Is Value Riskier Than Growth?

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Abstract

Yes! We study the time-varying risk patterns of value and growth stocks across business cycles. We find that the conditional market betas of value stocks covary positively with the expected market risk premium, and that value stocks are riskier than growth stocks in bad times when the expected market risk premium is high. The opposite is true for growth stocks. Methodologically, we measure time-varying risk by sorting conditional betas on the theoretically justified *expected* market risk premium, instead of the *ex post* realized market excess return. Our findings lend support to the predictions of recent rational asset pricing theory.

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1 Introduction

Are value stocks riskier than growth stocks? This question is at the crux of the ongoing debate on the exact economic interpretation of the value premium between rational asset pricing and behavioral finance.

Theoretically, the optimal investment model constructed in Zhang (2002) predicts that the conditional beta dispersion between value and growth is *asymmetric* across business cycles, i.e., it is positive in bad times but negative in good times.[1] The combination of asymmetric beta dispersion and countercyclical expected risk premium can potentially explain the coexistence of a high average value premium and a low unconditional beta dispersion between value and growth in a risk-based paradigm.

Empirically, while the countercyclicality of the expected market risk premium has long been established in the time series predictability literature, e.g., Fama and French (1989) and Ferson and Harvey (1991), the existence of the cyclical property of risk dispersion between value and growth is much more controversial. In fact, the bulk of the current literature has delivered a negative verdict on this issue. In a well-known study, Lakonishok, Shleifer, and Vishny (1994) conclude that "value strategies yield higher returns because these strategies exploit the suboptimal behavior of the typical investor and not because these strategies are fundamentally riskier." Subsequent studies reaching similar conclusions include La Porta (1996) and La Porta, Lakonishok, Shleifer, and Vishny (1997).

There is also a voluminous literature on predictive asymmetry in the second moments of stock returns using variants of the GARCH framework. Braun, Nelson, and Sunier (1995) report strong evidence of asymmetry in conditional volatilities, but weak or negligible evidence of asymmetry in conditional betas. Bekaert and Wu (2000) also report that

[1]Zhang (2002) demonstrates that, in a neoclassical framework, asymmetric risk dispersion can be driven by asymmetry in capital adjustment technology. Specifically, (i) the ability of adjusting capital allows companies to smooth dividends in the presence of exogenous shocks. The more flexibility companies have in this regard, the less business risk they face; (ii) In bad times, all companies want to scale back their productive capacity. This is especially true for value companies, as they are more inefficient than growth firms to begin with. Since adjusting capital downwards is difficult, the dividend streams of value companies will covary more with economic downturns; (iii)In good times, however, it is the growth companies' turn to face less flexibility, as the adjustment cost associated with expanding capacity is positive, albeit small. For value companies, investing is less urgent since their previously unproductive assets now become more efficient.

conditional betas do not show much asymmetry or time-variation. Cho and Engle (1999), on the other hand, find some evidence of asymmetric betas by applying the EGARCH model to daily individual stock data, and attribute their different results to the lack of cross-sectional variation in the sample used by Braun, Nelson, and Sunier (1995).[2] Outside the GARCH framework, Ang and Chen (2002) and Ang, Chen, and Xing (2002) examine downside and upside betas conditional on falling and rising markets. After finding that conditional betas defined this way exhibit little asymmetry relative to conditional correlations, they turn to downside correlation for a measure of asymmetric risk.

The current state of affairs concerning the relative risk of value and growth can perhaps be best summarized in Cochrane (2001). Cochrane asks: "what are the macroeconomic risks for which the Fama-French factors are proxies or mimicking portfolios?" and suggests that "there are hints of some sort of 'distress' or 'recession' factor at work." However, he also concedes that "unfortunately, empirical support for this theory is weak, since the HML portfolio does not covary strongly with other measures of aggregate financial distress." In fact, the evidence that value is not riskier than growth across all states of market performance, documented in Lakonishok, Shleifer, and Vishny (1994), has been hailed as substantiating an overreaction explanation of the value premium. For example, Shleifer (2000 page 19) asserts that: "Consistent with overreaction, ..., historically, portfolios of companies with high market to book ratios have earned sharply lower returns than those with low ratios. Moreover, high market to book portfolios appear to have higher market risk than do low market to book portfolios, and perform particularly poorly in extreme down markets and in recessions (Lakonishok *et al.* 1994)."[3]

In this article, we use a different econometric method to study the time-varying risk patterns of value and growth strategies. We sort conditional betas on the theoretically justified *expected* market risk premium, as opposed to *ex post* realized market excess return. Most previous studies utilize this latter, *ad hoc*, procedure either explicitly or implicitly.[4]

[2]As we show later, this is consistent with our point. Since value and growth portfolio betas react in opposite directions to changes of the expected market risk premium, a mixture of value and growth, such as the industry portfolios used by Braun, Nelson, and Sunier (1995), will weaken the time-variation of betas.

[3]Other well-known examples include Shiller (1999), Hirshleifer (2001), Barberis and Thaler (2002), and Daniel, Hirshleifer and Teoh (2002).

[4]Section V of Lakonishok, Shleifer, and Vishny (1994) uses this procedure explicitly. Braun, Nelson, and

We document that the conditional market betas of value stocks covary positively with the expected market risk premium, and that value stocks are riskier than growth stocks in bad times when the expected market risk premium is high. Conversely, growth portfolio betas covary negatively with the expected market risk premium, and growth stocks are riskier than value stocks in good times when the expected market risk premium is low.

We also illustrate why previous studies fail to unearth such asymmetric beta patterns. The reason lies in the fact that the ex post realized market excess return is largely correlated with its own unexpected component and less so with the expected market risk premium, which is driven by business cycle fluctuations.[5] Therefore, the procedure of using the realized market excess return as a measure of the state of the economy suffers from attenuation, which biases the estimates of the business cycle sensitivities of value and growth portfolio betas towards zero.[6]

To the best of our knowledge, the only other paper that documents similar cyclical patterns of risk for value and growth stocks is Lettau and Ludvigson (2001). Using the log consumption-wealth ratio as a conditioning variable, they show that value stocks are riskier than growth stocks because their returns are more highly correlated with consumption growth when risk or risk aversion is high. However, their use of consumption-wealth ratio has recently been brought into question by Brennan and Xia (2002).[7] Our paper differs

Sunier (1995) specify the conditional beta for portfolio p, β_{pt}, as:

$$\beta_{pt} = \alpha_\beta + \delta_\beta[\beta_{pt} - \alpha_\beta] + \lambda_p z_{pt} + \lambda_m z_{mt}$$

where z_{mt} and z_{pt} are standardized residuals for the market portfolio and portfolio p, respectively. When $\lambda_m < 0$, the term $\lambda_m z_{mt}$ allows for the asymmetry in conditional beta with respect to one-period-lagged shocks on the market return. Bekaert and Wu (2000) and Cho and Engle (1999) use a similar definition of beta asymmetry. Ang and Chen (2002) and Ang, Chen, and Xing (2002) define downside beta β^- and upside beta β^+ as, respectively,

$$\beta_i^- = \frac{\text{Cov}(r_{it}, r_{mt} | r_{mt} < \overline{r}_m)}{\text{Var}(r_{mt} | r_{mt} < \overline{r}_m)} \qquad \text{and} \qquad \beta_i^+ = \frac{\text{Cov}(r_{it}, r_{mt} | r_{mt} > \overline{r}_m)}{\text{Var}(r_{mt} | r_{mt} > \overline{r}_m)}$$

where r_{it} and r_{mt} are portfolio and market excess returns, respectively, and $\overline{r}_m$ denotes average market excess return.

[5]That ex post realized market excess returns generally do not have substantial in-sample predictive content for future output growth is documented in Fama (1981), Harvey (1989), and Stock and Watson (1989, 1999), among others.

[6]Attenuation arises in a univariate regression when the correlation between the regressor and the residual is not zero. See, for example, Green (1997), page 437.

[7]The debate is still ongoing. See Lettau and Ludvigson (2002).

from Lettau and Ludvigson (2001) in two important aspects. First, our empirical method is different, as we use a set of usual conditioning variables from the time series predictability literature. Second, our definition of risk is different, as we focus on *market* beta, instead of *consumption* beta as in Lettau and Ludvigson (2001).[8]

Our paper carries implications for a range of important issues. First, our results lend support to the proposition that the Fama and French (1993) book-to-market and size factors, HML and SMB, need not be mysterious, independent risk factors, but are better proxies of unconditional factors for conditional market or macroeconomic risk.[9]

Second and perhaps more importantly, we show that the *expected* market risk premium, not the *ex post* realized market excess return, should be used to measure the state of the economy and the time-varying risk of a trading strategy. Partly because of its intuitive appeal, the ex post market excess return has been used extensively for this purpose in other areas of capital markets research as well. For example, Bernard and Thomas (1989) argue that if beta mismeasurement is the explanation for the post-earnings-announcement drift, then the sign of the drift should vary according to whether the market excess return is positive or negative. They further interpret the evidence that the drift is consistently positive across all states of market returns as indicating an underreaction explanation of the drift. Our analysis suggests that a reevaluation of the risk of the earnings momentum strategy by sorting on the expected market risk premium may be warranted.[10]

[8]Some indirect evidence is also reported by Chen and Zhang (1998), who document that value stocks offer reliably higher returns in the United States, Japan, Hong Kong, and Malaysia, but not in the high-growth markets of Taiwan and Thailand. They interpret this international evidence as indicating that the risk spread between value and growth is smaller in good times and larger in bad times.

