Is Value Riskier Than Growth?

Ralitsa Petkova and Lu Zhang*

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Abstract

Yes! We study the time-varying risk patterns of value and growth stocks across business cycles. We find reliable evidence that value stocks are riskier than growth stocks in bad times when the expected market risk premium is high, and to a lesser extent, growth stocks are riskier than value stocks in good times when the expected market risk premium is low. Methodologically, we measure the time-variation of risk by sorting the conditional betas on the theoretically justified *expected* market risk premium, as opposed to the *ex post* realized market excess return. Our evidence lends support to the predictions of recent rational expectations theory on the value premium.

*William E. Simon Graduate School of Business Administration, University of Rochester, Rochester, NY 14627. We thank an anonymous referee for many insightful comments. Mike Barclay read our paper carefully and provided detailed suggestions. We have also benefited from Ana Albuquerque, Andrew Ang, Greg Bauer, Wayne Ferson, Rick Green, Ludger Hentschel, John Long, Bill Schwert, Cliff Smith, Jerry Warner, Stan Zin, and other seminar participants at Carnegie and Rochester. We are responsible for all the remaining errors. E-mail: petkovara@simon.rochester.edu and zhanglu@simon.rochester.edu.

1 Introduction

Are value stocks riskier than growth stocks? This question is at the crux of the lively debate on the economic interpretation of the value premium between the rational expectations school and behavioral finance.

The rational expectations theory of Zhang (2003) predicts that the difference between the betas of value and growth stocks is high when the price of risk is high, and low or even negative when the price of risk is low. This positive correlation between the difference in betas and the price of risk can explain why value stocks have substantially higher average returns even though there is little difference between the unconditional betas of value and growth stocks.

To investigate this time-varying beta pattern empirically, we first define good times as states with low values of the expected market risk premium, and bad times as states with high values of the expected market risk premium. We then sort the conditional market betas of value and growth stocks on the theoretically justified *expected* market risk premium. We find reliable evidence that, consistent with the efficient market hypothesis, the conditional market betas of value stocks are higher than those of growth stocks in bad times when the expected market risk premium is high, and to a lesser extent, the betas of growth stocks are higher than those of value stocks in good times when the expected market risk premium is low. (We refer to this pattern in the conditional betas below as the asymmetric beta.)

We also illustrate why previous studies fail to unearth such time-varying risk patterns for value and growth stocks. The main reason is that these studies define time-variation in risk with respect to the *ex post* realized market excess return, which is atheoretical and *ad hoc*. Since the realized market excess return is mainly correlated with its own unexpected component and less so with the expected market risk premium, this *ad hoc* procedure suffers from attenuation, which biases the estimates of the business cycle sensitivities of value and growth betas towards zero.

Our paper carries important implications for a range of issues in capital markets research. First, our results lend support to the proposition that the Fama and French (1992, 1993, 1996) book-to-market and size factors, HML and SMB, need not be some mysterious risk factors, but are rather better unconditional proxies for conditional market or macroeconomic risk than the market portfolio itself.

Several recent papers have reached similar conclusions. Theoretically, Campbell and Cochrane (2000) show that in an external habit model in which the market price of risk is time-varying and the conditional CAPM holds exactly, portfolio-based empirical models can perform better unconditionally than the consumption CAPM. Building on Berk, Green, and Naik (1999), Gomes, Kogan, and Zhang (2002) show that, in a single-factor conditional model, the cross-sectional relations between firm characteristics and expected returns can subsist even after one controls for typical empirical measures of beta. Empirically, 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) demonstrates 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 part of the risk premia on HML and SMB and perform as well as the Fama-French three-factor model in explaining the cross-section of returns.

