect will be magnified.

[73] The cost of capital for this firm, k^i, is likely to be a function of its financial condition, including its degree of financial leverage.

While the revenue beta is generally determined by the features of the industry in which the firm operates (e.g., cyclical vs. non-cyclical, discretionary vs. staple, nascent vs. mature), operating leverage is governed by several firm-specific factors. A principal factor is the capital intensity of the firm's operations (i.e., the amount of assets required to produce a unit of revenue, $A_t^i/\mathbb{R}_t^i$). Since capital costs are conditionally fixed in this model, the greater is $A_t^i/\mathbb{R}_t^i$, the greater will be the fixed cost share and operating leverage, and the more magnified the revenue beta effect will be for any given aggregate shock. However, the capital cost per unit of assets, k^i, also play a role in that firms with higher financing costs will be have a higher fixed cost share, all else equal. The level of k^i will depend on many factors but in the data analysis that follows, I make the simplifying assumption that it is a function of the firm's financial leverage (i.e., the asset-to-equity ratio, A_t^i/B_t^i, where *B* is equity book value).[74]

Importantly, the *level* of the the firm's cashflow margin, M_t^i, also impacts operating leverage. Although the revenue beta multiplier, $(1 - l^i)/M_t^i$ in *(20)*, will tend to be large for firms with high capital intensity, it will also be large for firms with low cashflow margins even if capital intensity is not high. To illustrate, I note that $(1-l^i)/M_t^i$ will equal 4 *both* for a firm with a 20% cashflow margin, but whose capital costs are 60% of revenue, *and* for a 10% margin firm whose capital costs are only 30% of revenue. For this reason, low margin firms will be more likely to have higher sensitivity to cashflow shocks, ceteris paribus.

2.4.1 Shock Sensitivity Attributes in Value-Sorted Portfolios

This simple model of the firm has identified four primary determinants of the firm's sensitivity to cashflow shocks: revenue beta, capital intensity, margins, and financial leverage. The cashflows of firms with the highest revenue beta, lowest profit margins, highest capital intensity and most financial leverage will be most vulnerable to negative aggregate shocks

[74] A more complete model of the cost of capital would account for rates of depreciation, the growth and stability of cashflows, as well as other risk factors, and would be time varying as macroeconomic and firm-specific conditions change.

and will benefit the most from positive shocks. In the context of the risk explanation of the value premium that I have advanced in this paper, and in *Paper 1*, such firms ought to be more feared by investors causing their stocks to be discounted and assigned to value portfolios. Accordingly, to investigate this hypothesis empirically, I compute revenue beta, capital intensity, margins, and financial leverage for book-to-market sorted portfolios of stocks from 1952 to 2019 and I compare the computations for value portfolios to those for growth portfolios.

The methodology I use here is similar to that used in previous sections of this paper. Combining data from *CRSP* and *Compustat*, I assign all stocks (drawn from NYSE, Nasdaq and AMEX) into book-to-price sorted decile portfolios at the end of June each year from from 1952 to 2019. For each year and each decile portfolio, I calculate the year-over-year revenue growth, profit margins (gross, operating and net), asset-to-revenue ratio and asset-to-equity ratio.[75] To compute the *typical* value of a portfolio characteristic (e.g., asset-to-revenue ratio) in any year, I sum the numerator across all portfolio constituents and divide that total by the sum of the denominator across all constituents.[76] Given that the book-to-market sorted portfolios are formed each year using June-end market values and prior fiscal year book values, and given that market prices reflect forward-looking risks, it is ambiguous as to which "year" should be used to compute the portfolio characteristics (i.e., should it be the current fiscal year in which the portfolio sorting is done, or the fiscal year following the portfolio sorts?). As a result of this ambiguity, I calculate, for every sorted portfolio, each characteristic using *both* the current fiscal year *and* the next fiscal year and I show both computations.[77] The results are shown in *Table 2.7* & *Table 2.8*. *Table 2.7* shows the

[75]The relevant data fields in the *Compustat Annual* database are REVT (revenues), GP (gross profit), OIADP (operating profit), NI (net profit), AT (assets), AT *minus* LT (equity)

[76]I refer to this weighting method as "total weighting" or "fundamental weighting". This methodology avoids the 'outlier' problems that arise when applying equal weighting or capitalization weighting to individual constituent ratios which can occasionally have unusually large or small values. For robustness, I also conducted the analysis using median portfolio values, with ostensibly similar results.

[77]For the asset-to-revenue ratio, for example, I calculate $A_t^i/\mathbb{R}_t^i$ and $A_{t+1}^i/\mathbb{R}_{t+1}^i$ separately for each sorted

results for current fiscal year characteristics while *Table 2.8* reflects the subsequent fiscal year.

Focusing on revenue growth in *Table 2.7*, the book-to-market sorting methodology clearly does a good job of predicting year-of-year growth rates, as one would expect; moving from Growth portfolios (Decile 1), with a mean growth rate of 13.85%, to Value portfolios (Decile 10), with a mean growth rate of -0.24%, the growth rate increases almost monotonically. The 14.1% revenue growth advantage for Decile 1 over Decile 10 portfolios is also *highly* statistically significant (*t-statistic* = 8.9). Remarkably, the book-to-market sorting also does a highly effective job of predicting profit margins (gross, operating and net), asset-to-revenue ratios and asset-to-equity ratios across portfolios. Specifically, the growth portfolios have economically (and statistically) larger margins, lower capital intensity, and lower financial leverage than value portfolios. In each case (with the exception of the asset-to-equity ratio), the portfolio characteristic increases or decreases monotonically across sorted deciles and the difference in values between Decile 1 and Decile 10 are highly statistically significant. The consistency and strength of these results across sorted portfolios highlights the role that these fundamental asset characteristics play in in explaining their riskiness.

The *Revenue Sensitivity* section in *Table 2.7* presents the results of time-series *OLS* regressions of the form shown in *equation (16)* for each book-to-market sorted portfolio. The intercept in these regressions reflects the long-term average revenue growth premium of each sorted portfolio (compared to the *All-Stock* portfolio) and, unsurprisingly, the values are large and significant for growth portfolios and small and significant for value portfolios. The slope term in these regressions is the *revenue beta* (the estimates for which are highly statistically significant for every decile portfolio). The revenue beta for growth stocks is 0.61, compared to 1.17 for the value stocks, which is a remarkable and convincing result. It is also noteworthy that the *R-squared* from these regressions, while large and meaningful

---

decile portfolio.

for every portfolio, are smallest for the growth portfolios; for example, R^2 averages 0.25 for Decile 1 and 2 regressions compared to 0.59 for Decile 9 and 10 regressions). This says that aggregate revenue growth, while an important driver of revenues for both growth *and* value portfolios, is significantly more important for the latter. The unexplained variability in revenue growth for Decile 1 and Decile 2 portfolios suggests that other (perhaps non-systematic) factors are important for the revenues of growth stocks.

Comparing *Table 2.7* to *Table 2.8*, it is evident that the results do not change meaningfully when the portfolio characteristics are computed as FY_{t+1}/FY_t rather than FY_t/FY_{t-1}; the same pattern of results is evident in both tables. This implies that the book-to-price portfolio sorting procedure, which does a good job of predicting fundamental portfolio characteristics in year t, remains a good predictor of those characteristics in year $t+1$. This result echoes the analysis of the value-minus-growth returns by holding period in *Table 2.14* & *Table 2.15* as part of the *Appendix* (which show that the book-to-market sorts remain a potent predictor of the value premium for several years after an initial portfolio sort), and is consistent with a world in which assets are discounted because they are riskier and where those risks derive from their fundamental characteristics which evolve slowly from one year to the next.

In this section, I have shown that value stocks have a higher revenue beta and a higher revenue beta multiplier than growth stocks; the revenues of value stocks are significantly more economically sensitive than growth stock revenues, and they have excess operating and financial leverage, and lower margins. These are precisely the characteristics that were revealed in *Equation (20)* to drive the sensitivity of a firm's cashflow to cashflow shocks. The results in this section are striking in several respects; they are highly consistent across sorted portfolios, they are economically and statistically highly significant, and they explain clearly the mechanisms underlying the excess cashflow sensitivity of value stocks.

2.5 Conclusion

In this paper, I have sought to complete the risk explanation of the value premium that I proposed in *Paper 1*. While that paper showed that, from an investor preference perspective, the value premium is explained by fears of near-term aggregate cashflow shocks, this paper has sought to explain why value firms are *especially* vulnerable to cashflow shocks and to relate the risk discounting of value stock prices to inherent, measurable, fundamental firm attributes. I introduced the *Cashflow Shock Elasticity of Price* of an asset in order to relate its discount rate to its cashflow shock sensitivity. Then I showed that value stocks exhibited significantly larger cashflow shock elasticity than growth stocks during past economic shocks (both observed and estimated). These results confirm that the investors' fear of cashflow shocks is central to the discounting of value stocks compared to growth stocks. Finally I identified the firm-level fundamental attributes that induce cashflow shock elasticity and I found convincing evidence that portfolios of value stocks have significantly more of these attributes than growth portfolios. This result provides a microeconomic justification for the outsized impact of aggregate shocks on value firms. In conjunction with *Paper 1*, the analysis and results in this paper show that investors fear and discount value stocks because those firms are especially vulnerable to near-term cashflow shocks, owing to their inherent fundamental characteristics, which renders them poor economic hedges at inconvenient times, and therefore riskier.

2.6 References

Asness, C., Moskowitz, T. and Pedersen, L.H., 2013. Value and Momentum Everywhere. *Journal of Finance* 68, 929-985

Bansal, R. and Yaron, A., 2004. Risks for The Long Run: A Potential Resolution of Asset Pricing Puzzles. *Journal of Finance* 59, 1481-1509

Buffett, W.E., 1984, The Superinvestors of Graham-and-Doddsville, Hermes: The Columbia Business School Magazine: 4–15

Campbell, J.Y. and Cochrane, J.H., 1999. By Force of Habit: A ConsumptionBased Explanation of Aggregate Stock Market Behavior. *Journal of Political Economy* 107, 205-251

Carlson, M., Fisher, A., and Giammarino, R., 2004. Corporate investment and asset price dynamics: Implications for the cross section of returns. *Journal of Finance* 59, 2577-2603

Daniel, K., and Titman, S., 1997. Evidence on the Characteristics of Cross Sectional Variation in Stock Returns. *Journal of Finance* 52, 1-33

Daniel, K., and Titman, S., 1998. Characteristics or Covariances? *The Journal of Portfolio Management* 24, 24-33

DeBondt, W.F.M., Thaler, R., 1985. Does the Stock Market Overreact? *Journal of Finance* 40, 793-805

DeBondt, W.F.M., Thaler, R., 1987. Further Evidence on Investor Overreaction and Stock Market Seasonality. *Journal of Finance* 42, 557-581

de Groot, Wilma and Huij, Joop and Zhou, Weili, 2012. Another Look at Trading Costs and Short-Term Reversal Profits. *Journal of Banking and Finance*, Vol. 36, No. 2, Available at SSRN: https://ssrn.com/abstract=1963131

Epstein, Larry G., and and Zin, Stanley E, 1989. Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework. *Econometrica* Vol. 57, No. 4 (Jul., 1989), pp. 937-969

Epstein, Larry G., and and Zin, Stanley E, 1991. Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: An Empirical Analysis. *Journal of Political Economy* Vol. 99, issue 2, 263-86

Fama, E.F. and French, K.R., 1992. The Cross-section of Expected Stock Returns. *Journal of Finance* 42, 427-465

Fama, E.F. and French, K.R., 1993. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics* 33, 3-56

Fama, E.F. and French, K.R., 1995. Size and Book-to-Market Factors in Earnings and Returns. *Journal of Finance* 50, 131-155

Fama, E.F. and French, K.R., 1996. Multifactor Explanations of Asset Pricing Anomalies. *Journal of Finance* 51, 55-84

Fama, E.F. and French, K.R., 1998. Value Versus Growth: The International Evidence. *Journal of Finance* 53, 1975-1999

Fama, E.F. and French, K.R., 2006. The Value Premium and the CAPM. *Journal of Finance* 61, 2163-2185

Fama, E.F. and French, K.R., 2012. Size, Value and Momentum in International Stock Returns. *Journal of Financial Economics* 105, 457-472

Fama, E.F. and French, K.R., 2020. The Value Premium. Fama-Miller Working Paper No. 20-01

Graham, B., and Dodd, D., 1934. Security Analysis. *New York, McGraw-Hill*

Lakonishok, J., Shleifer, A., and Vishny, R.W., 1994. Contrarian Investment, Extrapolation, and Risk. *Journal of Finance* 49, 1541-1578

Lettau, M. and Wachter, J.A., 2007. Why is Long-Horizon Equity Less Risky? A Duration-Based Explanation of the Value Premium. *Journal of Finance* 62, 55-92

Lev., B., & Srivastava, A., 2019. Explaining the Recent Failure of Value Investing. NYU Stern School of Business.