[9]Campbell and Cochrane (2000) demonstrate that in a model with time-varying expected risk premium in which a conditional consumption CAPM holds exactly, portfolio-based empirical models can be better approximate unconditional asset pricing models than the unconditional consumption CAPM. Gomes, Kogan, and Zhang (2002) show that, in a general equilibrium model of a production economy in which the single factor CAPM holds perfectly, the cross-sectional relations between firm characteristics and expected returns can subsist even after one controls for typical empirical measures of beta. Vassalou (2002) shows that a factor capturing news related to future GDP growth along with the market factor absorbs the ability of HML and SMB to explain the cross-section of equity returns. Petkova (2002) shows that HML and SMB are correlated with innovations in variables that predict the market return and its volatility, and when these innovations are present, HML and SMB lose their explanatory power. Finally, Brennan, Wang, and Xia (2002) show that tracking portfolios for innovations in the real interest rate and the maximum Sharpe ratio can explain the risk premia on HML and SMB and perform as well as the Fama and French (1993) three-factor model in explaining the cross-section of returns.

[10]See Griffin, Ji, and Martin (2002) for a recent example of applying the method advocated in this paper to investigate the time-varying risk of momentum strategies.

Third, the predictive asymmetry literature has traditionally focused on the relation between return and volatility, i.e., asymmetric volatility (as opposed to beta) or the leverage effect, following Black (1976) and Christie (1982). However, as shown in Schwert (1989) and Duffee (1995), the evidence on the link between leverage and asymmetric volatility is statistically weak. Our analysis indicates that the betas of firms with different characteristics react differently to return shocks. If the same economic mechanism underlying beta asymmetry (discussed in footnote 1) is also responsible for volatility asymmetry, then the degree of volatility asymmetry should vary across firms with different book-to-market ratios.[11] Testing this hypothesis may shed light on what drives the leverage effect, or whether it is related to leverage at all.

Finally, the popular risk-adjusted discount rate method in corporate valuation practice has traditionally emphasized the source of high risk in growth options. For example, in a widely used corporate finance textbook, Grinblatt and Titman (2001, page 392) state that "growth opportunities are usually the source of high betas, ..., because growth options tend to be most valuable in good times and have implicit leverage, which tends to increase beta, they contain a great deal of systematic risk." As growth (value) firms derive most of their values from growth options (assets-in-place), our evidence suggests that growth options are not always the source of high risk. Managers should pay more attention to the risk of assets-in-place in bad times, and to that of growth options in good times.

The rest of the paper is organized as follows. Section 2 first discusses the empirical methods we use to estimate the business cycle sensitivities of portfolio betas. It then goes on to establish empirically the pattern of asymmetric risk dispersion between value and growth across business cycles. Section 3 revisits Lakonishok, Shleifer, and Vishny (1994) and investigates the source of discrepancy between our findings and theirs. We summarize our results and offer some concluding remarks in Section 4.

[11] Kogan (2000) contains some discussion that asymmetry in capital adjustment may lead to asymmetric volatility.

2 Asymmetric Beta

2.1 Framework

To see why asymmetric beta affects expected returns, we start from the static CAPM, which states that:

$$\mathrm{E}[r_{it}] = \gamma\beta_i, \tag{1}$$

where r_{it} denotes the excess return of asset i, $\beta_i = \mathrm{Cov}[r_{it}, r_{mt}]/\mathrm{Var}[r_{mt}]$ is the unconditional beta, and r_{mt} is the market excess return. In contrast, the conditional CAPM says that:

$$\mathrm{E}_t[r_{it+1}] = \gamma_t\beta_{it}, \tag{2}$$

where $\beta_{it} = \mathrm{Cov}_t[r_{it+1}, r_{mt+1}]/\mathrm{Var}_t[r_{mt+1}]$ and γ_t is the expected market risk premium.

Taking unconditional expectation on both sides of (2) yields:

$$\mathrm{E}[r_{it+1}] = \gamma\bar{\beta}_i + \mathrm{Cov}[\gamma_t, \beta_{it}] = \gamma\bar{\beta}_i + \mathrm{Var}[\gamma_t]\varphi_i, \tag{3}$$

where φ_i is the beta-premium sensitivity, defined as:

$$\varphi_i \equiv \mathrm{Cov}[\beta_{it}, \gamma_t]/\mathrm{Var}[\gamma_t], \tag{4}$$

$\gamma = \gamma_t$ is the average market excess return, and $\bar{\beta}_i \equiv \mathrm{E}[\beta_{it}]$ is the expected beta.[12] Equation (3) shows that average return spreads depend on dispersions of expected betas as well as dispersions of beta-premium sensitivities. Stocks with betas that covary positively (negatively) with the expected market risk premium should earn higher (lower) than average unconditional expected returns. Furthermore, the part of the conditional beta that is correlated with the unexpected market excess return but uncorrelated with the expected market risk premium has no effect on average returns.[13]

Zhang (2002) constructs an economic model, which links betas and expected returns

[12]Note that the expected beta is not the same as the unconditional beta, though they are highly correlated.

[13]Jagannathan and Wang (1996) discuss a similar framework in which the beta-premium sensitivity affects average returns. They further perform cross-sectional tests on a version of the conditional CAPM using size and industry portfolios. However, they do not use book-to-market portfolios to examine the value premium, which is the focus of our study. Ferson and Harvey (1999) find evidence that loadings on some predictive variables provide significant cross-sectional explanatory power for the Fama-French 25 size and book-to-market portfolios. One can interpret these loadings as capturing some effects of the term φ_i in (3).

endogenously to firm characteristics through firms' optimal investment behavior. The model predicts that value stocks are more (less) risky than growth stocks in bad (good) times when the expected market risk premium is high (low). In other words, the beta-premium sensitivity should be significantly positive for value stocks and significantly negative for growth stocks.

In contrast, Lakonishok, Shleifer, and Vishny (LSV 1994) contend that value strategies earn higher returns because they are contrarian to naive strategies followed by other investors.[14] Part of their argument is based on the evidence that value stocks are not fundamentally riskier than growth stocks in bad states of the world, defined as extreme down markets.

In the sequel we examine whether there exists significant cross-sectional variation in beta-premium sensitivities across portfolios. The goal is to shed more light on the relative empirical merits of the aforementioned two competing theories of the value premium.

2.2 Econometric Issues

To compute the beta-premium sensitivity defined in (4), we regress the conditional beta on the expected market risk premium, both of which are unobservable. We discuss in this subsection the econometric issues involved in estimating the beta-premium sensitivity and in testing its equality across value and growth portfolios.

Expected Market Risk Premium

Following Ferson and Harvey (1991), we estimate the expected market risk premium by regressing realizations of the market excess return on a set of conditioning variables, including a constant term:

$$r_{mt+1} = \delta_0 + \delta_1 \mathrm{DIV}_t + \delta_2 \mathrm{DEF}_t + \delta_3 \mathrm{TERM}_t + \delta_4 \mathrm{TB}_t + e_{mt+1} \quad (5)$$

$$\hat{\gamma}_t = \hat{\delta}_0 + \hat{\delta}_1 \mathrm{DIV}_t + \hat{\delta}_2 \mathrm{DEF}_t + \hat{\delta}_3 \mathrm{TERM}_t + \hat{\delta}_4 \mathrm{TB}_t \quad (6)$$

[14]In particular, these investors tend to get overly excited about stocks that have done very well in the past and buy them up to the extent that they become overpriced. Similarly, they overreact to stocks that have done very badly and oversell them so that these stocks become underpriced. Value investors bet against such naive investors and hence they outperform the market.

The estimated expected risk premium $\hat{\gamma}_t$ is just the fitted component in (5).[15]

Our choice of conditioning variables follows the time-series predictability literature. These are: (i) the dividend yield, DIV_t, computed as the sum of dividend payments accruing to the CRSP value-weighted portfolio over the previous 12 months, divided by the contemporaneous level of the index (Campbell and Shiller (1988) and Fama and French (1988)). We compute the dividend yield using CRSP value-weighted portfolio returns with and without distributions; (ii) the default premium, DEF_t, defined as the yield spread between Moody's Baa and Aaa corporate bonds (Keim and Stambaugh (1986) and Fama and French (1989)). Data on the default yield is available from the monthly database of the Federal Reserve Bank of Saint Louis; (iii) the term premium, TERM_t, defined as the yield spread between a long-term and a one-year Treasury bond (Campbell (1987) and Fama and French (1989)). The time series of government bond yields are obtained from the Ibbotson database; (iv) and the one-month Treasury bill rate, TB_t (Fama and Schwert (1977) and Fama (1981)), taken from CRSP.

Conditional Beta

We use two approaches to estimate time-varying portfolio betas. First, we regress portfolio excess returns on the contemporaneous market excess returns using data in a rolling window. The length of the window includes 36, 48, and 60 months.