Second, 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 when gauging 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 capital markets research. 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 with the sign of the market excess return. They further interpret the evidence that the drift is consistently positive across all states of the market excess return as indicating an underreaction interpretation of the drift. Our analysis suggests that it is necessary to reevaluate of the risk of the earnings momentum strategy by examining its covariation with the expected market risk premium.[1]

[1]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, following Black (1976) and Christie (1982), the time-varying volatility literature has traditionally focused on asymmetric volatility, which is the empirical phenomenon that return volatility rises after stock price falls. A popular explanation is the leverage effect, which posits that a drop in the stock price raises the firm's financial leverage, resulting in higher equity risk and hence higher return volatility. There are two problems with this explanation. As shown in Schwert (1989) and Duffee (1995), the evidence on the link between leverage and asymmetric volatility is statistically weak. Moreover, if higher leverage leads to an increase in return volatility due to higher risk, then beta should rise as well. However, the literature has so far delivered a negative verdict on asymmetric beta, e.g., Braun, Nelson, and Sunier (1995), Bekaert and Wu (2000), and Ang and Chen (2002).

Our analysis indicates that, first, when we follow the theoretical predictions and measure asymmetry empirically with respect to the *expected* return shocks, as opposed to the *ex post* return shocks used in previous studies, we do observe beta asymmetry. Second, the conditional betas of firms with different characteristics react differently to expected return shocks, and this can explain further why previous studies fail to document beta asymmetry using *diversified* portfolios. Third, if the economic mechanism underlying beta asymmetry (discussed in Section 2) is also responsible for asymmetric volatility, then the degree of volatility asymmetry should also vary across firms with different book-to-market ratios. Testing this hypothesis may shed more light on what drives the leverage effect or whether it relates to leverage at all.

Finally, the popular risk-adjusted discount rate method for corporate valuation 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) assert 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." The theoretical model of Gomes, Kogan, and Zhang (2002) also says that growth options are always riskier than assets in place, because these options are "leveraged" on existing assets. As growth firms derive most of their values from growth options, and value firms from assets in place, our evidence suggests that growth options are not always the source of high risk. Managers should assign higher cost of capital to assets in place, especially in bad times.

The rest of the paper is organized as follows. Section 2 motivates our analysis in the context of the relevant literature. Section 3 contains our empirical framework for estimating the business cycle sensitivities of portfolio betas. We present our findings in Section 4, and discuss in Section 5 the implications of our work for previous studies, most notably, Lakonishok, Shleifer, and Vishny (1994). Finally, Section 6 concludes.

2 Background

Among the competing explanations for the value premium, we focus on the rational expectations theory of Zhang (2003) and the over-extrapolation hypothesis of Lakonishok, Shleifer, and Vishny (1994, hereafter LSV).

Zhang (2003) argues that the asymmetric beta dispersion between value and growth results from the asymmetry in capital adjustment technology, i.e., it is much more costly for firms to downscale than to expand their production capacity. His reasoning has multiple steps. First, the ability to adjust production capacity allows firms to smooth dividends in the presence of exogenous shocks. The more flexibility companies have in this regard, the less risk they face, e.g., Jermann (1998) and Boldrin, Christiano, and Fisher (2001). Second, in bad times, almost all firms want to scale down. This is especially acute for value firms, since they are less productive than growth firms to begin with, e.g., Fama and French (1995). Since downscaling is difficult, the dividend streams of value companies will covary more with economic downturns. Third, in good times, it is the growth firms' turn to face less flexibility: they want to invest more given their already productive assets. For value firms, expanding is less urgent since their previously unproductive assets now become more productive. As expanding production capacity is relatively easy, the dividend streams of growth firms do not covary much with economic booms. The net effect of this asymmetric adjustment cost is a high risk dispersion between value and growth firms in bad times, and a low or even negative risk dispersion in good times.

To our knowledge, the only other paper that documents a similar pattern 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 the returns of value stocks are more highly correlated with consumption growth rate than growth stocks in bad times when risk or risk aversion is high.[2] Our paper differs in two important aspects. First, our empirical method is different, as we use a set of common conditioning variables from the time series predictability literature. Second, our definition of risk is different, as we focus on the *market* beta, as opposed to the *consumption* beta as in Lettau and Ludvigson (2001).

In the behavioral finance literature, however, LSV contend that value strategies earn higher returns because they are contrarian to naive strategies followed by irrational investors. These investors tend to get overly excited about stocks that have done well in the past and buy them up to the extent that they become overpriced. Similarly, they overreact to stocks that have done badly and oversell them so that these stocks become underpriced. Value investors bet against such naive investors and hence they outperform the market.