Losq, E., and Chateau, J., 1982. A Generalization of the CAPM Based on a Property of the Covariance Operator. *The Journal of Financial and Quantitative Analysis* Vol. 17, no. 5, Cambridge University Press, pp. 783–97

Nagel, Stefan, 2011. Evaporating Liquidity. *NBER Working Paper* No. w17653, Available at SSRN: https://ssrn.com/abstract=1971476

O'Neill, Ciarán, 2022. Value Stocks are Riskier - *Paper 1. PhD. Dissertation, EDHEC PhD. in Finance*

Rubinstein, M., 1976. The valuation of uncertain income streams and the pricing of options. *The Bell Journal of Economics* Vol. 7, No. 2

Stein, C., 1973. Estimation of the mean of a multivariate normal distribution. *Proceedings of the Prague Symposium on Asymptotic Statistics* September, 345-381

Weil, P., 1990. Nonexpected Utility in Macroeconomics. *The Quarterly Journal of Economics* Vol. 105, No. 1 (Feb., 1990), pp. 29-42

Zhang, L., 2005. The Value Premium *Journal of Finance* 60, 67-103

2.7 Appendix: Historical Clues About the Riskiness of Value Stocks

2.7.1 Magnitude and Persistence of the Value Premium

In *Table 2.9*, I show the long-term mean returns, standard deviations, standard errors, and Sharpe ratios for market-capitalization-weighted univariate sorted-decile portfolios of US equities for the period from January 1952 to December 2019.[78] On average over this time period, capitalization-weighted excess returns for US value stocks (Decile 10), have exceeded the returns for growth stocks (Decile 1) by approximately 4-5% per annum.[79] (In *Table 2.10*, I present similar summary statistics for equal-weighted portfolios. In general, equal-weighted returns are larger than capitalization-weighted returns across all deciles and for the value-minus-growth spread, which averages 7 to 10% per year depending on the univariate sorting ratio used.)

These data lend strong support to the existence of a value premium in the pricing of US equities. The excess return premium earned by value stocks is economically and statistically large and is not explained by either the volatility of their returns or a small cap effect. The persistence of these large excess returns over such a long period of time is difficult to explain in a framework where the value premium is caused by the correction of temporary pricing errors that derive from irrational investor behavior.

[78] This table is taken from O'Neill (2022) and is an updated and expanded version of *Table 1* in Lettau & Wachter (2007).

[79] All portfolio return data for univariate sorts on earnings-to-price (E/P), cashflow-to-price (C/P), dividend-to-price (D/P) and book-to-market (B/M) in *Table 2.9* are taken from Ken French's website which in turn takes its fundamental data from *Compustat* and its pricing data from *CRSP*, covering most NYSE, AMEX and NASDAQ stocks. See $https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\_library.html$. Except book value data which is hand collected from Moody's Manuals and is available back to 1926. Also, although I include statistics for D/P for comparison to *Table 1* in Lettau & Wachter (2007), this ratio is less useful than the others as a measure of value since a high dividend yield can just reflect a firm's dividend payout policy, rather than indicating a discounted stock.

2.7.2 The Value Premium & *CAPM*

The value premium is also not explained by *CAPM* betas, as shown in *Table 2.11*. To generate this table, I ran *Ordinary Least Squares (OLS)* regressions of the excess portfolio return ($R_i - r_f$) against the excess return of the value-weighted *CRSP* Index ($R_m - r_f$) for each valuation ratio and each sorted decile, where r_f is the one-month treasury bill.

$$R_i - r_f = \alpha_i + \beta_i(R_m - r_f) + \epsilon_i \tag{80}$$

Looking at the *Table 2.11*, the alpha coefficients from these regressions are, for the most part, increasing in deciles when moving from growth to value. At the extremes, the alphas for the growth portfolios are negative and significant, and the value portfolio alphas are positive and significant. In every case, the alpha on the portfolio that is long value and short growth is economically and statistically large, suggesting that the premium return earned by value stocks cannot be solely attributed to higher *CAPM* betas. Even if *some* portion of the value premium can be attributed to *CAPM* betas, some other risk factor(s) has stronger explanatory power.

A similar result was observed in Lettau & Wachter (2007) for the 1952-2002 period but it is notable here that the result holds even after incorporating the perverse value-minus-growth returns which were experienced in the decade following the Great Recession (shown in the far right column of *Table 2.9*).[80] However, the alphas in my study are meaningfully

[80] In the decade following the Great Recession, average annual capitalization-weighted returns on value stocks were more than 5% lower than growth stock returns (data from Ken French's website for the period 12/31/2009-12/31/2019 using univariate sorts on market-book ratios and simple annualization, taking 12 times the monthly average return of growth decile minus the value decile). This "lost decade" in the profitability of value strategies has caused some to question the persistence of the value premium and even whether it has ever existed (see, for example, Lev & Svristava (2019) and Fama & French (2020)). I do not address this issue directly in this paper. Given the long-term evidence in *Table 2.9* & *Table 2.10* (which *includes* return from the 2009 to 2019 period, and other periods when value stocks underperformed growth stocks), I take it as given that the value premium exists (and deserves an explanation), albeit with time-variability. I also point out that the negative returns to value stocks after 2009 coincided with two extreme contractionary shocks to the US economy (the Great Recession and the Coronavirus pandemic and related lockdowns). If these shocks are the types of unanticipated negative risk events that value stocks are more exposed to and are discounted for, then a decade or more of negative relative returns for value strategies can still be consistent with risk-discounting of value stocks and their above-average expected returns. To use an insurance industry analogy,

lower than those observed in Lettau & Wachter (2007). The fact that the long-term *CAPM* alphas have declined following the inclusion of the post-2009 data is not solely attributable to the perverse returns on value stocks which ensued. It is also because the "*CAPM* riskiness" of value and growth portfolios underwent a marked structural shift during and after the Great Recession. This can be gleaned from *Table 2.12*, where I show the results from rolling 250-trading-day *OLS* regressions of capitalization-weighted portfolio excess returns on the excess returns to the capitalization-weighted *CRSP* Index over different time periods.[81] These regressions identify a marked shift in the *CAPM* riskiness of growth and value stocks in and after 2009, with value stocks becoming one standard deviation more risky than usual and growth stocks one standard deviation less risky. In other words, investors in value stocks experienced perverse value-growth returns after 2009 *despite* taking on additional *CAPM* beta risk, illustrating both the ineffectiveness of the *CAPM* to explain the value premium (and the likelihood that some other risk factors are pertinent), and the pronounced time variability of the premium itself.

2.7.3 Time Variability and Asymmetry of the Value Premium

Even though the poor returns from value stocks after 2009 have not caused the long-term value premium to disappear, it is instructive to ask how unusual those returns have been compared to prior history. Do they represent a break with the past (i.e., a new pricing regime), or the typical time variability of the premium? In *Figure 2.1*, I plot the rolling 10-Year mean capitalization-weighted return of the value-minus-growth portfolio.[82] The data, which is monthly, is from Prof. Ken French's website and I use only book-to-market

---

a similar phenomenon is frequently observed property & casualty insurance market when, after a large natural catastrophe like a hurricane or an earthquake, prior written insurance policies turn out to be unprofitable for the insurers resulting to a "hard-pricing" cycle of higher insurance premiums.

[81] In this table, I only show data for Decile 1 (Growth) and Decile 10 (Value) portfolios formed by sorting book-to-market ratios. Data from Prof. Ken French's website

[82] Monthly data from July 1926 to June 2019. Decile 1 (Growth) and Decile 10 (Value) portfolios formed using sorted book-to-market ratios.

sorted portfolios because this data has the deepest history (i.e., back to 1926). As shown in *Figure 2.1*, there have been at least *six* occasions since 1926 when the trailing ten-year value premium has been negative (1958, 1961, 1973, 1999, 2012, 2015-2019). Thus, the recent perverse value premium is not unique. But it is, nevertheless, remarkable for (a) having the most perverse premium in history (-5.5% at year end 2019 compared to half of that, or less, for each of the other lengthy drawdowns), and (b) having the longest sustained period of negative ten-year value-minus-growth returns in history (67 months, compared to a range of 4 months to 37 months for the other drawdowns).

However, as uncommon as the recent perverse value-minus-growth returns have been, they may not be *statistically* aberrant in the context of the full history. In *Figure 2.2*, I plot a frequency distribution of the rolling ten-year mean value premium. From 1926 to 2019, the mean ten-year value premium is 6.14% and the standard deviation is 5.50%. For illustration purposes, if I assume that ten-year mean returns are normally distributed ($\mu = 6.14\%, \sigma = 5.50\%$), then an observed ten-year value premium of 0% would be a -1.12 standard deviation event. That is, we should expect to observe negative ten-year value-minus-growth returns approximately 13.13% of the time. The *actual* frequency of observed negative ten-year value-minus-growth returns in Prof. Ken French's data (as shown in *Figure 2.1* & *Figure 2.2*) is 14.8%, which is statistically similar. Indeed, a ten-year mean value-minus-growth return of -5.5% (as was observed in December 2019) would be a -2.12 standard deviation event which, under normality, ought to be observed 1.7% of the time, or about 17 months in this sample. The actual observed frequency is 7 months.[83]

These observations confirm (a) that the US value premium has been time-varying (a feature that must be part of any comprehensive risk explanation of the premium), and (b) that the perverse returns to value stocks after the Great Recession may not be the death knell

[83] For completeness, in this data ten-year value-growth returns at or above +2.12 standard deviations were only observed in 1 month, compared to 17 expected.

for the value premium.[84] This time variability of the value premium is more easily explained by time varying risks than behavioral pricing errors; if the value premium derives from irrational investor behavior that is rooted in *enduring* human flaws (e.g., short-sightedness, extrapolation, or excessive exhuberance/pessimism), then one might expect more stability in value-minus-growth return year after year.

The value premium has also been asymmetric, deriving largely from the outperformance of value stocks rather than the underperformance of growth stocks. In *Table 2.13*, I show the mean relative contributions to the value premium from growth and value portfolios historically and in *Figure 2.3* I plot how these relative contributions have varied over time.