Second, we follow the conditional market regression method of Shanken (1990) and assume that the conditional beta is a linear function of state variables, known at time t:

$$r_{it+1} = \alpha_i + (b_{i0} + b_{i1}\text{DIV}_t + b_{i2}\text{DEF}_t + b_{i3}\text{TERM}_t + b_{i4}\text{TB}_t)\, r_{mt+1} + \epsilon_{it+1} \quad (7)$$

$$\hat{\beta}_{it} = \hat{b}_{i0} + \hat{b}_{i1}\text{DIV}_t + \hat{b}_{i2}\text{DEF}_t + \hat{b}_{i3}\text{TERM}_t + \hat{b}_{i4}\text{TB}_t \quad (8)$$

where $\hat{\beta}_{it}$ denotes the fitted conditional beta for portfolio i from (8) at the beginning of time t.

[15] Harvey (2001) shows that forecasts of market returns are not improved with nonparametric techniques, which suggests that linear conditional expectations are a reasonable approximation.

Beta-Premium Sensitivity

To estimate the beta-premium sensitivity φ_i defined in (4), we regress conditional portfolio betas on the estimated expected market risk premium:

$$\hat{\beta}_{it} = c_i + \varphi_i \hat{\gamma}_t + \eta_{it} \qquad i = 1, \ldots, N \tag{9}$$

where $\hat{\beta}_{it}$ is either a rolling beta or a fitted beta series from (8) and N is the number of portfolios.

Measurement Errors

There are a few sources of measurement errors in the beta-premium regression (9) that may affect our statistical inferences.

First, $\hat{\gamma}_t$, the estimated expected market risk premium, is only a proxy for the true premium, and acts as a generated regressor in (9). We therefore need to take into account the sampling variation in $\hat{\gamma}_t$ in drawing statistical inference.

Second, on the left hand side of (9), $\hat{\beta}_{it}$ is only a proxy for the true conditional beta. If we estimate beta using the conditional market regression, then inferences on φ_i based on a multi-stage regression of (5), (7), and (9) may be biased. The reason is that both $\hat{\beta}_{it}$ and $\hat{\gamma}_t$ are estimated using the same set of instrumental variables, and their measurement errors may be correlated. We deal with this problem by estimating $\hat{\beta}_{it}$, $\hat{\gamma}_t$, and $\hat{\varphi}_i$ *simultaneously* via GMM, thereby taking into account all the measurement errors in making statistical inference. The set of orthogonality conditions we use is as follows:

$$\mathrm{E}\left[[r_{it+1} - \alpha_i - (\mathbf{Z}_t r_{mt+1})\mathbf{b}_i] \, [\iota \;\, \mathbf{Z}_t r_{mt+1}]^T \right] = 0 \tag{10}$$

$$\mathrm{E}\left[[r_{mt+1} - \mathbf{Z}_t \boldsymbol{\delta}] \, \mathbf{Z}_t^T \right] = 0 \tag{11}$$

$$\mathrm{E}\left[[\mathbf{Z}_t \mathbf{b}_i - c_i - \varphi_i \mathbf{Z}_t \boldsymbol{\delta}] \, [\iota \;\, \mathbf{Z}_t \boldsymbol{\delta}]' \right] = 0 \tag{12}$$

where $\mathbf{Z}_t \equiv [1 \;\, \mathrm{DIV}_t \;\, \mathrm{DEF}_t \;\, \mathrm{TERM}_t \;\, \mathrm{TB}_t]$ is a vector of instrumental variables including a constant term, $\mathbf{b}_i \equiv [b_{i0} \;\, b_{i1} \;\, b_{i2} \;\, b_{i3} \;\, b_{i4}]^T$ and $\boldsymbol{\delta} \equiv [\delta_0 \;\, \delta_1 \;\, \delta_2 \;\, \delta_3 \;\, \delta_4]^T$ are vectors of regression coefficients, and ι is a vector of ones. For each portfolio i, there are in total 13 moment conditions and 13 parameters so the system is exactly identified. Moreover, to test the null hypothesis of equal beta-premium sensitivity across extreme portfolios $H_0 : \varphi_1 = \varphi_{10}$, we stack the moment conditions of portfolio 1 and 10 together and estimate the parameters jointly in one step. The standard Wald test can then be carried out in the usual way.

If the rolling-window regression is used in estimating beta, then the measurement error in beta is less likely to be correlated with the measurement error in the expected market risk premium. Moreover, since the error in beta only enters the left-hand side of the beta-premium regression (9), its effect can be absorbed into the disturbance term η_{it} (Green 1997, page 436). Therefore, in this case we only adjust for the sampling variation in $\hat{\gamma}_t$ via GMM. The set of moment conditions we use is then:

$$\mathrm{E}\left[\left[r_{mt+1} - \mathbf{Z}_t \boldsymbol{\delta}\right] \mathbf{Z}_t^T\right] = 0 \qquad (13)$$

$$\mathrm{E}\left[\left[\beta_{it}^R - c_i - \varphi_i \mathbf{Z}_t \boldsymbol{\delta}\right] \left[\iota \ \mathbf{Z}_t \boldsymbol{\delta}\right]'\right] = 0 \qquad (14)$$

where β_{it}^R denotes the rolling beta of portfolio i at time t.

2.3 Results

In this subsection, we present our results on the cross-sectional variation of beta-premium sensitivity. We use monthly data on asset returns and instrumental variables for the period from January of 1927 to December of 2001. The target assets consist of the Fama-French factors (HML, SMB, and the market excess return), as well as a set of ten portfolios sorted by book-to-market, a set of ten portfolios sorted by size, and a set of 25 portfolios sorted by size and book-to-market.[16]

Informal Tests

To start, we report directly the average conditional portfolio betas in different states of the business cycle. This is perhaps the most straightforward, albeit informal, way to examine the time-variation of risk for all the portfolios.

[16]Return series for these assets are those of Davis, Fama, and French (2000) and are from Ken French's website. The ten size portfolios are constructed at the end of each June using the June market equity and NYSE breakpoints. The ten book-to-market portfolios are formed at the end of each June using NYSE breakpoints. The book value used in June of year t is the book equity for the last fiscal year end in $t-1$. Market equity is computed as price times shares outstanding at the end of December of year $t-1$. The 25 portfolios are the intersections of five portfolios formed on size and five portfolios formed on book-to-market.

Table 1 : Average Rolling Betas Sorted on the Expected Market Risk Premium

This Table reports average rolling betas of Fama and French 25 portfolios, 10 book-to-market portfolios, and 10 size portfolios, in good and bad times, defined by sorting on the expected market risk premium. Four states of the world are defined: "Worst" is identified with the worst 10% expected market risk premium months; "−" is the remaining below average risk premium months other than the 10% worst; "+" is the above average risk premium months other than the 10% best; and "Best" is the 10% best months in the sample. HML denotes the return spread between value and growth and t-statistics are for testing the hypothesis that the HML beta is zero. SMB denotes the return spread between Small and Big and t-statistics are for testing the hypothesis that the SMB beta is zero.

Panel A: Fama-French 25 Portfolios

	Low	2	3	4	High		Low	2	3	4	High
	Worst						−				
Small	1.47	1.34	1.21	1.14	1.15	Small	1.27	1.18	1.04	1.00	1.05
2	1.46	1.22	1.14	1.10	1.18	2	1.29	1.11	0.99	1.02	1.12
3	1.35	1.13	1.05	1.03	1.10	3	1.23	1.04	1.01	1.00	1.06
4	1.22	1.04	1.01	1.00	1.10	4	1.15	1.02	0.99	1.00	1.09
Big	1.00	0.91	0.84	0.88	0.93	Big	1.04	0.95	0.87	0.93	1.00
	+						Best				
Small	1.55	1.40	1.31	1.22	1.34	Small	1.87	1.72	1.74	1.56	1.69
2	1.27	1.20	1.16	1.18	1.32	2	1.35	1.42	1.33	1.38	1.61
3	1.22	1.15	1.11	1.12	1.30	3	1.27	1.25	1.29	1.19	1.62
4	1.11	1.12	1.10	1.11	1.34	4	1.01	1.13	1.14	1.33	1.71
Big	0.98	0.96	0.93	1.02	1.16	Big	0.95	0.94	0.97	1.29	1.62

Panel B: 10 B/M Portfolios

	Worst	−	+	Best
Low	1.08	1.11	1.02	0.93
2	1.01	1.02	1.01	1.00
3	0.97	1.00	1.00	0.95
4	0.96	0.95	1.04	1.08
5	0.89	0.89	0.94	0.97
6	0.92	0.93	1.04	1.08
7	0.92	0.94	1.06	1.27
8	0.97	0.98	1.05	1.28
9	1.00	0.99	1.19	1.59
High	1.09	1.09	1.35	1.81
HML	-0.15	-0.11	0.08	0.33
t-stat	-7.47	-8.30	4.38	26.84

Panel C: 10 Size Portfolios

	Worst	−	+	Best
Small	1.22	1.08	1.39	1.75
2	1.25	1.12	1.34	1.62
3	1.27	1.14	1.28	1.46
4	1.24	1.12	1.23	1.37
5	1.18	1.10	1.21	1.37
6	1.15	1.08	1.19	1.29
7	1.10	1.06	1.17	1.23
8	1.08	1.05	1.11	1.12
9	1.00	1.00	1.07	1.11
Big	0.92	0.96	0.92	0.93
SMB	0.27	0.13	0.20	0.28
t-stat	14.31	11.32	28.56	17.82

Table 2 : Average Fitted Betas Sorted on the Expected Market Risk Premium

This Table reports average fitted betas of Fama and French 25 portfolios, 10 book-to-market portfolios, and 10 size portfolios, in good and bad times, defined by sorting on the expected market risk premium. Four states of the world are defined: "Worst" is identified with the worst 10% expected market risk premium months; "−" is the remaining below average risk premium months other than the 10% worst; "+" is the above average risk premium months other than the 10% best; and "Best" is the 10% best months in the sample. HML denotes the return spread between value and growth and t-statistics are for testing the hypothesis that the HML beta is zero. SMB denotes the return spread between Small and Big and t-statistics are for testing the hypothesis that the SMB beta is zero.