To support their over-extrapolation hypothesis, LSV present evidence that value stocks are not fundamentally riskier than growth stocks in bad states of the world, defined as extreme down markets. Subsequent studies reaching similar conclusions include La Porta (1996) and La Porta, Lakonishok, Shleifer, and Vishny (1997). The behavioral finance literature has hailed this evidence as substantiating the 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." Other prominent examples include Shiller (1999), Hirshleifer (2001), Barberis and Thaler (2002), and Daniel, Hirshleifer and Teoh (2002).

The current state of affairs concerning the relative risk of value and growth is perhaps best summarized in Cochrane (2001). "What are the macroeconomic risks for which the Fama-French factors are proxies or mimicking portfolios?" Cochrane asks, and suggests

[2] However, Brennan and Xia (2002) have recently questioned their use of the consumption-wealth ratio. The debate is still ongoing. See Lettau and Ludvigson (2002).

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 summary, the extant evidence seems disproportionally in favor of the overreaction hypothesis. But as we will show in this paper, LSV's evidence is specific to their sample, and more importantly, their interpretation does not necessarily follow from their evidence.

3 Empirical Framework

To see how time-varying 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, γ is the unconditional market risk premium, and $\beta_i = \mathrm{Cov}[r_{it}, r_{mt}]/\mathrm{Var}[r_{mt}]$ is the unconditional beta where r_{mt} denotes 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: both are conditional on the information set at time t.

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:

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

$\gamma = \mathrm{E}[\gamma_t]$ is the average market excess return, and $\bar{\beta}_i \equiv \mathrm{E}[\beta_{it}]$ is the average beta.[3] Equation (3) shows that average return spread depends on the spread in average betas and that in beta-premium sensitivities. Stocks with betas that covary positively with the expected market risk premium should earn higher returns than those with betas that covary negatively with

[3]The average beta $\bar{\beta}_i$ is not identical to the unconditional beta β_i because of Jensen's inequity.

the expected market risk premium. Importantly, the part of the conditional beta that is correlated with the unexpected market excess return, but uncorrelated with the expected market excess return, has *no* effect on average returns.

Jagannathan and Wang (1996) discuss a similar framework in which the beta-premium sensitivity affects average returns. They perform cross-sectional tests on 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 beta-premium sensitivity.

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

First, following Fama and French (1989) and Ferson and Harvey (1991), we estimate the expected market risk premium by regressing the realized market excess returns on a set of conditioning variables, including an intercept:

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

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

The estimated expected risk premium $\hat{\gamma}_t$ is defined as the fitted component in (5).[4]

Our choice of conditioning variables follows the time series predictability literature. These variables include: (i) the dividend yield, DIV, 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, e.g., 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, defined as the yield spread

[4] Harvey (2001) shows that forecasts of market returns are not improved much with nonparametric techniques. This suggests that linear conditional expectation is a reasonable approximation.

between Moody's Baa and Aaa corporate bonds, e.g., 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, defined as the yield spread between a long-term and a one-year Treasury bond, e.g., 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, e.g., Fama and Schwert (1977) and Fama (1981), taken from CRSP.

Next, 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 is 36, 48, or 60 months. Second, we follow the conditional market regression method of Shanken (1990) and assume that the conditional beta is a linear function of the conditioning variables, known at time t:

$$\begin{aligned} r_{it+1} &= \alpha_i + \left(b_{i0} + b_{i1}\mathrm{DIV}_t + b_{i2}\mathrm{DEF}_t + b_{i3}\mathrm{TERM}_t + b_{i4}\mathrm{TB}_t\right) r_{mt+1} + \epsilon_{it+1} && (7) \\ \hat{\beta}_{it} &= \hat{b}_{i0} + \hat{b}_{i1}\mathrm{DIV}_t + \hat{b}_{i2}\mathrm{DEF}_t + \hat{b}_{i3}\mathrm{TERM}_t + \hat{b}_{i4}\mathrm{TB}_t && (8) \end{aligned}$$

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

Finally, to estimate the beta-premium sensitivity φ_i defined in (4), we regress the 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.