Table 2.13 shows that the long-term mean capitalization-weighted value premium of 5.2% is comprised of 4.5% from ”outperforming value” (versus *CRSP* Index) and only 0.7% from ”underperforming growth”.[85] The pattern is similar for the 1952-2019 period and for equal-weighted returns.[86] *Figure 2.3* plots the rolling ten-year contributions to the value premium from value and growth separately in a stacked bar graph. This chart confirms that the premium is driven primarily by outperforming value portfolios most of the time (e.g., in 93% of the rolling 10-year periods in the full sample, the contribution from ”outperforming value” accounts for half or more of the total premium). It also shows that, with few exceptions (i.e., early 1970s and late 1990s) the ten-year mean market-relative return of value and growth portfolios have the opposite sign from each other. Indeed, the correlation coefficient of the ten-year relative returns of value and growth portfolios is -0.42 in the full sample, which suggests that outperforming value and underperforming growth share a common risk explanation, but without the effect being perfectly symmetric.

---

[84] If the extreme negative cashflow shock of the Financial Crisis/Great Recession is an example of the risk that causes value stocks to be discounted in the first place, and if those risks remained elevated for years after 2009, then the ”lost decade” for value stocks from 2009-2019 can be entirely consistent with a risk explanation of the value premium.

[85] Prof. Ken French data, 1926 to 2019, book-to-market sorted portfolios only.

[86] For equal-weighted returns, the value premium for the full period is 13.4% with 11.38% deriving from ”outperforming value”.

Figure 2.4 and *Figure 2.5* further reveal that the factors underlying the return dynamics for value and growth portfolios are not exact mirror images of each other. *Figure 2.4* charts the rolling 250-trading-day *CAPM* beta of growth and value portfolios to the *CRSP* Index (capitalization weighted) from 1926 to 2019. On average, the beta of the value portfolio is larger than the growth beta (1.29 versus 1.07, although this result is skewed by unusually large value betas in the 1930s and 1940s) and it also has more volatility (0.44 standard deviation versus 0.14). Given that we know the *CAPM* does not explain the value premium well, it must be true that value stocks sometimes outperform a rising stock market with higher *CAPM* beta, and sometimes outperform a declining market with a lower beta. In other words, some other risk factor(s), in addition to beta, is(are) involved.[87]

Figure 2.5 plots the rolling 250-trading-day correlation coefficient of value and growth returns with *CRSP* Index returns (all returns capitalization weighted) from 1926 to 2019. Over the full period, growth returns are meaningfully more correlated with the market, on average, than value returns (0.95 correlation coefficient versus 0.86) and the growth correlation exhibits less volatility over time (standard deviation of 0.02 versus 0.06). Only rarely in this long sample does the value portfolio have as tight a correlation with the market as the growth portfolio. Growth stocks, it seems, comove more sympathetically with the whims of the market than value stocks, which is a further indication of an asymmetry in underlying risk drivers.[88]

Overall, the asymmetrical importance of *value-minus-market* returns to the value pre-

[87]It is also noteworthy that the correlation coefficient between the *CAPM* beta of value and growth over the full time period in *Figure 2.4* is -0.72 which is large and highlights time variability in investor's beliefs about the relative riskiness of these assets.

[88]*Table 2.17* offers additional insights. It shows the relative performance of the Russell 1000 & 2000 indices, by style, during the three sharpest market sell offs in the 20 years through December 2019. During the 2000/2001 market decline that followed the bursting of the "internet bubble", large and small growth stocks declined 50% while value stocks were close to unchanged. In contrast, value stocks fared worse than growth stocks in the 2008/2009 Financial Crisis decline and during the Covid-19 decline in 2020. These latter two selloffs corresponded with abrupt declines in aggregate economic activity whereas the former did not, suggesting that value stock prices are particularly sensitive to negative economic shocks, while the growth stock prices may be more sensitive to changes in risk premia.

mium, compared to *market-minus-growth* returns, is easier to explain in a framework where value stocks possess an asymmetric risk exposure, than it is to explain in a framework where investors are more irrational in the pricing of value stocks than they are in the pricing of growth stocks.

2.7.4 Value Premium by Holding Period

Whether value and growth stocks share common risk drivers or not, if the value premium has a risk explanation, then the time horizon over which riskier stocks earn premium returns, should mirror the horizon over which they are exposed to the underlying risk. If the risk is short lived, then the horizon of the reward should be short, and if the risk is long lived (e.g., if it derives from slowly-evolving asset fundamentals), then the premium return should be long lived too. In the analysis thus far, I have emphasized a one-year holding period for sorted portfolios, but in this subsection I examine the efficacy of value-sorted portfolios over longer horizons.

To facilitate this, I need a different source of portfolio data than Prof. Ken French's website. Prof. French's high-quality dataset has been widely vetted and used in many prior academic studies. And even though it has been widely used, this data can still be employed in novel ways to generate insights into the dynamics of the value premium, as I have shown above. However, this data is limited in the kinds of research questions it can answer. For example, it can not be used to test alternative portfolio formation rules (e.g., forming portfolios *more* than once a year, or using other valuation ratio sorts, or combinations of sorts). Neither can it be used to test alternative portfolio weighting schemes (i.e., other than monthly equal weighting or cap-weighting). It also cannot be used to evaluate portfolio holding periods greater than one year.[89] To overcome these limitations here, I generate my own book-to-market portfolio sorts (and calculate my own portfolio returns)

[89] Recall that the univariate sorted data on Ken French's website assumes that portfolios are reformed each year at the end of June and rebalanced every month using either equal-weighting or market value weighting.

in order to examine the potency of the value effect for portfolio holding periods which are longer than one year.[90]

Specifically, I use the *CRSP*-*Compustat* merged database to consider the largest 99.5% of actively traded companies with a *CRSP* share code of 10 or 11 at the end of June each year from 1952 to 2019.[91] Book values are taken from the *Compustat* Annual database and market values are taken from *CRSP*. To calculate the book-to-market ratio for a given stock, I use the June-end market values and I use most recent *then-known* fiscal year book value, as long as it was reported at least four months before the end of June. (This differs from Prof. Ken French's approach which takes market values from the end of the prior calendar year and book values from the last fiscal year ending in the prior calendar year.)[92] Stocks are ranked by book-to-market at the end of June each year, as usual, and assigned to decile portfolios.

Table 2.14 and *Table 2.15* illustrate how the value premium evolves as the portfolio holding period is lengthened. Following each June-end portfolio formation, I calculate subsequent *buy-and-hold* portfolio returns over multi-horizon holding periods (ranging from 1 year to 10 years) using monthly return data. Stocks remain in their assigned portfolio for the duration of the holding period and their weightings in the portfolio evolve naturally each month based on their monthly total returns relative to the other stocks in the same portfolio. If a stock is acquired or delisted during the holding period, its weight in the portfolio at the date of the corporate action is reallocated to the remaining stocks in the portfolio

[90]In *Table 2.18* in the *Appendix*, I also explore, with mixed results, the effect on the value premium of conditioning the initial portfolio sorts on the length of time that the underlying stocks have been in the ”value” and ”growth” deciles (i.e., the value & growth gestation period).

[91]For those *CRSP* permnos with multiple permcos, I consider only the permco with the largest market value on a given date.

[92]Prof. Ken French's methodology is conservative, but it also uses data which is stale. Each June, its rankings are generated using market values which are six months old and book values which are *at least* six months old. In fact, when following Prof. French's approach, even for a company on a December fiscal year end, there is *never* any portfolio formation month when the book-to-market ratio so calculated, reflects the most recently known market value and book value; the fiscal year end book value is not known until it is reported *after* December and by that time, the market value will have changed.

in proportion to the then-prevailing portfolio weights. This approach captures a buy-and-hold-and-reinvest portfolio strategy with minimal trading. (Again, this methodology differs from Prof. French's approach of re-applying a portfolio-weighting scheme each month in between annual portfolio sorts. I believe that my approach minimizes trading in the portfolio after the initial formation date, and provides a purer measure of the holding period return that is attributable to the initial value sort.)

Table 2.14 and *Table 2.15* each contain two panels of data. The first shows the mean *Year N* (N = 1, .., 10) returns of each decile portfolio and each holding period, and the second shows the standard deviation. (For each sorted decile, the *Year N* mean return is the weighted portfolio return in the *Nth* year after the portfolio was formed, averaged across the total number of years that portfolios were formed.) At formation, all portfolio constituents are equal-weighted but thereafter the constituent weights evolve based on the buy-and-hold-and-reinvest just described. The results in *Table 2.14* allow for *overlapping holding periods*. That is, a stock initially assigned to a portfolio in, say, June 1970 will be included in that 1970-base-year portfolio for up to 10 years. However, that same stock may also be assigned to a decile portfolio in June 1971 and held in that 1971-base-year portfolio for up to 10 years. Thus, new base-year portfolios are formed each year (1952-2019) and there can be overlapping constituents and returns across base-year portfolios. The results in *Table 2.15* are for *non-overlapping holding periods*, i.e., the *Year-N* portfolio returns reflect information only for base-year portfolios formed every *N* years.

Looking at the value-minus-growth mean returns (the "V-G" column on the right-hand side of *Table 2.14*), the *Year 1* value premium averages 7.69%, which is similar to the one-year estimates from Ken French's data.[93] Remarkably, *as the portfolio holding period is extended, the value premium remains strong in subsequent years*. In *Year 2* for example, the V-G spread is even larger (10.8%) and in *Year 3*, value stocks continue to outperform growth stocks by more than 8%. This pattern of sustained outperformance continues

[93] See *Table 2.9*.

through Year 7, meaning that, in this long sample, it was possible to exploit the value effect using book-to-market portfolio sorts that were 72 months stale. It is difficult to reconcile this result with the behavioral hypothesis of the value premium. The behavioral hypothesis presumes that the premium derives from irrational pricing errors which are eventually corrected, but this result suggests that these ”errors” are left uncorrected for many years, which is unlikely in competitive financial markets. Instead, this result is more consistent with a risk-based explanation of the value premium in which the fundamental characteristics of the constituent stocks in the value portfolio define the risk and are slow to change, meriting sustained high expected returns for long periods. (The numbers in *Table 2.15*, representing non-overlapping holding periods, confirm the findings from *Table 2.14*, albeit with more variability in mean returns across portfolios and holding periods, as is expected since each number in *Table 2.15* is calculated from a smaller sample of observations than the corresponding number in *Table 2.14*.)

As an interesting aside, the calculations in *Table 2.16* are performed similarly to those in *Table 2.14* (in that they are based on overlapping holding periods) but rather than adopt a buy-and-hold-and-reinvest portfolio methodology, returns are calculated by equal-weighting the surviving constituents of the original base-year portfolio *every month*. I noted in *Paper 1* that monthly equal-weighting (as is used in Prof. Ken French’s data library for example) implies costless trading in the portfolio each month and can bias the measured value premium upwards if stock prices commonly exhibit short-term technical price reversals.[94] By comparing the ”V-G” column in *Table 2.16* to *Table 2.14*, this effect is plainly evident; for *every* year following portfolio formation, the value premium, V-G, in *Table 2.16* is larger than in *Table 2.14*, often by more than two percentage points per year. Because of this, I believe the methodology used in *Table 2.14* produces a purer measure of the value effect, untainted by portfolio trading artifacts, especially as the holding period is lengthened.

[94] See, for example, Nagel (2011) and de Groot, Huij & Zhou (2012) for evidence on the existence of, and potential trading profits from, short-term reversals.