Panel A: Fama-French 25 Portfolios

	Low	2	3	4	High		Low	2	3	4	High
			Worst						−		
Small	1.20	1.26	1.12	1.01	1.00	Small	1.38	1.26	1.24	1.09	1.15
2	1.29	1.09	1.01	0.98	0.97	2	1.36	1.14	1.05	1.05	1.13
3	1.31	1.08	0.95	0.88	0.86	3	1.25	1.13	1.01	0.97	1.05
4	1.26	1.04	0.93	0.78	0.91	4	1.21	1.04	0.98	0.92	1.07
Big	1.02	0.94	0.84	0.73	0.71	Big	1.02	0.95	0.83	0.85	1.04
			+						Best		
Small	1.61	1.22	1.28	1.14	1.27	Small	1.87	1.50	1.50	1.39	1.56
2	1.36	1.17	1.06	1.10	1.28	2	1.20	1.27	1.21	1.31	1.55
3	1.20	1.14	1.06	1.05	1.28	3	1.16	1.15	1.22	1.23	1.64
4	1.13	1.05	1.03	1.10	1.28	4	0.97	1.09	1.14	1.38	1.71
Big	1.01	0.96	0.89	1.01	1.34	Big	0.97	0.93	1.03	1.32	1.76

Panel B: 10 B/M Portfolios

	Worst	−	+	Best
Low	1.13	1.08	1.04	0.95
2	1.00	1.02	1.03	0.98
3	1.01	1.01	1.00	0.92
4	0.94	0.93	0.97	1.09
5	0.89	0.88	0.90	0.99
6	0.86	0.90	0.97	1.15
7	0.79	0.88	1.02	1.28
8	0.75	0.89	1.06	1.33
9	0.77	0.98	1.20	1.58
High	0.87	1.09	1.31	1.70
HML	-0.32	-0.15	0.05	0.40
t-stat	-16.44	-17.65	4.94	34.40

Panel C: 10 Size Portfolios

	Worst	−	+	Best
Small	1.08	1.18	1.27	1.60
2	1.16	1.25	1.29	1.46
3	1.13	1.17	1.22	1.37
4	1.10	1.15	1.17	1.28
5	1.08	1.13	1.17	1.29
6	1.08	1.11	1.14	1.25
7	1.09	1.11	1.12	1.17
8	1.04	1.06	1.08	1.13
9	0.98	1.01	1.05	1.12
Big	0.94	0.94	0.94	0.93
SMB	0.22	0.21	0.16	0.15
t-stat	19.21	41.56	21.16	9.22

Four states of the world are defined: (i) the months with the worst 10% observations of the expected market risk premium; (ii) the remaining months with the expected market risk premium below its average; (iii) the months with the expected market risk premium above its average but other than the 10% very best; and (iv) the months with the 10% very best observations.

We report results of this exercise using both rolling and fitted conditional betas in Tables 1 and 2, respectively. Table 1 shows that in bad times when the expected market risk premium is at its peak, the rolling beta dispersion of High and Low is about 0.90 and almost zero in good times when the expected market risk premium is at its bottom.[17] The time-varying pattern of the market beta of HML is similar in that it is positive in bad times and negative in good times. This pattern of asymmetric beta is also observed in Table 2, which reports the average fitted betas across the different states of the business cycle. The beta dispersion between High and Low remains at about 0.75 in bad times; and becomes negative, -0.26, in good times with the lowest expected market risk premium. Similar, but weaker, patterns are also found for small and large firms.[18]

The asymmetric covariation of value and growth (and small and big) portfolio betas with the expected market risk premium is also evident in Figure 1. This figure plots the lead-lag correlation structure of various portfolio betas with the expected market risk premium. As we can observe, value (small) portfolio betas covary positively, while growth (big) portfolio betas covary negatively, with the expected market risk premium. This pattern applies to for both the rolling and the fitted beta series. The degree of asymmetry between value and growth seems higher than that between small and large stocks.

Formal Tests

Are the asymmetric beta dispersions across business cycle states reported in Tables 1 and 2 statistically significant? We investigate this issue in this subsection.

Table 3 reports the results for the cross-sectional variation of beta-premium sensitivities

[17]The length of the rolling window is 60 months. The results from using 36- and 48-month rolling windows are similar and hence omitted to save space.

[18]The time-variation of the small-minus-big portfolio beta is not new. For example, Chan and Chen (1988) document similar evidence.

Figure 1 : Correlation Structure: Conditional Betas and the Expected Market Risk Premium

This figure presents the correlation structures of the conditional fitted betas of value and growth (Panel A) and small and big (Panel B), and the conditional rolling betas of value and growth (Panel C) and small and big (Panel D) with the expected market risk premium.

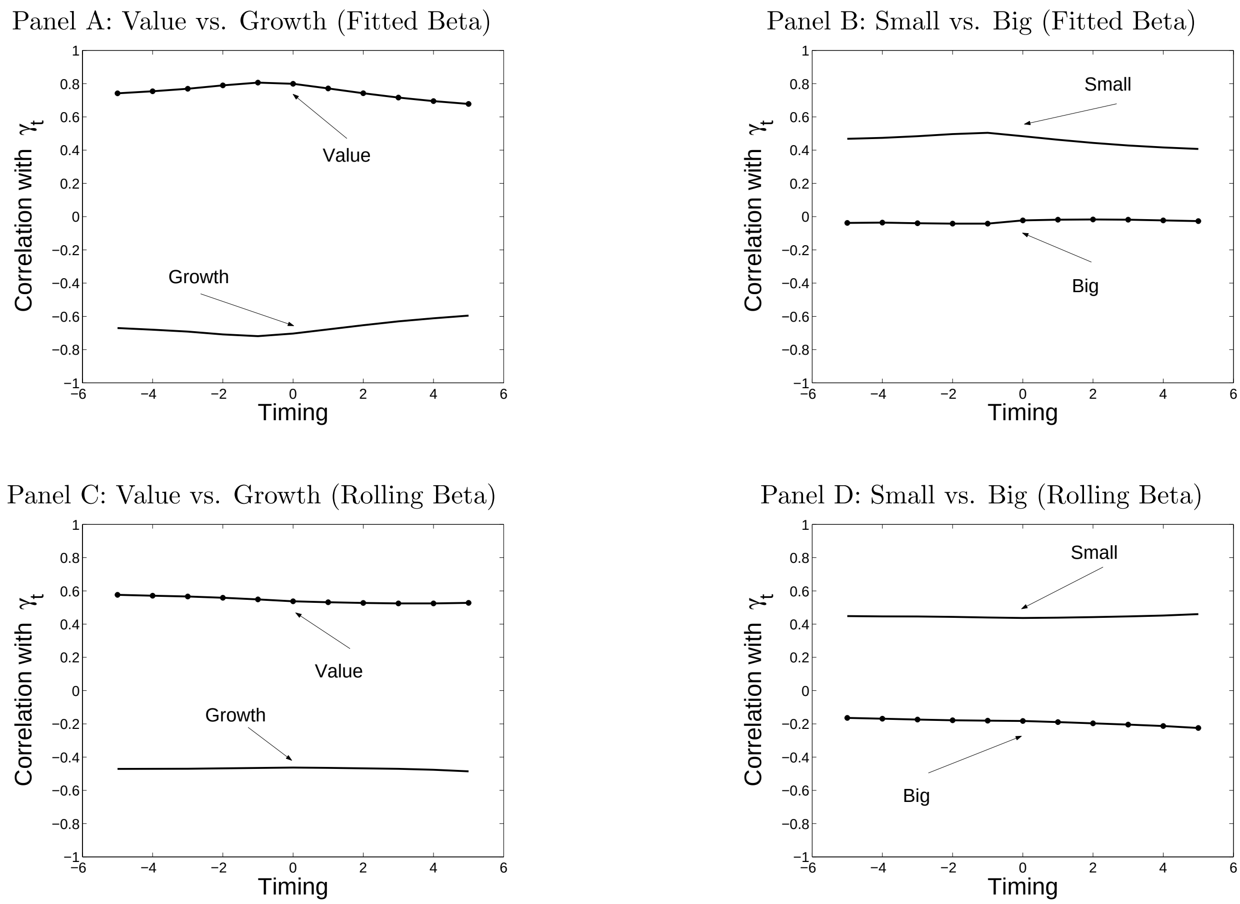


Table 3 : Cross-Sectional Variations of Rolling Beta-Premium Sensitivity

This Table reports the cross-sectional variation of beta-premium sensitivity φ_i and its t-statistics across Fama-French 25 portfolios, 10 book-to-market portfolios, 10 size portfolios, and HML and SMB. Conditional betas are estimated using 60-month rolling-window regression and the expected market risk premium is assumed to be a linear function of state variables, including constant, dividend yield, term premium, default premium, and 1-month Treasury bill rate. Beta-premium sensitivity is computed as the slope coefficient from regressing conditional beta on the expected market risk premium. The t-statistics are corrected for heteroskedasticity and autocorrelation using the Newey-West estimator with 6 lags. The Wald test statistic and p-value on the equality of φ_i across two extreme portfolios are also reported.

Panel A: Fama-French 25 Portfolios

	Low	2	3	4	High		Low	2	3	4	High
	φ_i						t_{φ_i}				
Small	21.57	19.95	23.18	20.10	24.30	Small	2.37	2.08	2.01	2.13	1.98
2	-5.17	8.36	11.45	13.71	17.63	2	-1.27	1.77	1.91	2.01	1.84
3	-1.67	5.68	10.32	9.00	23.21	3	-0.48	1.43	2.03	1.82	2.12
4	-7.93	4.42	6.15	14.31	26.99	4	-1.94	1.39	1.60	2.17	2.19
Big	-3.87	-0.44	6.93	16.21	25.28	Big	-2.14	-0.30	2.41	2.19	2.02

Panel B: 10 B/M Portfolios

	φ_i	t_{φ_i}	Wald	p
Low	-6.81	-1.95	4.46	0.035
2	-1.77	-1.36		
3	-2.08	-1.14		
4	6.46	2.28		
5	5.04	2.48		
6	8.50	2.19		
7	14.32	2.09		
8	13.29	2.16		
9	24.15	2.14		
High	27.53	1.92		
HML	20.42	1.99		

Panel C: 10 Size Portfolios

	φ_i	t_{φ_i}	Wald	p
Small	25.52	2.08	4.35	0.037
2	17.28	1.97		
3	10.70	2.12		
4	7.55	1.80		
5	8.99	1.98		
6	7.50	2.02		
7	6.06	1.55		
8	2.75	1.81		
9	4.80	1.83		
Big	-1.23	-1.47		
SMB	2.84	1.07		

across the 25 size and B/M portfolios, 10 B/M portfolios, and 10 size portfolios. Conditional betas are estimated using a 60-month rolling-window regression.[19]

As we can observe, there exists a strong relation between the beta-premium sensitivity and firm characteristics. The conditional betas of value (small) stocks covary positively with the expected market risk premium, while the betas of growth (large) stocks covary negatively with the expected market risk premium. HML has a conditional beta that is significantly positively correlated with the expected market risk premium. The same is true for SMB but

[19]Results from using 36- and 48-month rolling window are similar and thus omitted.

Table 4 : Cross-Sectional Variations of Fitted Beta-Premium Sensitivity

This Table reports the cross-sectional variation of beta-premium sensitivity φ_i and its t-statistics across Fama-French 25 portfolios, 10 book-to-market portfolios, 10 size portfolios, and HML and SMB. Conditional betas and the expected market risk premium are assumed to be linear functions of a vector of state variables, constant, dividend yield, term premium, default premium, and 1-month Treasury bill rate. Beta-premium sensitivity is computed as the slope coefficient from regressing the fitted conditional beta on the expected market risk premium. The t-statistics are corrected for heteroskedasticity and autocorrelation using the Newey-West estimator with 6 lags. The Wald test statistic and p-value on the equality of φ_i across two extreme portfolios are also reported.

Panel A: Fama-French 25 Portfolios

	φ_i Low	2	3	4	High		t_{φ_i} Low	2	3	4	High
Small	33.11	8.33	14.98	15.64	24.62	Small	1.85	0.31	0.89	1.02	1.48
2	-3.32	7.92	8.08	13.99	26.04	2	-0.29	0.73	0.68	1.28	1.81
3	-6.70	2.64	11.71	15.51	36.44	3	-0.53	0.42	1.67	1.76	2.34
4	-13.13	2.91	9.78	28.61	36.86	4	-2.12	0.65	1.60	2.55	2.36
Big	-2.28	-0.27	9.50	27.27	42.65	Big	-0.69	-0.07	1.65	2.51	1.77

Panel B: 10 B/M Portfolios

	φ_i	t_{φ_i}	Wald	p
Low	-7.67	-1.65	4.01	0.045
2	-0.17	-0.04		
3	-3.61	-1.06		
4	7.63	1.51		
5	5.31	1.08		
6	13.55	2.07		
7	23.06	2.48		
8	27.50	2.39		
9	37.11	2.25		
High	37.86	2.05		
HML	33.34	2.12		

Panel C: 10 Size Portfolios

	φ_i	t_{φ_i}	Wald	p
Small	22.43	1.25	1.40	0.237
2	12.47	0.92		
3	10.79	1.10		
4	7.64	0.80		
5	9.18	1.15		
6	7.36	1.22		
7	3.48	0.76		
8	4.26	1.37		
9	6.91	2.45		
Big	-0.06	-0.04		
SMB	-3.78	-0.47		

the effect there is weaker. Moreover, the Wald test on the null hypothesis that the beta-premium sensitivity is equal across extreme portfolios is rejected at conventional significance level.

Table 4 reports the cross-sectional variation of beta-premium sensitivity when the conditional beta is estimated as a linear function of instrumental variables. We continue to observe the pattern of beta asymmetry for book-to-market portfolios, but the effect for size portfolios is now insignificant.[20]

Macroeconomic Risk

We now show that the asymmetric risk pattern also shows up in some dimension of macroeconomic risk. The macroeconomic variable we focus on is the growth rate of industrial production. Unlike most other macroeconomic series, this series is available at monthly frequency, which seems vital to capturing adequately the time-variation in betas.

To construct the growth rate of industrial production, we use monthly observations for the index of industrial production available from the monthly database of the Federal Reserve Bank of Saint Louis. Industrial production growth is defined as the change in the log of the index and it covers the period from February of 1940 to December of 2001.

Following Chen, Roll, and Ross (1986), we estimate conditional portfolio betas with respect to industrial production growth by regressing excess portfolio returns on the unexpected or the news component of the growth series. The unexpected component is identified as the residual from a regression of realized industrial production growth on its one-period-lagged values and a set of state variables, including a constant, the dividend yield, the term premium, the default premium, and the one-month Treasury bill rate. These variables seem to predict one-month ahead industrial production growth reasonably well. The adjusted R^2 is 16% and the hypothesis that all slope coefficients are jointly zero is strongly rejected with a p-value of zero.

Because industrial production at time t is actually the flow during month t, its growth rate

[20]The effect of beta asymmetry observed in value and growth portfolios becomes stronger when we add portfolio-average B/M into the set of instrument variables in estimating conditional betas. The results are not reported to save space. The theoretical foundation that firm characteristics are correlated with beta is provided recently by Gomes, Kogan, and Zhang (2002). Lewellen (1999) and Avramov and Chordia (2001) confirm this prediction empirically.

measures the change of industrial production lagged by about a month. To keep industrial production growth contemporaneous with portfolio returns, we thus lead it by one month in estimating the rolling betas.

We still need to obtain a measure of the expected premium for this dimension of macroeconomic risk. One way to proceed is to construct mimicking portfolios by regressing industrial production growth on a set of base assets, and then regress the mimicking portfolio returns on a set of state variables and define the fitted returns as the expected premium. However, we fear that too many sources of the generated-regressor problem may weaken the power of the test. Therefore, we make the simplifying assumption that the expected risk premium associated with innovations in industrial production growth can be approximated as a linear function of the default premium.[21] Although the functional form assumption is admittedly strong, the sign pattern of the beta-premium sensitivity depends on the countercyclicality of the expected risk premium (and hence its positive correlation with the default premium). This seems to be a much weaker assumption.

Table 5 shows that the asymmetric risk dispersion between value and growth persists when betas are measured with respect to unexpected industrial production growth. Value (small) stocks again have countercyclical betas and growth (large) stocks have procyclical betas. However, this evidence is only preliminary because of the simplifying assumption stated above.

3 Are Contrarian Strategies Riskier? LSV Revisited

Our paper is not the first to look at the relative riskiness of value and growth stocks across business cycles. Lakonishok, Shleifer, and Vishny (1994) examine a similar question but reach the opposite conclusion. In this section, we seek to understand the source of discrepancy between our results and LSV's.

[21]Default premium receives special attention in our proxy for the expected risk premium, because of its well-known ability to track business cycle fluctuations (Stock and Watson [1989, 1999] and Bernanke [1990]). Moreover, Jagannathan and Wang (1996) also assumes that the conditional market risk premium is a linear function of default premium in their implementation of the conditional CAPM.

Table 5 : Cross-Sectional Variations of Beta-Premium Sensitivity — Rolling Beta With Respect To Unexpected Industrial Production Growth

This Table reports the cross-sectional variations of beta-premium sensitivity φ_i^{IP} and its t-statistics across Fama-French 25 portfolios, 10 book-to-market portfolios, 10 size portfolios, and HML and SMB. Conditional betas are estimated using 60-month rolling-window regression of portfolio returns on unexpected growth rate of industrial production. The expected premium of risk associated with unexpected industrial production growth is assumed to be a linear function of the default premium. Beta-premium sensitivities are computed as the slope coefficients from regressing conditional betas on the expected risk premium. The t-statistics are corrected for heteroskedasticity and autocorrelation using the Newey-West estimator with 6 lags. The Wald statistics, which test the equality of the sensitivities for two extreme portfolios, and their p-values are also reported.