2.7.5 Further Observations & Analysis

2.7.5.1 Value Premium by Gestation Period

Table 2.18 presents some initial results of an analysis which asks if the length of time that a stock has been a ”growth” or ”value” asset before being assigned to a portfolio (i.e., the value/growth *gestation period*), has any effect on the subsequent returns to that portfolio. Stock are ranked by book-to-market at the end of June each year, as usual, but the constituents of the growth and value deciles are each then assigned to subportfolios depending on how many years, of the previous five (including the current year) that the stock had been in that decile, or the next adjacent decile. For example, a value gestation period of 5 years means a stock has been in Decile 10 or 9 in each of the last 5 years. This could be considered a ”mature value” subgroup while a 1-year gestation is ”immature value”. For growth portfolios, the results of this conditioning are inconclusive; there is no obvious, meaningful differences in returns between subportfolios. For the value portfolios, there is a tendency for ”mature value” to have larger mean returns than ”immature value” in the early years after portfolio formation. While this may be related to a short-term negative price momentum effect that is present for newly minted value stocks but absent for mature value stocks, the result is also consistent with a risk explanation of the value premium in which the risks for mature value stocks are well established and appropriately discounted in their prices. For both growth and value portfolios, the longer the gestation period, the lower the standard deviation of portfolio returns at every holding period which is an additional factor favoring the mature value portfolio.

2.8 Tables & Figures for Paper 2

This page intentionally left blank

Table 2.1: List of *National Bureau of Economic Research* Expansions and Contractions, 1929 - 2020. Source: *NBER*

			Contractions (Peak-Trough)		Expansions (Trough-Peak)	
	Starting Month	Ending Month	# Months	GDP Decline %	# Months	Annual GDP %
1.	August 1929	March 1933	43	-26.7	21	-
2.	May 1937	June 1938	13	-18.2	50	7.3
3.	February 1945	October 1945	8	-12.7	80	9.3
4.	November 1948	October 1949	11	-1.7	37	1.5
5.	July 1953	May 1954	10	-2.6	45	6.9
6.	August 1957	April 1958	8	-3.7	39	4.0
7.	April 1960	February 1961	10	-1.6	24	5.6
8.	December 1969	November 1970	11	-0.6	106	4.9
9.	November 1973	March 1975	16	-3.2	36	5.1
10.	January 1980	July 1980	6	-2.2	58	4.3
11.	July 1981	November 1982	16	-2.7	12	4.4
12.	July 1990	March 1991	8	-1.4	92	4.3
13.	March 2001	November 2001	8	-0.3	120	3.6
14.	December 2007	June 2009	18	-5.1	73	2.8
15.	February 2020	April 2020	2	-19.2	128	2.3
		Average	12.5	-6.8	61.4	4.7
		Median	10	-2.7	50.0	4.4

Table 2.2: Peak to Trough Mean Percentage Monthly Capitalization-Weighted Price-Only Returns for Book-to-Market Sorted Portfolios During *NBER* Contractions. Data from *CRSP* and *Compustat*. *NBER* contractions use the same numbering scheme as *Table 2.1*

	S&P Peak Month	S&P Trough Month	Growth 1	2	3	4	*Growth & Value Deciles* 5	6	7	8	9	Value 10	V-G 10-1	V-G 10+9 - 1+2
							Monthly Price Returns, %							
1.	7/29	2/33	-3.3	-2.5	-2.4	-3.7	-3.4	-3.3	-3.3	-2.9	-1.9	-2.3	0.9	0.7
2.	3/37	3/38	-5.0	-4.7	-5.4	-5.5	-4.8	-4.3	-5.0	-6.3	-6.7	-9.8	-4.8	-3.4
3.	-	-	-	-	-	-	-	-	-	-	-	-	-	-
4.	6/48	6/49	-0.7	-1.1	-1.2	-1.9	-1.2	-1.3	-2.0	-1.9	-2.1	-2.4	-1.7	-1.3
5.	1/53	9/53	-0.7	-1.1	-1.0	-1.2	-1.2	-1.1	-1.4	-1.7	-1.7	-2.0	-0.9	-0.8
6.	6/57	12/57	-2.5	-2.4	-2.6	-2.1	-1.9	-2.1	-3.6	-3.8	-3.3	-5.3	-2.8	-1.8
7.	1/60	10/60	-1.3	-0.8	-1.6	-1.0	0.2	-1.3	-1.4	-1.6	-1.6	-2.7	-1.4	-1.1
8.	6/69	6/70	-2.3	-3.2	-2.4	-3.7	-2.4	-3.2	-2.9	-2.9	-3.2	-3.6	-1.3	-0.7
9.	10/73	12/74	-3.4	-3.0	-2.9	-3.2	-2.4	-2.5	-2.4	-2.8	-2.9	-2.0	1.4	0.7
10.	10/79	3/80	-1.4	-0.8	-0.7	0.1	-1.2	-1.2	-1.1	-2.0	-1.6	-2.1	-0.7	-0.7
11.	1/81	7/82	-2.0	-0.7	-1.2	-1.4	-1.9	-0.9	-0.6	-0.1	0.0	0.0	2.0	1.4
12.	6/90	10/90	-2.8	-3.0	-5.0	-3.9	-2.6	-4.0	-5.7	-3.9	-4.5	-5.9	-3.1	-2.3
13.	2/01	9/01	-4.2	-3.2	-2.4	-2.1	-1.3	-0.6	-1.8	-2.2	0.6	-1.1	3.0	3.4
14.	6/07	2/09	-3.4	-2.6	-2.2	-2.8	-3.1	-3.4	-3.6	-5.6	-4.7	-3.6	-0.1	-1.1
15.	1/20	3/20	-3.8	-5.6	-6.3	-8.2	-9.5	-9.8	-12.6	-13.7	-13.9	-18.8	-15.0	-11.6
		Mean	-2.6	-2.5	-2.7	-2.9	-2.6	-2.8	-3.4	-3.7	-3.4	-4.4	-1.7	-1.3

Table 2.3: Trough to Peak Mean Percentage Monthly Capitalization-Weighted Price-Only Returns for Book-to-Market Sorted Portfolios During *NBER* Expansions.. Data from *CRSP* and *Compustat*. *NBER* expansions use the same numbering scheme as *Table 2.1*

	S&P Peak Month	S&P Trough Month	Growth 1	2	3	4	*Growth & Value Deciles* 5	6	7	8	9	Value 10	V-G 10-1	V-G 10+9 - 1+2
							Monthly Price Returns, %							
1.	2/33	3/37	2.5	2.4	2.5	3.7	2.6	4.0	3.6	4.5	4.4	5.1	2.6	2.3
2.	6/38	2/45	0.7	0.9	0.6	0.8	1.1	0.8	1.2	1.3	2.1	2.5	1.8	1.5
3.	10/45	5/48	-0.2	0.1	0.0	0.3	0.1	0.0	0.5	0.7	0.6	0.2	0.4	0.5
4.	6/49	1/53	1.5	1.3	1.0	1.2	1.6	1.6	1.5	1.7	1.6	2.4	0.9	0.6
5.	9/53	6/57	1.8	1.4	1.7	1.2	1.9	1.6	1.4	2.1	1.4	1.4	-0.4	-0.2
6.	12/57	1/60	2.0	1.2	1.1	1.5	1.9	1.3	0.9	2.2	2.3	2.5	0.5	0.8
7.	10/60	6/69	0.7	0.7	0.6	0.5	0.6	1.0	0.9	1.2	1.2	1.2	0.5	0.5
8.	6/70	10/73	1.5	1.4	1.1	0.8	0.4	0.8	0.7	1.1	1.1	1.0	-0.5	-0.4
9.	12/74	10/79	0.7	0.9	1.3	1.5	1.4	1.3	1.6	1.8	2.0	2.4	1.7	1.4
10.	3/80	1/81	5.0	4.1	3.9	4.5	4.1	3.2	2.4	2.1	2.2	2.0	-2.9	-2.4
11.	7/82	6/90	1.4	1.5	1.5	1.5	1.3	1.3	1.4	1.0	1.5	1.6	0.2	0.1
12.	10/90	2/01	1.4	1.5	1.4	1.3	1.1	1.3	1.4	1.4	1.5	1.7	0.3	0.1
13.	9/01	6/07	0.4	0.6	1.0	0.8	1.1	1.0	1.1	1.1	0.9	1.8	1.4	0.9
14.	2/09	1/20	1.4	1.3	1.2	1.2	1.3	1.2	1.0	1.3	1.2	1.2	-0.2	-0.1
15.	3/20	12/21	3.6	3.1	3.2	2.6	2.3	3.2	2.0	3.4	4.2	4.4	0.8	0.9
		Mean	1.6	1.5	1.5	1.6	1.5	1.6	1.4	1.8	1.9	2.1	0.5	0.4

Table 2.4: Mean Year-Over-Year Dividend Growth for Book-to-Price Sorted Portfolios During *NBER* Expansions & Contractions, 1950 to 2020. Data from *CRSP* and *Compustat*. *NBER* contractions and expansions use the same numbering scheme as *Table 2.1*

	All Deciles	Growth 1	2	3	4	5	6	7	8	9	Value 10	V-G 10-1	V-G 10+9 - 1+2
						Growth & Value Deciles							
						Dividend Growth ***NBER Contractions****, %*							
5.	5.3	18.8	1.9	3.3	4.5	7.1	3.8	-0.7	1.8	13.9	-4.5	-23.4	-5.7
6.	-1.8	3.1	1.7	2.1	-8.6	-4.9	-7.9	-11.7	1.8	-2.4	-6.9	-10.0	-7.1
7.	1.4	6.1	2.6	-0.1	5.6	0.0	0.3	-4.1	-0.7	0.2	-3.1	-9.2	-5.8
8.	-2.7	17.8	2.5	2.0	-2.1	0.7	-5.1	0.4	-4.6	-8.5	-12.2	-30.0	-20.5
9.	7.5	15.4	10.6	8.9	7.1	2.0	6.8	3.7	8.3	9.8	-2.3	-17.7	-9.2
10.	9.8	9.2	16.5	18.4	15.9	17.3	12.6	5.8	0.3	1.1	-8.0	-17.2	-16.3
11.	5.0	-6.3	13.7	11.2	6.7	8.4	4.9	6.0	5.1	3.2	-11.0	-4.8	-7.6
12.	-5.3	-12.1	15.6	-0.9	7.5	0.7	-1.2	-1.9	8.7	-24.4	-26.9	-14.8	-27.4
13.	0.5	3.5	4.4	3.4	-0.1	-2.2	-1.0	-21.9	-7.6	18.4	-33.6	-37.1	-11.5
14.	-0.2	0.2	4.4	8.7	-4.6	4.3	-16.4	-4.2	-7.9	-58.7	-65.6	-65.8	-64.5
15.	0.9	0.0	4.7	1.7	6.8	12.6	-1.6	-5.7	-0.7	14.2	-22.1	-22.0	-6.2
Mean	1.9	5.1	7.1	5.3	3.5	4.2	-0.5	-3.1	-1.2	-3.0	-17.8	-22.9	-16.5
						Dividend Growth ***NBER Expansions****, %*							
5.	9.6	12.6	16.3	8.1	9.2	9.0	7.5	7.1	5.5	6.8	1.0	-11.6	-10.6
6.	1.3	6.6	6.6	2.2	0.2	2.2	1.1	-6.7	1.1	-7.5	-6.4	-13.0	-13.5
7.	6.3	11.3	9.4	8.2	5.4	5.8	7.5	3.7	4.9	2.4	0.1	-11.2	-9.1
8.	2.3	6.3	6.0	4.0	2.2	4.4	1.5	3.5	-1.3	-3.6	-5.3	-11.7	-10.6
9.	10.2	16.8	15.2	12.1	15.9	8.1	7.4	5.3	3.9	6.7	2.0	-14.9	-11.7
10.	7.3	26.1	12.0	14.2	15.8	8.9	3.1	6.8	3.9	-9.6	-4.8	-30.9	-26.3
11.	5.3	11.7	13.9	15.1	8.4	9.0	10.0	7.2	4.8	-3.4	-4.5	-16.2	-16.8
12.	3.1	5.6	9.3	4.6	5.3	3.4	4.7	0.7	-1.7	-6.1	-8.9	-14.5	-14.9
13.	9.9	14.1	37.3	2.3	13.6	10.5	8.5	6.0	12.4	12.1	1.5	-12.6	-18.9
14.	9.2	18.8	10.4	13.1	12.3	7.6	8.2	6.3	8.7	7.3	6.1	-12.7	-7.9
Mean	6.4	13.0	13.6	8.4	8.8	6.9	5.9	4.0	4.2	0.5	-1.9	-14.9	-14.0

Table 2.5: Mean Annual Capitalization-Weighted Price-Only Return for Book-to-Price Sorted Portfolios by Deciles of Filtered Cashflow Shocks.. Data from *CRSP*, *Compustat* and O'Neill (2022) *Paper 1*.