Panel A: Fama-French 25 Portfolios

	Low	2	3	4	High		Low	2	3	4	High
	φ_i^{IP}						$t_{\varphi_i^{\text{IP}}}$				
Small	8.80	28.99	16.66	15.12	42.07	Small	0.37	1.84	1.12	1.01	3.82
2	-0.73	22.99	20.76	2.50	19.61	2	-0.05	1.79	2.38	0.32	1.90
3	-4.21	-7.50	-9.01	-8.46	13.36	3	-0.37	-0.64	-0.98	-1.18	1.53
4	-15.66	-8.81	-20.51	-22.66	-9.10	4	-1.57	-0.94	-2.55	-3.57	-1.15
Big	-23.57	0.57	1.90	-10.73	8.64	Big	-2.89	0.09	0.26	-1.41	1.03

Panel B: 10 B/M Portfolios

	φ_i^{IP}	$t_{\varphi_i^{\text{IP}}}$	Wald	p
Low	-20.19	-2.41	43.41	0.00
2	-15.62	-2.01		
3	-2.51	-0.33		
4	3.16	0.46		
5	-0.53	-0.07		
6	-4.62	-0.57		
7	-2.18	-0.32		
8	-21.14	-2.69		
9	6.58	0.92		
High	18.86	2.24		
HML	14.82	2.24		

Panel C: 10 Size Portfolios

	φ_i^{IP}	$t_{\varphi_i^{\text{IP}}}$	Wald	p
Small	30.15	1.78	46.45	0.00
2	15.51	1.13		
3	11.12	0.97		
4	8.75	0.78		
5	-4.89	-0.49		
6	-5.30	-0.58		
7	0.38	0.04		
8	-24.75	-3.19		
9	-17.53	-2.14		
Big	-9.23	-1.53		
SMB	25.34	2.86		

3.1 LSV's Approach

LSV contend that "value stocks would be fundamentally riskier than glamor (growth) stocks if, first, they underperform glamor stocks in some states of the world, and second, those are on average 'bad' states, in which the marginal utility of wealth is high, making value stocks unattractive to risk-averse investors." LSV then proceed with a three-step procedure to see whether value stocks are riskier. First, they look at the performance of value and growth strategies over time and ask how often value underperforms growth. Then, they check whether the times when value underperforms growth are recessions, times of severe market declines, or "bad" states of the world. Finally, they look at some traditional measures of risk, such as beta and volatility of returns for value and growth stocks.

Frequency of Value Underperforming Growth

Below we replicate LSV's analysis using a long sample ranging from January of 1927 to December of 2001. First, we find that value underperforms growth in 45% of monthly, 43% of annual, 33% of 3-year holding period, and 27% of 5-year holding period return observations.[22] These numbers are much higher than the respective numbers (27% in annual returns, 10% in 3-year returns, and 0% in 5-year returns) reported in Table VI in LSV, which is based on a much shorter sample from 1968 to 1989. If anything, LSV greatly underestimate the frequency of underperformance of value strategies.

Performance of Value and Growth in Good and Bad Times

Second, LSV compare the performance of value and growth portfolios in the worst months for the stock market. We replicate this exercise in Table 6. Panel A is borrowed from Table VII of LSV, while Panel B uses our long sample and presents the average returns of value and growth in each of four states of the world: (i) the 10% worst stock market return months; (ii) the remaining negative return months other than the 10% worst; (iii) the positive return months other than the 10% best; and (iv) the 10% best months in the sample. Following LSV, the average value-minus-growth returns for each state are also reported along with the t-statistics for testing that the returns are zero.

[22] Following LSV, we also compute overlapping 3-year and 5-year holding period returns.

Table 6 : Performance of Value and Growth in Good and Bad Times

This table examines the performance of value and growth strategies in good and bad times. Panel A reports portfolio returns in monthly percentages in good and bad times, defined by sorting on ex post realized market excess returns in LSV's sample. Four states of the world are defined: "Worst" is identified with worst 10% market return months; "−" is the remaining negative market excess return months other than the 10% worst; "+" is the positive return months other than the 10% best; and "Best" is the 10% best months in the sample. Panel B reports the counterpart of Panel A using the long sample. V-G denotes the spread between value (equally-weighted portfolios 9 and High) and growth (equally-weighted portfolios Low and 2) and t-statistics are for testing the hypothesis that V-G spreads are zero.

	Panel A: Average Returns Sorted on Market Excess Returns — LSV Sample											
	Low	2	3	4	5	6	7	8	9	High	V-G	t-stat
Worst	-11.20	-11.00	-10.40	-10.00	-9.70	-9.10	-9.30	-9.20	-9.80	-10.20	1.10	1.80
−	-2.90	-2.80	-2.60	-2.50	-2.30	-2.00	-2.10	-2.00	-1.80	-2.20	0.80	2.99
+	3.80	4.00	3.90	3.70	3.60	3.70	3.80	3.70	3.80	3.90	-0.10	-0.17
Best	11.40	11.40	11.90	11.30	11.20	11.30	11.70	12.60	13.30	14.80	2.60	1.73
	Panel B: Average Returns Sorted on Market Excess Returns — Long Sample											
	Low	2	3	4	5	6	7	8	9	High	V-G	t-stat
Worst	-9.47	-8.98	-8.62	-9.28	-8.39	-9.40	-9.25	-9.26	-10.88	-11.64	-2.00	-2.98
−	-2.27	-2.05	-2.00	-2.01	-1.59	-1.74	-1.90	-1.83	-1.90	-2.30	0.10	0.28
+	3.04	3.06	2.98	2.90	2.78	2.92	2.93	3.16	3.40	3.66	0.50	2.70
Best	9.92	9.73	9.32	10.11	9.85	10.59	11.58	11.46	13.34	13.87	1.70	3.13

A comparison between Panel A and Panel B in Table 6 reveals that, contrary to LSV, who find that value outperforms growth in the market's worst 10% months in their short sample, we find that value underperforms growth in the worst months of the long sample. For example, the first row of Table 6 shows that in the worst times, the Low portfolio lost 9.5% per month compared to 11.6% for the High portfolio and the average return of value-minus-growth is -2% per month with a t-statistic of -2.98. Consistent with LSV, we find that in the very best months of market returns value substantially outperforms growth, as indicated by the return spread of 4% per month between High and Low. The average value-minus-growth return in the top 10% state is 1.7% per month with a t-statistic of 3.13. Therefore, even using LSV's metric we find that the value strategy exposes investors to a greater downside risk.

Unconditional Risk Measures

Finally, for completeness, we also present in Table 7 some unconditional risk measures, including market betas and volatility. Interestingly, even the unconditional beta spread between Low and High for the 10 B/M portfolios in the long sample is as much as 0.40, higher than the 0.10 reported by LSV and the effective zero emphasized by Fama and French (1992) in their sample from 1963 to 1990. However, the unconditional beta of HML is only 0.14, which seems rather low.

3.2 Discussion

We now have two methods for measuring time-varying portfolio risk, i.e., sorting on the expected market risk premium and sorting on the ex post realized market excess return. How are these two procedures related? Which one is better? We provide some answers below.

What Is Risk?

In a static world such as the traditional CAPM, the measure of risk is simple and is given by the unconditional market beta. In a more realistic dynamic world, the right measure of risk can be hard to obtain. This measurement difficulty of the conditional beta can be

Table 7 : Unconditional Risk Measures

This table reports the results of market regression including intercept α, slope β, and their t-statistics, as well as annualized means m and volatilities σ for Fama-French 25 portfolios, 10 size portfolios, and 10 B/M portfolios. The intercept α's are in percent.

Panel A: Fama-French 25 Portfolios

	Low	2	3	4	High	Low	2	3	4	High
			m					σ		
Small	0.10	0.14	0.16	0.19	0.21	0.44	0.38	0.33	0.31	0.34
2	0.10	0.15	0.16	0.17	0.18	0.28	0.28	0.26	0.27	0.31
3	0.12	0.14	0.15	0.16	0.17	0.27	0.23	0.24	0.24	0.30
4	0.12	0.13	0.14	0.15	0.17	0.22	0.22	0.22	0.25	0.32
Big	0.11	0.11	0.12	0.13	0.17	0.19	0.19	0.20	0.24	0.30
			α					t_α		
Small	-0.57	-0.18	0.14	0.39	0.48	-2.60	-1.04	0.84	2.41	2.79
2	-0.26	0.14	0.27	0.30	0.31	-1.83	1.17	2.45	2.49	1.99
3	-0.15	0.14	0.22	0.28	0.19	-1.35	1.61	2.33	2.69	1.30
4	0.00	0.01	0.15	0.19	0.16	-0.01	0.16	1.92	1.78	1.04
Big	-0.01	-0.01	0.06	0.04	0.21	-0.11	-0.15	0.66	0.31	1.23
			β					t_β		
Small	1.65	1.53	1.40	1.32	1.40	14.80	12.10	16.32	17.15	15.88
2	1.24	1.25	1.19	1.23	1.36	19.51	24.10	18.01	19.19	19.04
3	1.27	1.13	1.14	1.12	1.38	32.31	34.80	23.68	22.02	14.92
4	1.07	1.10	1.09	1.18	1.45	26.68	29.11	29.45	15.71	13.90
Big	0.98	0.92	0.98	1.12	1.29	57.54	47.51	2.50	15.14	11.94

Panel B: 10 B/M Portfolios

	Low	2	3	4	5	6	7	8	9	High	HML
m	0.11	0.12	0.12	0.11	0.13	0.13	0.14	0.15	0.17	0.17	0.04
σ	0.20	0.19	0.19	0.21	0.20	0.22	0.24	0.24	0.29	0.33	0.12
α	-0.08	0.05	0.04	-0.06	0.12	0.06	0.09	0.21	0.22	0.14	-0.02
t_α	-1.07	0.98	0.76	-0.89	1.58	0.69	0.95	2.01	1.72	0.83	-0.12
β	1.01	0.98	0.95	1.06	0.98	1.07	1.13	1.14	1.31	1.42	0.14
t_β	45.98	46.11	39.06	23.01	28.82	19.16	16.96	16.53	14.26	14.39	1.79

Panel C: 10 Size Portfolios

	Small	2	3	4	5	6	7	8	9	Big	SMB
m	0.18	0.16	0.15	0.15	0.15	0.14	0.14	0.13	0.13	0.11	0.02
σ	0.37	0.32	0.29	0.27	0.26	0.24	0.23	0.22	0.21	0.18	0.11
α	0.26	0.10	0.10	0.11	0.09	0.08	0.08	0.05	0.03	0.01	-0.24
t_α	1.35	0.72	0.88	1.06	1.03	1.14	1.19	0.96	0.74	0.28	-2.20
β	1.47	1.40	1.33	1.26	1.26	1.21	1.16	1.11	1.08	0.93	0.20
t_β	13.52	21.43	23.49	25.06	27.42	32.89	37.85	51.25	53.49	113.37	5.64

greatly alleviated using beta-premium sensitivity, which, according to (3), gives a convenient *unconditional* measure of the effects that *conditional* betas have on unconditional average returns.

As evident from (3), if value stocks are riskier than growth stocks, then their betas must covary highly positively with the expected market risk premium. In other words, the betas of value stocks must be higher than those of growth stocks when the expected market risk premium is high. This indeed seems to be the case, as shown in Panel B of Tables 1 and 2.

In view of this evidence, we find it hard to understand LSV's definition of good and bad states by sorting on *ex post* market excess returns. The realized market excess return is at best a very noisy proxy for the expected market risk premium. More importantly, LSV seem to identify good (bad) states with times of high (low) market excess returns. The problem is that if the realized market excess return is, on average, positively correlated with expected market risk premium (this correlation is 0.11 in our sample), then what LSV call good (bad) states are actually bad (good) states in terms of business cycle conditions! It is well-known that the expected market risk premium is countercyclical, e.g., Fama and French (1989), and that the ex post market excess return is negatively correlated with recent economic growth, e.g., Chen (1991).

Timing

Timing may to be the key to understanding LSV's notion that value stocks would be fundamentally riskier than growth stocks if (i) they underperform growth in some states of the world, and (ii) these are on average bad states, in which the marginal utility of wealth is high. It could be that what LSV really mean is the following: going *into* the recession, the *prices* of value stocks drop faster than those of growth stocks. So when one looks back standing at the recession point, value will indeed underperform growth in terms of realized returns during the periods right before the recession.

This does not need to be inconsistent with our notion that value is riskier in recessions and should earn higher expected returns. Effectively, what we say is that, going *out* of the recession, the realized returns of value stocks during the periods right after the recession will be higher than those of growth stocks, as the prices of value stocks have been depressed in the recession.

Following LSV, we plot in Figure 2 the annual returns of value-minus-growth (defined to be the equal-weighted returns of B/M portfolios 9 and 10 minus the equal-weighted returns of B/M portfolios 1 and 2) from 1927 to 2000 along with the NBER recession dummy. The figure shows that value both under- and out-performs growth in recessions. In fact, the frequency of value outperforming growth is higher than that of underperforming. More interestingly, the relative performance of value versus growth varies across different stages of a recession. This is most evident in the Great Depression. Value underperforms growth consecutively during the first three years of the depression from 1929 to 1931 and then outperforms growth slightly in 1931 and then dramatically in 1932.

This pattern of value first sinking below and then rising above growth can also be observed in annual returns during the periods of 1938, 1953–54, 1957–58, 1981–82, and 1990–1991, but not for the other five recessions dated by NBER. These other recessions generally last less than or about a year and do not go from the beginning to the end of any calender year, so we suspect that here time aggregation and phase shifting may be hiding interesting return variations. To investigate this possibility, we plot in Figure 3 the monthly returns of value-minus-growth during these periods. Except for the recession of 1945, the pattern of value going down first and up later is clearly visible during all other recessions.

This subtle timing issue highlights the need of using predictive variables that can track business cycle fluctuations closely, preferably at monthly frequency. Simply looking at the relative performance of value and growth over the whole recession duration, or equivalently, sorting their returns on some crude measures of the business cycles, will not shed much light on the time-varying risk of value-minus-growth. It is well-known that the ex post market excess return does not track business cycle fluctuations very well (see footnote 5). In short, we conclude that LSV's method is intrinsically flawed.

Attenuation

We have argued above that LSV's approach can be misleading from an economic perspective. We examine their approach again in this subsection, but this time from a statistical point of view.

Figure 2 : Year-by-year Returns of Value Minus Growth

This figure presents the annual buy-and-hold returns for the value minus growth portfolio returns. *R* denotes NBER recessions.

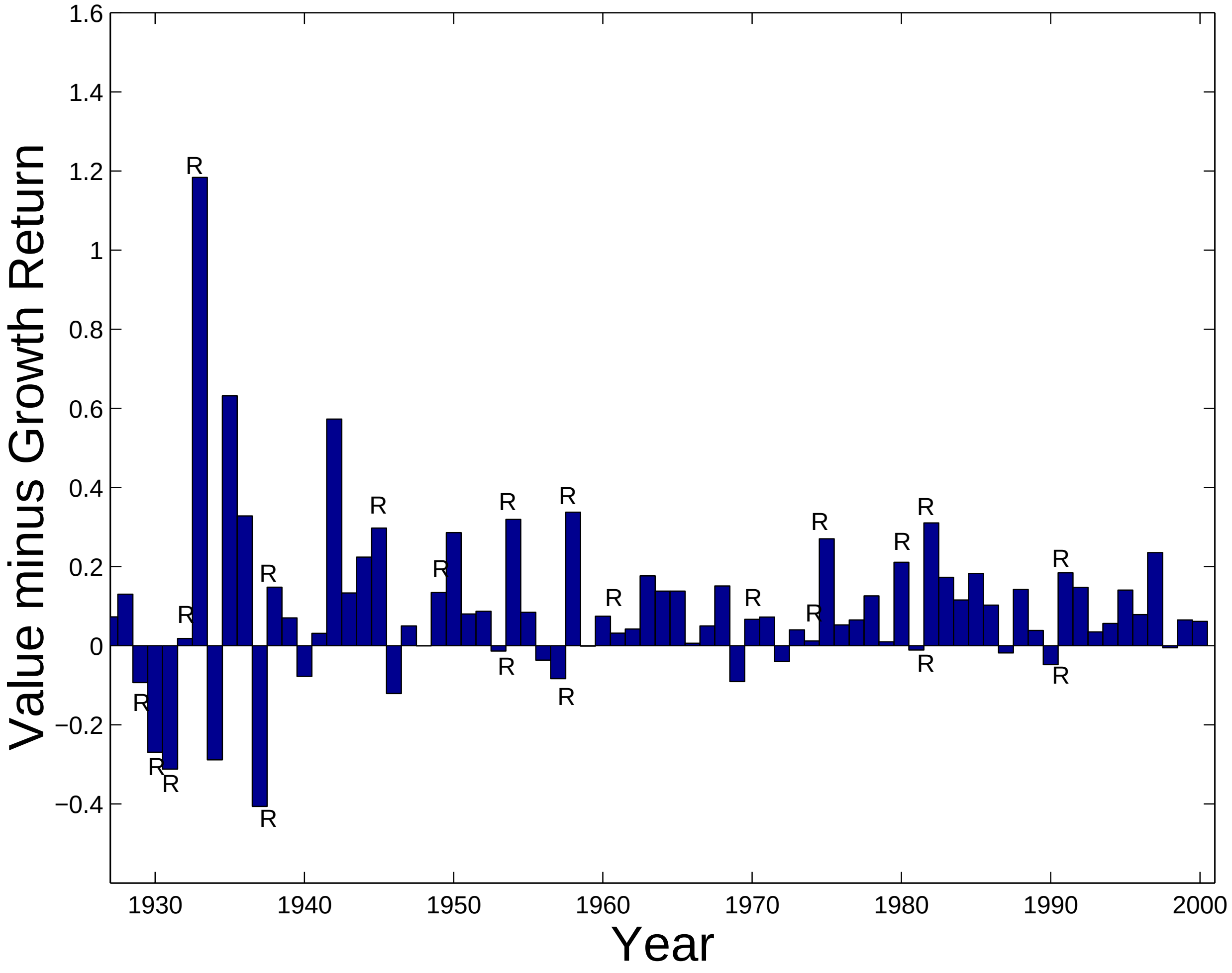
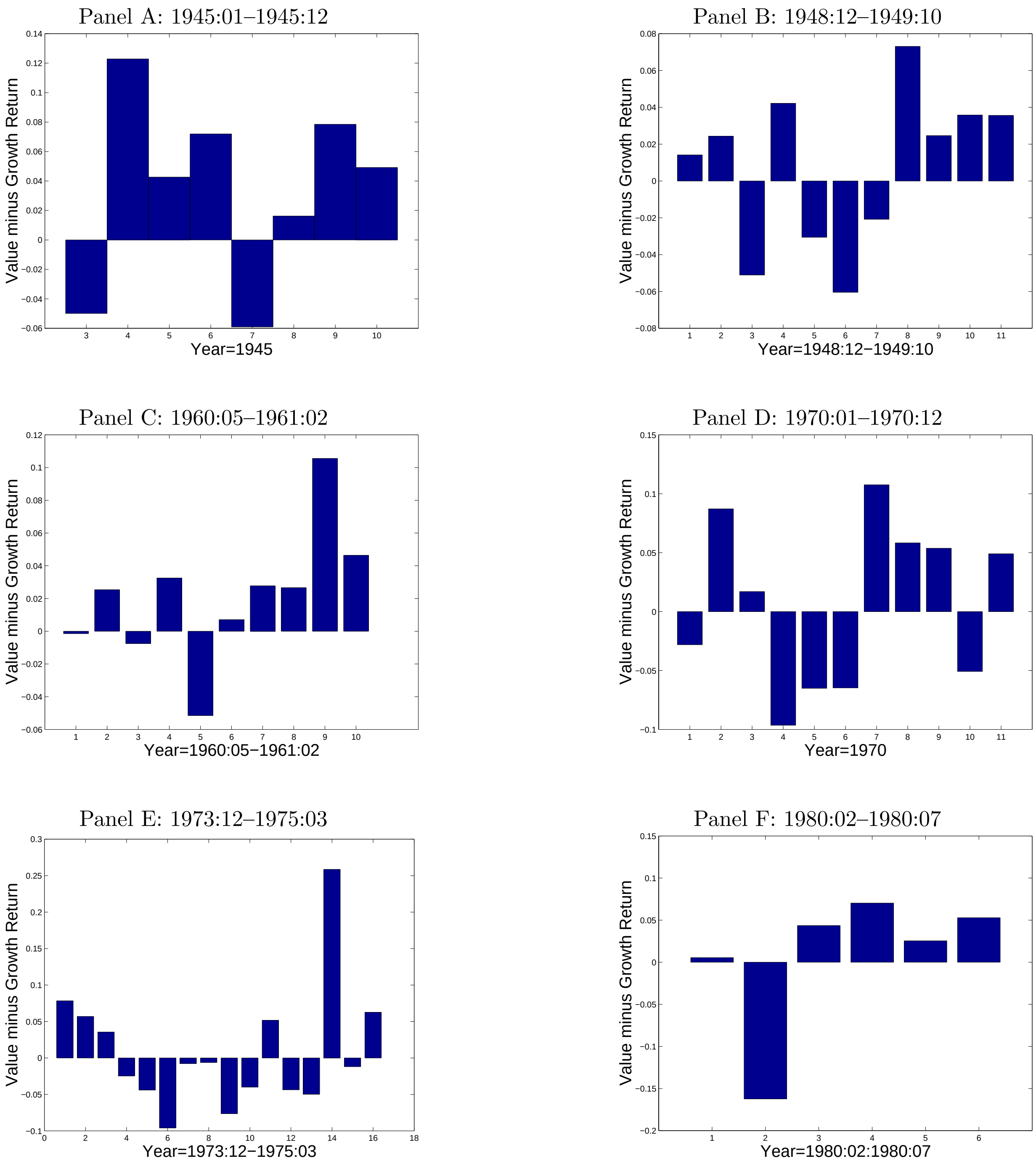