	Shock Decile	Growth 1	2	3	4	*Growth & Value Deciles* 5	6	7	8	9	Value 10	V-G 10-1	V-G 10+9 - 1+2
						Price-Only Returns, %							
Negative	1	10.7	11.9	7.7	3.2	3.2	4.7	2.5	4.8	9.2	6.4	-4.3	-3.5
	2	30.3	24.3	23.9	20.9	22.4	20.5	22.4	31.6	28.4	28.3	-2.0	1.0
	3	6.0	7.4	4.5	8.5	7.2	5.0	1.7	1.2	2.6	1.1	-4.9	-4.8
	4	3.2	8.2	11.2	8.0	9.4	12.6	9.2	11.6	13.2	17.7	14.5	9.7
	5	8.0	11.0	11.9	13.8	12.6	14.6	13.4	14.8	16.6	17.0	9.0	7.3
	6	18.7	14.2	11.6	10.9	11.2	6.6	8.2	11.6	10.6	8.3	-10.4	-7.0
	7	1.1	2.2	-1.5	-3.7	-0.2	2.8	4.4	1.1	2.7	4.1	3.0	1.8
	8	-0.1	-1.5	-1.0	0.2	1.8	1.6	-1.2	0.9	1.6	5.5	5.6	4.3
	9	2.8	6.0	7.2	7.3	8.8	9.7	8.3	11.9	13.4	18.7	15.9	11.7
Positive	10	11.1	13.0	17.7	15.3	14.7	15.8	16.3	13.3	17.2	17.6	6.5	5.4

Table 2.6: Mean Year-over-Year Capitalization-Weighted Dividend Growth for Book-to-Price Sorted Portfolios by Deciles of Filtered Cashflow Shocks. Data from *CRSP*, *Compustat* and O'Neill (2022) *Paper 1*.

			Growth				*Growth & Value Deciles*					Value	V-G	V-G
		All	1	2	3	4	5	6	7	8	9	10	(10-1)	(10+9) - (1+2)
							Dividend Growth, %							
Negative	1	0.2	6.7	25.5	7.4	3.5	1.2	-3.4	-2.0	6.2	-17.4	-24.7	-31.3	-37.0
	2	3.1	9.4	7.2	2.9	4.7	4.6	4.1	0.5	-2.0	-6.6	-4.3	-13.7	-14.0
	3	4.6	15.7	11.3	8.3	4.9	6.9	5.2	3.6	2.8	-2.9	-5.2	-20.9	-18.0
	4	4.7	9.7	10.1	10.9	7.9	4.7	4.3	2.5	-0.4	-1.5	-4.9	-14.6	-13.0
Shock	5	5.5	13.3	10.8	10.0	7.6	6.3	7.8	4.7	4.9	0.2	-1.4	-14.7	-13.0
Deciles	6	6.6	14.6	10.2	7.7	7.2	3.7	5.8	3.5	6.8	5.8	8.0	-6.6	-5.0
	7	5.6	6.3	9.0	9.6	6.6	11.1	5.1	5.6	4.6	3.0	-1.4	-7.7	-7.0
	8	2.7	8.6	8.3	2.0	6.0	4.7	5.8	-3.1	1.6	9.0	-4.5	-13.1	-6.0
	9	11.9	17.3	16.7	13.1	16.4	7.5	11.4	9.1	9.5	11.0	4.1	-13.2	-9.0
Positive	10	8.2	16.6	15.3	10.1	12.8	8.7	8.8	7.5	7.3	3.7	2.1	-14.4	-13.0
(10 - 1)		8.0	9.9	-10.2	2.7	9.3	7.5	12.1	9.5	1.1	21.1	26.8		
(10 + 9) - (1 + 2)		8.4	8.9	-0.4	6.4	10.5	5.2	9.7	9.0	6.3	19.3	17.6		

Table 2.7: Fundamental Characteristics (FY_t) for Book-to-Price Sorted Portfolios, Average Values 1952 to 2019. Data from *CRSP* & *Compustat*.

			Growth				*Growth & Value Deciles*					Value	V - G	t-stat
		All	1	2	3	4	5	6	7	8	9	10	10-1	
							Values in %							
Revenue	μ	5.9	13.9	11.3	9.4	6.8	5.7	6.0	4.9	3.5	2.0	-0.2	-14.1	-8.91
Growth, %	σ	5.9	8.7	7.7	6.9	6.3	7.4	8.0	6.7	7.6	7.6	9.7	11.2	-
Gross	μ	29.5	39.5	35.8	33.1	30.6	29.4	28.1	28.4	25.6	24.9	23.9	-15.6	-12.85
Margin, %	σ	3.7	7.7	6.3	5.6	5.0	4.7	4.2	4.5	4.6	5.3	6.4	8.1	-
Operating	μ	12.0	14.8	13.8	13.8	12.6	11.8	11.7	11.8	10.4	8.8	9.4	-5.4	-7.71
Margin, %	σ	1.5	3.0	2.3	2.8	2.4	2.2	2.8	3.5	2.9	3.2	5.0	5.4	-
Net	μ	5.7	8.0	7.7	7.2	6.5	5.9	5.7	5.3	4.6	2.9	1.0	-7.2	-5.89
Margin, %	σ	1.7	2.3	2.0	2.3	1.6	1.5	1.4	1.8	2.4	3.6	9.8	4.1	-
Asset to	μ	183	99	116	136	157	173	199	230	225	251	271	172	5.60
Revenue	σ	67	21	40	64	92	88	101	118	121	203	252	247	-
Assets to	μ	353	266	272	292	321	349	360	401	399	411	369	104	3.56
Equity	σ	132	116	117	138	158	169	168	181	193	237	211	141	-
Revenue	α	-	0.10	0.09	0.04	0.02	-0.01	-0.01	-0.01	-0.03	-0.04	-0.07	-	-
Sensitivity	s.e.	-	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	-	-
	β	-	0.61	0.55	0.97	0.91	1.08	1.15	0.93	1.11	1.07	1.17	-	-
	s.e.	-	0.17	0.10	0.08	0.07	0.08	0.09	0.08	0.08	0.09	0.14	-	-
	R^2	-	0.17	0.32	0.70	0.72	0.72	0.72	0.72	0.74	0.69	0.51	-	-

Table 2.8: Fundamental Characteristics (FY_{t+1}) for Book-to-Price Sorted Portfolios, Average Values 1952 to 2019. Data from *CRSP & Compustat*.

			Growth				*Growth & Value Deciles*					Value	V - G	t-stat
		All	1	2	3	4	5	6	7	8	9	10	10-1	
							Values in %							
Revenue	μ	5.9	12.2	10.3	7.5	6.8	6.2	5.4	4.1	4.8	3.0	1.4	-10.8	-8.4
Growth, %	σ	6.0	6.4	7.1	6.4	7.3	6.9	8.3	7.3	6.9	8.0	8.4	8.6	-
Gross	μ	29.8	39.5	35.9	32.9	30.5	29.2	28.3	28.4	25.3	25.6	25.0	-14.5	-12.7
Margin, %	σ	3.6	7.2	6.1	5.9	4.9	4.6	3.8	4.6	4.8	5.5	6.1	7.6	-
Operating	μ	12.0	14.4	13.6	13.6	12.4	11.6	11.7	11.5	10.3	9.5	10.5	-4.0	-6.5
Margin, %	σ	1.6	3.0	2.5	2.8	2.5	2.3	2.6	3.5	3.0	3.9	4.0	4.1	-
Net	μ	5.7	7.5	7.3	7.1	6.3	5.8	5.6	4.8	4.4	3.5	3.1	-5.9	-8.59
Margin, %	σ	1.8	3.2	2.5	2.4	1.7	1.6	1.3	2.8	2.7	3.3	4.7	3.2	-
Asset to	μ	185	102	117	139	160	175	203	234	226	256	273	171	5.32
Revenue	σ	69	23	40	68	96	90	102	118	124	211	264	258	-
Assets to	μ	359	263	274	299	328	356	369	414	407	418	381	118	4.1
Equity	σ	135	107	114	143	165	176	176	189	198	235	213	137	-
Revenue	α	-	0.09	0.05	0.02	0.01	0.01	-0.02	-0.02	-0.01	-0.03	-0.05	-	-
Sensitivity	s.e.	-	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	-	-
	β	-	0.50	0.85	0.89	1.00	0.99	1.23	1.05	0.98	1.02	1.10	-	-
	s.e.	-	0.12	0.11	0.07	0.09	0.07	0.08	0.08	0.08	0.11	0.12	-	-
	R^2	-	0.22	0.50	0.69	0.67	0.73	0.78	0.74	0.72	0.58	0.51	-	-

Table 2.9: Capitalization-Weighted Annualized Excess Returns for Sorted Value and Growth Portfolios, January 1952 to December 2019. All return data from Ken French's website. Stocks are sorted into decile portfolios in June of each year based on earnings-to-price (E/P), cashflow-to-price (C/P), dividend-to-price (D/P) or book-to-market ratio (B/M) using fiscal year-end fundamental data from the prior calendar year, and calendar year-end prices. Simple annualization is used (mean monthly returns are multiplied by 12, and standard deviations by the square root of 12. Risk free rate is the one-month treasury bill rate.

Metric	**Growth** 1	2	3	4	5	*Growth & Value Deciles* 6	7	8	9	**Value** 10	'52-'19 V-G	'10-'19 V-G
					Panel A: Mean Excess Returns (% per year)							
E/P	6.90	6.01	7.46	7.24	7.57	9.01	9.81	10.41	11.35	11.98	5.08	-5.52
C/P	6.74	7.32	6.91	7.64	8.13	8.64	9.05	9.51	10.16	11.62	4.88	-6.40
D/P	7.25	6.92	7.50	8.33	7.21	8.24	8.37	9.22	8.57	7.74	0.48	2.34
B/M	6.78	7.62	7.81	7.46	8.17	8.82	7.44	9.70	10.53	10.81	4.02	-5.52
					Panel B: Standard Deviation (% per year)							
E/P	18.82	15.68	14.98	14.64	14.89	14.54	14.76	15.43	16.30	17.76	14.09	11.26
C/P	18.41	15.63	15.08	15.01	15.24	15.02	14.75	15.06	15.31	17.87	14.1	12.94
D/P	19.05	16.89	16.25	15.56	15.63	14.62	14.42	13.86	14.03	15.06	17.08	14.20
B/M	16.99	15.46	15.18	15.34	14.85	14.46	15.39	15.82	16.66	20.40	15.49	15.57
					Panel C: Standard Error of Mean Return							
E/P	0.65	0.54	0.52	0.51	0.52	0.51	0.51	0.54	0.57	0.62	0.49	0.98
C/P	0.64	0.54	0.52	0.52	0.53	0.52	0.51	0.52	0.53	0.62	0.49	1.13
D/P	0.66	0.59	0.56	0.54	0.54	0.51	0.50	0.48	0.49	0.52	0.59	1.24
B/M	0.59	0.54	0.53	0.53	0.52	0.50	0.54	0.55	0.58	0.71	0.54	1.36
					Panel D: Sharpe Ratio							
E/P	0.37	0.38	0.50	0.49	0.51	0.62	0.66	0.67	0.70	0.67	0.36	-0.49
C/P	0.37	0.47	0.46	0.51	0.53	0.51	0.61	0.63	0.66	0.65	0.35	-0.49
D/P	0.38	0.41	0.46	0.50	0.46	0.56	0.58	0.66	0.61	0.51	0.03	0.17
B/M	0.40	0.49	0.51	0.49	0.55	0.61	0.48	0.61	0.63	0.53	0.26	-0.35

Table 2.10: Equal-Weighted Annualized Excess Returns for Sorted Value and Growth Portfolios, January 1952 to December 2019. All return data from Ken French's website. Stocks are sorted into decile portfolios in June of each year based on earnings-to-price (E/P), cashflow-to-price (C/P), dividend-to-price (D/P) or book-to-market ratio (B/M) using fiscal year-end fundamental data from the prior calendar year, and calendar year-end prices. Simple annualization is used (mean monthly returns are multiplied by 12, and standard deviations by the square root of 12. Risk free rate is the one-month treasury bill rate.

Metric	**Growth**				*Growth & Value Deciles*					**Value**	'52-'19	'10-'19
	1	2	3	4	5	6	7	8	9	10	V-G	V-G
					Panel A: Mean Excess Returns (% per year)							
E/P	7.21	8.89	9.06	9.69	10.19	10.84	11.52	12.24	13.37	14.53	7.32	-1.96
C/P	6.88	8.25	9.43	9.98	10.67	11.13	12.43	12.45	13.59	14.81	7.94	-4.37
D/P	9.23	10.49	10.15	10.76	10.89	10.75	11.10	11.31	10.31	8.97	-0.25	-1.53
B/M	4.79	7.41	8.83	9.77	10.23	10.55	11.94	12.02	13.59	14.90	10.11	-1.20
					Panel B: Standard Deviation (% per year)							
E/P	21.65	18.91	17.69	16.76	16.55	16.04	15.94	16.26	16.90	19.40	9.86	7.43
C/P	21.41	18.71	17.37	16.56	16.40	16.28	16.47	16.56	18.02	19.79	10.53	9.16
D/P	19.43	17.64	16.80	16.52	15.94	15.39	14.67	14.27	13.70	15.06	12.59	8.63
B/M	23.49	20.51	19.28	18.81	18.01	17.53	17.25	17.44	18.14	21.38	13.57	12.09
					Panel C: Standard Error of Mean Return							
E/P	0.75	0.66	0.61	0.58	0.58	0.56	0.55	0.57	0.59	0.67	0.34	0.62
C/P	0.74	0.65	0.60	0.58	0.57	0.57	0.57	0.58	0.63	0.59	0.37	0.76
D/P	0.68	0.61	0.58	0.57	0.55	0.53	0.51	050	0.48	0.52	0.44	0.72
B/M	0.82	0.71	0.67	0.65	0.63	0.61	0.60	0.61	0.63	0.74	0.47	1.01
					Panel D: Sharpe Ratio							
E/P	0.33	0.47	0.51	0.58	0.63	0.68	0.72	0.75	0.79	0.75	0.74	-0.26
C/P	0.32	0.44	0.54	0.60	0.65	0.68	0.75	0.75	0.75	0.75	0.75	-0.48
D/P	0.47	0.59	0.60	0.65	0.68	0.70	0.76	0.79	0.75	0.60	-0.02	-0.18
B/M	0.20	0.36	0.46	0.52	0.57	0.60	0.69	0.69	0.75	0.70	0.75	-0.10

Table 2.11: *CAPM* Regressions for Sorted Portfolios, January 1952 to December 2019. All return data from Ken French's website. For each valuation ratio and for each decile portfolio, I run an OLS regression of the monthly excess return on the portfolio on the monthly excess return on the market. Simple annualization is used (mean monthly returns are multiplied by 12, and standard deviations by the square root of 12. Risk free rate is the one-month treasury bill rate.

	Growth				*Growth & Value Deciles*					**Value**	1952 - 2019
	1	2	3	4	5	6	7	8	9	10	V-G
					Book-to-Market						
α	-1.12	0.27	0.60	0.32	1.40	2.35	0.64	2.80	3.26	2.41	3.53
s.e.	0.75	0.57	0.56	0.68	0.74	0.78	0.87	0.94	0.99	1.41	1.90
β	1.07	1.00	0.98	0.97	0.92	0.88	0.92	0.94	0.99	1.14	0.07
s.e.	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.03	0.04
R^2	0.87	0.91	0.91	0.87	0.84	0.80	0.79	0.77	0.77	0.68	0.00
					Earnings-to-Market						
α	-1.67	-1.37	0.54	0.51	0.69	2.55	3.19	3.66	4.30	4.35	6.02
s.e.	0.94	0.64	0.69	0.69	0.69	0.78	0.91	0.94	1.00	1.10	1.71
β	1.16	1.00	0.94	0.91	0.93	0.89	0.90	0.92	0.96	1.04	-0.13
s.e.	0.02	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.03
R^2	0.83	0.89	0.86	0.86	0.85	0.86	0.81	0.77	0.75	0.74	0.02
					Cashflow-to-Market						
α	-1.81	0.01	-0.10	0.66	1.12	0.85	2.57	2.95	3.50	4.12	5.92
s.e.	0.86	0.65	0.67	0.68	0.73	0.81	0.86	0.90	0.91	1.16	1.71
β	1.15	1.00	0.95	0.95	0.95	0.91	0.88	0.89	0.91	1.03	-0.12
s.e.	0.02	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.03
R^2	0.86	0.89	0.87	0.87	0.85	0.81	0.77	0.76	0.76	0.72	0.02
					Dividend-to-Price						
α	-1.54	-1.00	-0.04	1.21	0.20	1.74	1.97	3.27	2.92	2.69	4.24
s.e.	0.88	0.71	0.73	0.76	0.83	0.82	0.80	0.87	1.02	1.37	1.88
β	1.20	1.08	1.02	0.97	0.95	0.88	0.87	0.81	0.77	0.69	-0.51
s.e.	0.02	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.03	0.04
R^2	0.86	0.88	0.87	0.84	0.81	0.79	0.79	0.74	0.65	0.45	0.19

Table 2.12: Rolling 250-day *CAPM* Beta of Growth & Value Portfolio (Book-to-Market Sorting). All data from Ken French. Rolling standard OLS *CAPM* regressions using trailing 250 trading day excess returns.

	1952 - 2019		*1952 - 2008*		*2008 - 2019*	
	Value Beta	Growth Beta	Value Beta	Growth Beta	Value Beta	Growth Beta
Mean	1.09	1.12	1.03	1.15	1.37	0.98
Std. D.	0.26	0.12	0.23	0.10	0.21	0.12

Table 2.13: Contributions to the Mean Annual Value Premium from Growth & Value Portfolios, July 1926 - December 2019.

Data from Ken French. Sorts based on book-to-market ratio. Simple annualization of mean monthly returns.

	Cap-Weighted Mean Return, %			**Equal-Weighted Mean Return, %**		
Period	Growth	CRSP Index	Value	Growth	CRSP Index	Value
1926 - 2019	10.58	11.28	15.76	9.26	11.28	22.66
1952 - 2019	10.92	11.49	14.94	8.92	11.49	19.04

Table 2.14: Equal-Weighted, Buy-and-Hold Returns for Sorted Portfolios Over Multiple Holding Periods, 1952 - 2019 (Overlapping Data). . Book-to-Market sorts. Data from CRSP & Compustat.

Year	Growth				*Growth & Value Deciles*					Value	V-G
	1	2	3	4	5	6	7	8	9	10	
					Mean Returns %						
1	10.28	11.76	13.10	13.92	13.81	15.06	15.73	16.83	18.09	17.96	7.69
2	9.77	12.89	13.72	14.19	15.07	15.88	16.65	16.94	18.67	20.58	10.81
3	10.18	13.72	13.04	14.95	15.16	14.82	15.64	16.52	17.46	18.88	8.70
4	10.88	12.47	12.66	12.96	14.10	14.97	15.02	15.04	16.95	18.28	7.40
5	11.57	11.96	11.96	13.25	13.99	14.28	14.95	15.77	16.94	17.80	6.23
6	11.90	12.25	13.56	12.30	13.35	13.82	14.26	15.75	15.79	17.95	6.04
7	12.04	13.79	13.26	12.78	13.41	13.26	14.80	15.34	15.14	17.30	5.27
8	12.22	12.24	13.81	12.79	13.04	13.94	14.53	13.90	14.64	14.68	2.46
9	11.80	12.40	13.56	14.11	13.32	14.56	12.87	15.32	14.38	13.92	2.11
10	12.39	13.69	12.34	13.07	13.79	13.21	13.56	15.42	13.41	12.69	0.30
					Standard Deviations %						
1	27.30	24.59	23.54	21.83	21.21	19.90	19.75	21.83	23.78	25.69	-1.61
2	26.54	24.02	22.27	21.93	21.78	21.77	21.10	20.17	22.18	26.07	-0.47
3	25.52	23.76	22.45	21.65	21.22	20.86	21.17	22.91	23.34	26.41	0.89
4	24.87	22.25	22.12	20.20	20.89	20.76	20.74	21.92	24.18	25.10	0.24
5	24.37	22.32	20.61	21.23	20.30	21.72	22.33	21.12	23.92	24.11	-0.26
6	23.38	21.57	22.32	20.61	21.59	20.14	22.09	23.22	24.35	26.38	3.00
7	22.11	22.43	20.81	19.99	20.52	20.47	21.98	22.33	25.48	25.71	3.61
8	21.98	21.14	22.09	20.15	19.30	20.21	21.22	21.44	23.25	26.77	4.79
9	20.76	20.17	19.90	21.66	19.04	20.19	20.15	22.77	24.47	26.07	5.32
10	21.59	19.97	18.95	19.35	19.91	20.08	20.79	23.06	22.72	25.48	3.90

Table 2.15: Equal-Weighted, Buy-and-Hold Returns for Sorted Portfolios Over Multiple Holding Periods, 1952 - 2019 (Non-Overlapping Data). Book-to-Market sorts. Data from CRSP & Compustat.