Figure 3 : Monthly Returns of Value Minus Growth in Six Recessions

This figure presents monthly returns of value minus growth for six indicated recession periods.



Implicitly, the sorting procedure in Table VII of LSV regresses the realized portfolio return (as a proxy for the expected return or the conditional beta) on the realized market excess return:

$$\beta_{it} = c_i^{\text{LSV}} + \varphi_i^{\text{LSV}} r_{mt+1} + \eta_{it}^{\text{LSV}}. \tag{15}$$

The interesting question is how the estimated sensitivity φ_i^{LSV} relates to the theoretical beta-premium sensitivity φ_i, on which we focus.

To see this, we start by substituting the $\hat{\gamma}_t$ term in (9) using (5) to get:

$$\beta_{it} = c_i + \varphi_i r_{mt+1} - \varphi_i e_{mt+1} + \eta_{it}. \tag{16}$$

A comparison of (16) with (15) yields that $\eta_{it}^{\text{LSV}} = -\varphi_i e_{mt+1} + \eta_{it}$. It follows immediately that LSV's informal procedure does not satisfy one of the key assumptions in classic regression theory, i.e., that the covariance between the regressor and the residual in (15) should be zero. The reason is that, as evident from (5), the realized market excess return r_{mt+1} is correlated with its unexpected component e_{mt+1}. Consequently, LSV's estimates of the business cycle sensitivities of both value and growth betas are biased towards zero as a result of attenuation. Moreover, the more volatile the unexpected market excess returns, the more severe the downward bias.

To get a sense of the magnitude of the attenuation, Table 8 reports the regression of the conditional betas on the ex post market excess returns. The difference between Table 8 and Tables 3 and 4 is astonishing! None of the t-statistics associated with the beta-market sensitivities in Table 8 is significant and the standard Wald test fails to reject the null hypothesis that the spread between beta-premium sensitivities of value and growth strategies is zero. Nevertheless, it is not at all surprising that we observe such a severe downward bias, since it is well-known that the realized market excess return is much more volatile than the expected market risk premium. Interestingly, our way of regressing beta on the expected market risk premium, which is estimated using a set of predictive variables, is an exact application of the instrumental-variable estimation, the standard cure of attenuation prescribed by econometrics textbooks (e.g., Green 1997, pages 288–295).

In summary, we conclude that our approach of estimating the time-varying risk of value

Table 8 : Cross-Sectional Variations of Beta-Market Sensitivity — Rolling Beta and Ex Post Market Excess Returns

This Table reports the cross-sectional variations of beta-market sensitivity φ_i^{LSV}, its t-statistics across Fama-French 25 portfolios, 10 book-to-market portfolios, 10 size portfolios, and HML and SMB. Conditional betas are estimated using 60-month rolling-window regression and beta-market sensitivity is computed as the slope coefficient from regressing conditional betas on ex post realized market excess returns. The t-statistics are corrected for heteroskedasticity and autocorrelation using the Newey-West estimator with 6 lags. The Wald statistics, which test equal φ_i^{LSV}s for two extreme portfolios, and their p-values are also reported.

Panel A: Fama-French 25 Portfolios

	Low	2	3	4	High		Low	2	3	4	High
	φ_i^{LSV}						$t_{\varphi_i^{\text{LSV}}}$				
Small	0.02	-0.14	-0.10	-0.08	0.04	Small	0.08	-0.56	-0.42	-0.35	0.16
2	-0.34	-0.18	-0.12	0.01	0.11	2	-1.99	-1.29	-0.69	0.07	0.56
3	-0.26	-0.12	-0.00	0.11	0.22	3	-1.98	-1.34	-0.04	0.82	1.00
4	-0.17	-0.07	0.06	0.15	0.23	4	-1.60	-0.83	0.71	0.97	0.89
Big	0.01	0.02	0.14	0.26	0.22	Big	0.25	0.40	1.54	1.44	0.74

Panel B: 10 B/M Portfolios

	φ_i^{LSV}	$t_{\varphi_i^{\text{LSV}}}$	Wald	p
Low	-0.02	-0.34	0.85	0.36
2	-0.03	-0.46		
3	-0.03	-0.50		
4	0.03	0.30		
5	0.07	0.91		
6	0.15	1.50		
7	0.20	1.26		
8	0.17	1.04		
9	0.21	0.90		
High	0.26	1.04		
HML	0.31	1.48		

Panel C: 10 Size Portfolios

	φ_i^{LSV}	$t_{\varphi_i^{\text{LSV}}}$	Wald	p
Small	-0.04	-0.14	0.07	0.79
2	-0.09	-0.50		
3	-0.07	-0.49		
4	-0.12	-0.94		
5	-0.05	-0.44		
6	-0.03	-0.32		
7	-0.05	-0.69		
8	-0.03	-0.64		
9	0.04	0.74		
Big	0.04	1.27		
SMB	-0.21	-1.93		

and growth is both theoretically and econometrically more justifiable than that of LSV.

4 Conclusion

We have shown that, while there does not exist much difference in unconditional betas between value and growth, their conditional market beta dispersion displays intriguing business cycle patterns. In particular, value stocks have conditional betas that covary *positively*, and growth stocks have conditional betas that covary *negatively*, with the expected market risk premium. Moreover, value stocks are more (less) risky than growth stocks in bad (good) times when the expected market risk premium is high (low). We also demonstrate that the previously documented weak, and even negative, evidence of beta asymmetry is actually defined with respect to the realized market excess returns. A strong empirical presence of this form of beta asymmetry, while interesting in itself, is *irrelevant* for explaining the cross-section of average returns. Our results lend support to a risk-based explanation of the value premium, and cast doubt on the overreaction interpretation.

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