Year	Growth				*Growth & Value Deciles*					Value	V-G
	1	2	3	4	5	6	7	8	9	10	
					Mean Returns, %						
1	10.28	11.76	13.10	13.92	13.81	15.06	15.73	16.83	18.09	17.96	7.69
2	4.84	8.38	8.58	9.12	9.79	11.06	12.91	12.46	15.48	15.85	11.01
3	2.76	7.56	5.28	6.48	7.12	7.48	9.95	10.04	9.99	9.82	7.06
4	11.15	12.26	8.79	11.48	11.99	11.13	11.71	11.50	11.86	13.58	2.43
5	1.86	3.77	5.52	4.06	11.11	9.19	8.51	11.10	10.97	10.24	8.38
6	1.24	3.42	7.44	5.54	4.45	4.73	2.72	4.85	6.52	7.89	6.66
7	11.33	9.61	6.04	7.86	4.94	7.41	13.37	11.29	5.68	14.71	3.38
8	5.45	3.93	9.52	4.83	3.64	5.71	7.07	6.64	7.34	9.44	3.98
9	5.52	4.67	6.29	5.91	5.69	7.54	7.18	8.06	11.51	7.24	1.72
10	-5.14	-5.46	-3.49	-3.81	-5.78	3.91	-3.95	-0.41	-0.43	-8.82	-3.68
					Standard Deviations, %						
1	27.30	24.59	23.54	21.83	21.21	19.90	19.75	21.83	23.78	25.69	-1.61
2	25.88	21.35	19.86	18.23	17.92	17.51	19.18	17.57	19.90	23.89	-2.00
3	23.48	23.37	20.35	19.33	19.95	19.12	21.87	21.24	21.54	24.18	0.70
4	26.28	18.67	15.61	14.76	16.03	13.44	15.90	14.90	16.26	21.07	-5.21
5	20.52	13.78	13.01	15.38	17.48	14.54	14.56	13.06	13.16	13.79	-6.74
6	18.48	19.79	23.76	16.16	16.82	17.20	16.96	18.77	22.90	21.94	3.46
7	22.48	21.76	25.55	19.67	22.76	20.48	24.62	22.74	25.57	31.01	8.53
8	21.43	18.01	17.38	10.57	14.00	14.23	15.42	16.98	17.69	20.22	-1.21
9	14.99	18.45	18.52	18.10	17.95	22.18	19.30	18.78	23.32	24.13	9.13
10	13.88	16.03	13.06	14.20	12.61	16.10	14.44	15.51	17.61	16.17	2.29

Table 2.16: Equal-Weighted, Buy-and-Hold Returns for Sorted Portfolios Over Multiple Holding Periods, 1952 - 2019 (Overlapping Data). Equal-weighting reapplied each month. Book-to-Market sorts. Data from CRSP & Compustat.

Year	Growth				*Growth & Value Deciles*					Value	V-G
	1	2	3	4	5	6	7	8	9	10	
					Mean Returns, %						
1	13.32	12.56	13.74	14.97	14.93	16.05	17.20	19.38	19.98	21.35	8.03
2	10.34	14.07	14.39	15.87	16.34	16.83	18.39	19.66	21.45	23.93	13.59
3	13.91	15.68	15.42	17.12	17.11	16.93	17.34	19.36	21.58	22.75	8.84
4	13.94	15.17	15.53	14.97	15.77	17.03	17.44	17.87	20.25	24.11	10.17
5	14.04	14.31	15.57	15.39	16.19	16.85	17.23	18.82	21.08	23.11	9.07
6	14.11	14.34	15.58	15.73	16.56	17.42	17.98	20.08	19.12	22.32	8.21
7	14.08	16.75	16.71	15.50	17.03	17.10	18.31	18.57	20.12	22.04	7.96
8	13.71	15.01	16.89	15.43	16.75	17.24	17.61	18.52	17.72	20.27	6.56
9	13.57	16.03	17.21	17.69	16.93	18.59	16.31	18.62	18.28	18.90	5.33
10	16.33	17.60	16.44	17.79	16.98	17.73	15.86	18.81	17.45	17.06	-0.73

Table 2.17: Total Returns for Russell Style Indices During Sharp Market Declines (2000-2020). Data from FTSE Russell.

	03/26/2000 - 09/17/2001	09/14/2008 - 02/28/2009	02/10/2020 - 03/23/2020
Russell 1000	-31.9%	-40.7%	-33.3%
Russell 1000 Growth	-51.6%	-37.6%	-29.4%
Russell 1000 Value	-6.5%	-43.9%	-37.6%
Russell 2000	-26.1%	-45.5%	-39.4%
Russell 2000 Growth	-51.9%	-43.7%	-36.6%
Russell 2000 Value	16.8%	-47.2%	-42.4%

Table 2.18: Multi-Horizon Equal-Weighted Buy-and-Hold Returns for Growth and Value Portfolios Formed Each June with Gestation Conditioning, 1952 - 2019 (Overlapping Data). Book-to-Market sorts. Data from CRSP & Compustat.

Horizon			*Growth - Decile 1 Gestation - # years*					*Value - Decile 10 Gestation - # years*		
Year	1	2	3	4	5		1	2	3	4	5
					Mean Annual Returns, %					
1	8.71	10.43	7.98	8.41	10.69	12.63	19.70	16.48	18.34	19.33
2	9.29	7.10	7.39	8.58	10.46	23.63	16.33	18.07	22.00	20.17
3	9.30	10.26	7.88	9.03	10.73	15.93	16.77	21.87	19.99	19.40
4	9.84	8.63	6.95	12.42	10.51	15.29	15.48	20.71	20.59	17.22
5	11.77	11.31	10.05	13.97	8.95	15.22	19.75	15.78	19.05	16.54
6	11.97	11.95	13.57	8.95	10.59	15.93	17.37	19.52	16.74	16.47
7	12.03	11.08	10.81	12.69	11.66	15.29	19.96	14.27	16.90	15.85
8	12.83	8.35	11.93	10.89	11.69	12.01	14.42	20.14	15.93	14.00
9	7.76	10.81	14.87	12.30	10.78	17.98	23.56	11.23	11.91	13.73
10	13.20	13.01	13.39	12.21	11.96	20.76	14.03	12.32	12.93	13.04
					Standard Deviations, %					
1	32.70	30.20	28.42	29.70	21.53	29.86	33.34	29.19	26.14	24.25
2	32.52	30.58	32.00	25.48	20.93	36.02	32.56	27.13	33.65	25.04
3	30.78	29.70	27.46	27.85	21.68	36.98	27.40	34.84	28.21	24.73
4	30.81	29.6	26.20	26.59	20.59	25.97	29.02	30.93	28.74	23.33
5	33.83	29.29	25.84	25.62	19.77	25.99	26.94	27.51	31.02	22.44
6	31.53	28.19	23.65	16.60	18.49	29.85	31.15	30.90	31.18	24.49
7	29.53	26.06	23.63	26.11	16.50	28.81	27.40	26.60	25.19	22.90
8	28.81	26.67	22.82	26.49	16.69	27.98	26.07	34.61	34.34	23.40
9	29.07	22.55	24.44	24.54	16.69	37.17	38.34	29.78	26.12	23.29
10	30.87	25.12	24.85	23.78	17.85	35.80	45.58	27.14	28.28	22.19

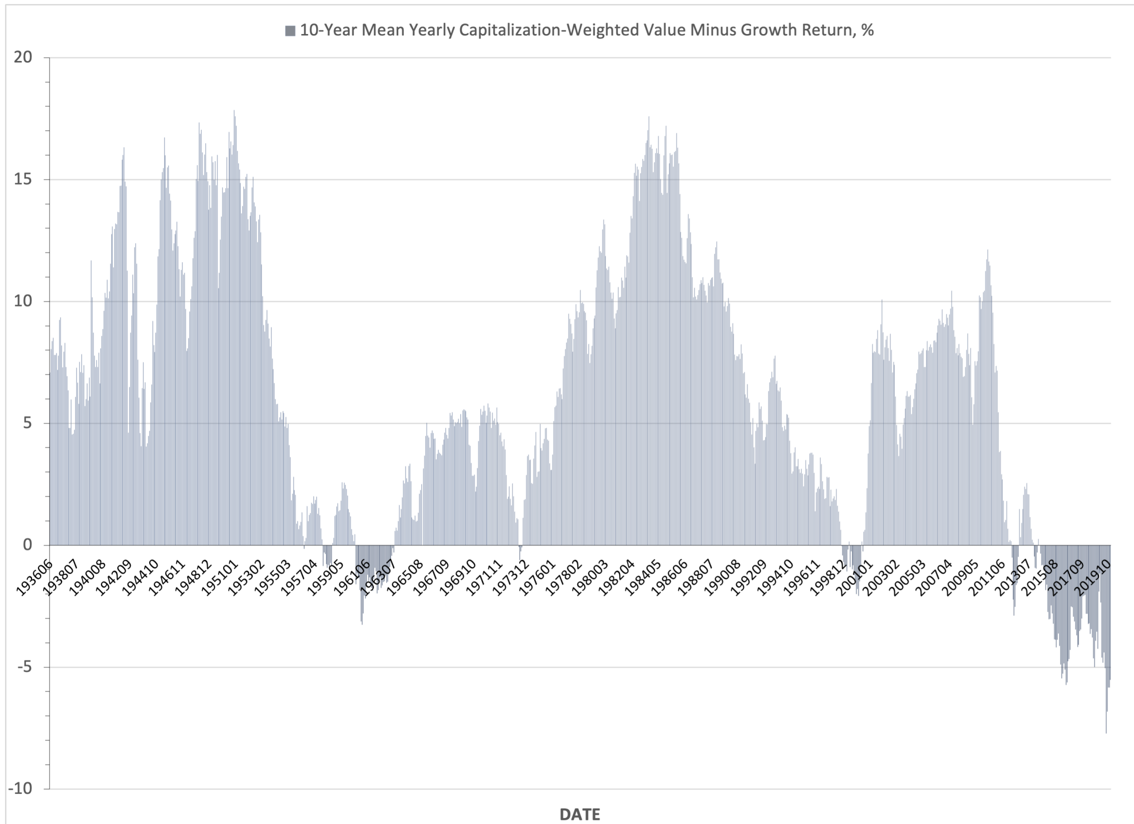

Figure 2.1: Rolling 10-Year Mean Cap-Weighted Value Minus Growth Returns, June 1936 to December 2019. Book-to-market sorts only. Data from Ken French

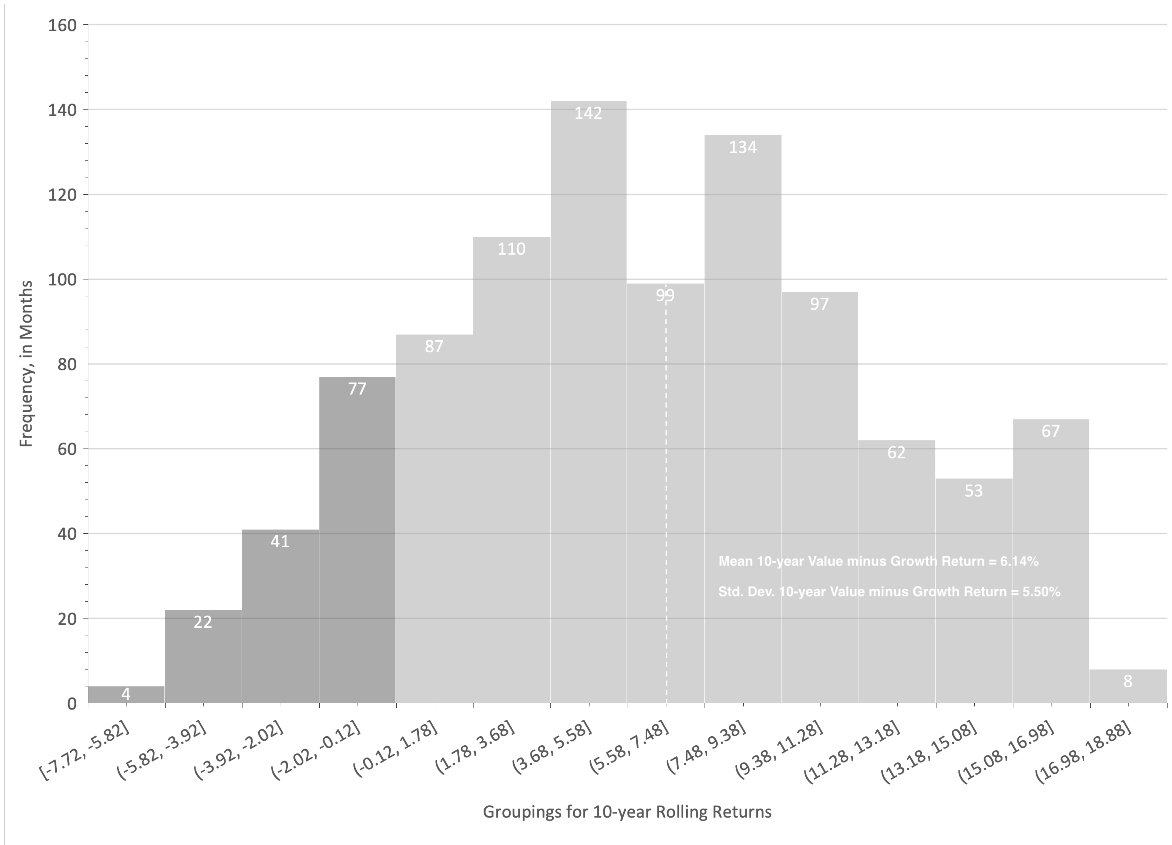

Figure 2.2: Histogram of Rolling 10-Year Mean Cap-Weighted Value Minus Growth Returns, June 1936 to December 2019. Book-to-market sorts only. Data from Ken French

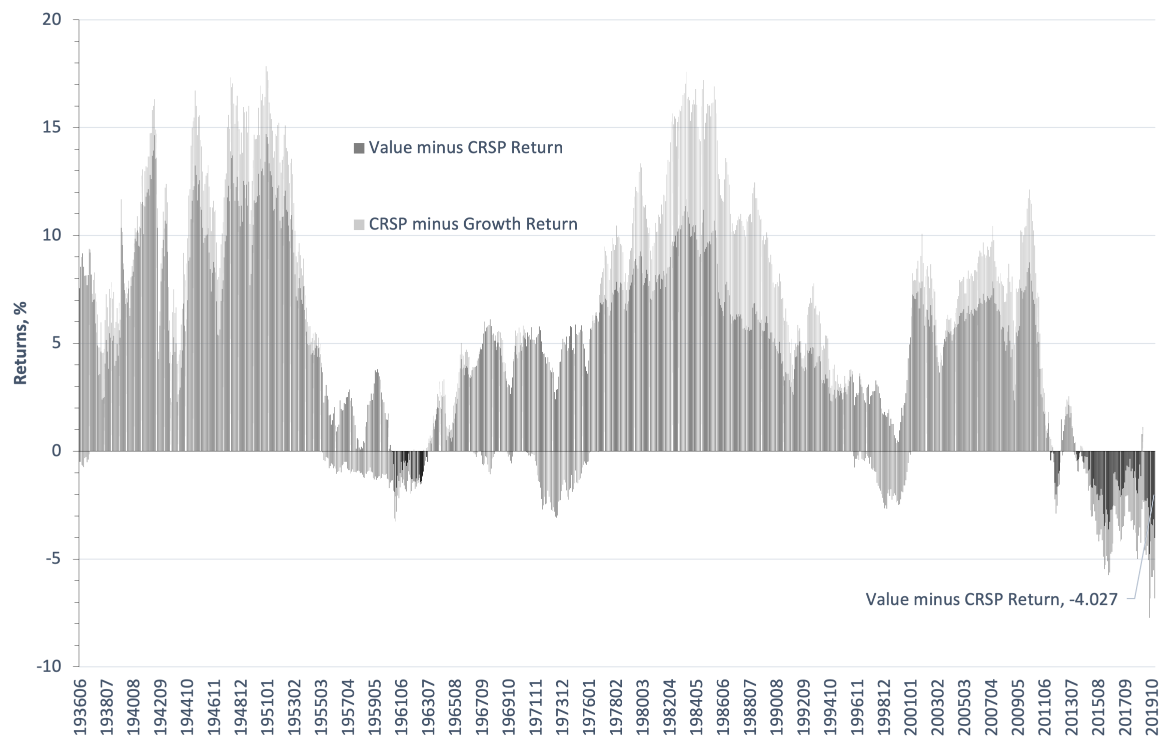

Figure 2.3: Rolling 10-Year Contributions of Value and Growth Returns to the Value Premum, June 1936 to December 2019. Book-to-market sorts only. Data from Ken French

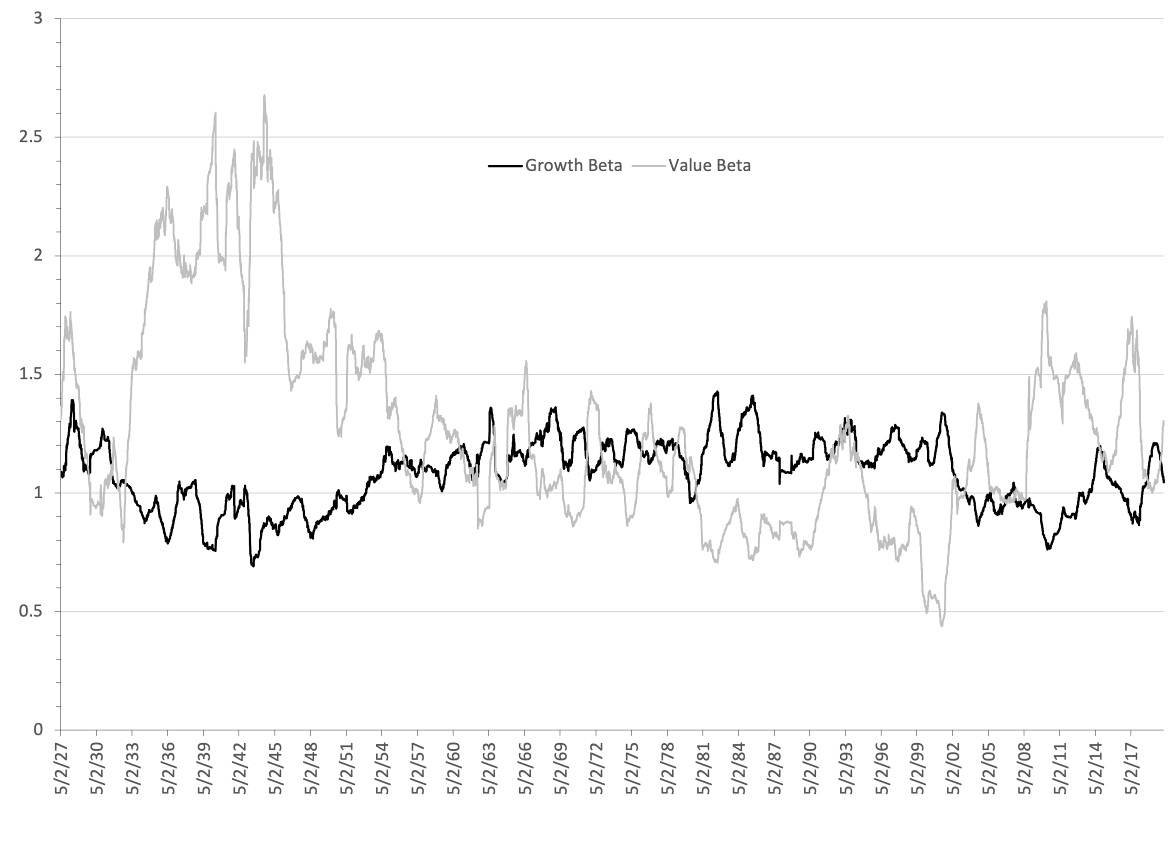

Figure 2.4: Rolling 250-day *CAPM* Beta of Cap-Weighted Growth, Value Portfolios to Cap-Weighted CRSP Index, 1926 to 2019. Book-to-market sorts. Data from Ken French

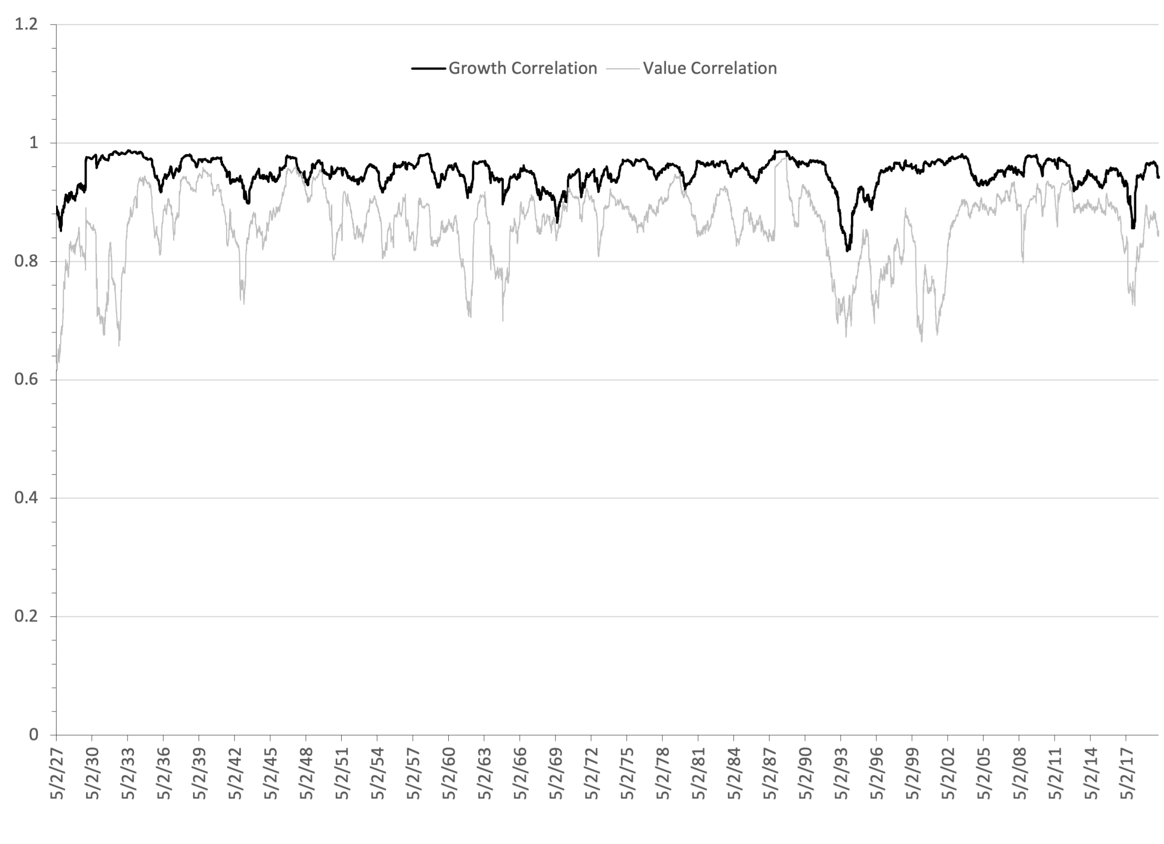

Figure 2.5: Rolling 250-day Correlation of Cap-Weighted Growth, Value Portfolios to Cap-Weighted CRSP Index, 1926 to 2019. Book-to-market sorts. Data from Ken French