There are a few sources of measurement error in the beta-premium regression (9) that can affect our statistical inferences. First, the estimated expected market risk premium, $\hat{\gamma}_t$, is only a proxy for the true premium, and is hence 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) are likely to 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 can be correlated. We deal with this problem by estimating $\hat{\beta}_{it}$, $\hat{\gamma}_t$, and $\hat{\varphi}_i$ *simultaneously* by GMM, thereby taking into account all the measurement errors in making statistical inference. The set of orthogonality conditions we use is naturally:

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

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

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

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 two extreme portfolios, we stack the moment conditions of the two portfolios together and estimate the parameters jointly in one step. We can then carry out the standard Wald test on linear restrictions.

If we use the rolling-window regression in estimating betas, then the measurement error in beta is less likely to correlate with that 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 use GMM to adjust for the sampling variation in $\hat{\gamma}_t$. The set of moment conditions we use is:

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

$$\mathrm{E}\left[\left[\widetilde{\beta}_{it} - c_i - \varphi_i\mathbf{Z}_t\boldsymbol{\delta}\right][\iota\ \mathbf{Z}_t\boldsymbol{\delta}]'\right] = 0 \tag{14}$$

where $\widetilde{\beta}_{it}$ denotes the rolling beta of portfolio i at time t.

4 Findings

We present our findings in this section. Section 4.1 discusses the data and summary statistics of portfolio returns used in our study. Several recent papers have questioned the statistical robustness of time series predictability of aggregate stock market returns.[5] We thus present in Section 4.2 some supporting evidence of the countercyclical expected market risk premium in our sample. The center of our inquiry is Section 4.3, which reports the results of our tests on the cyclical variation of portfolio betas. Finally, we investigate in Section 4.4 whether the beta-premium sensitivity is priced in a cross-sectional regression framework and whether it is sufficiently large to account for the value premium.

4.1 Data and Descriptive Statistics

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 (B/M), a set of ten portfolios sorted by size, and a set of 25 portfolios sorted by size and B/M.[6] Monthly asset returns series are those used by Davis, Fama, and French (2000) and are from Ken French's website. The sample period we use is from January 1927 to December 2001, except for portfolio 55, the large-value portfolio, which has missing data prior to July 1931. So for that portfolio, we start the sample period from July 1931.

We report in Table 1 the summary statistics for the size and book-to-market portfolios, including mean, volatility, and unconditional market regressions. Interestingly, even the unconditional beta spread between portfolios Low and High in the ten B/M portfolios is as much as 0.40 for in our sample. This number is higher than the 0.10 reported by LSV using the sample from 1968 to 1989 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.

4.2 Stock Market Predictability and Business Cycles

The rational expectations theories predict that the expected market excess return is time-varying and inversely related to the business cycle. Intuitively, in bad times, investors may

[5]Examples include Stambaugh (1999), Ang and Bekaert (2001), and Goyal and Welch (2002); see also Lewellen (2002) and Campbell and Yogo (2002) for the other side of the debate.

[6]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 : Summary Statistics for the Test Portfolios (January 1927 to December 2001, 900 Monthly Observations)

This table reports the results from unconditional market regressions, including the intercept α, the slope β, and their t-statistics, as well as the annualized means m and volatilities σ for the Fama-French 25 portfolios, ten size portfolios, and ten B/M portfolios. α's are in monthly percent. All the t-statistics are adjusted using the Newey-West (1987) method with 6 lags.

	Panel A: 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	-0.16
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 B: 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

	Panel C: 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

become more risk averse and thus require higher compensation for taking on additional risk, e.g., Campbell and Cochrane (1999). In a heterogeneous-agent framework, the cross-sectional volatilities of labor income growth and consumption growth rates tend to increase in economic downturns, e.g., Storesletten, Telmer, and Yaron (2003). As a result, the cross-sectional average of investors' intertemporal rates of substitution becomes more countercyclical, giving rise to a higher price of risk, e.g., Constantinides and Duffee (1996). Finally, the amount of risk in the economy evolves endogenously in a general equilibrium production economy, e.g., Gomes, Kogan, and Zhang (2002). In particular, irreversible investment implies that the scale of production cannot be easily reduced during recessions, increasing the volatility of stock market returns.

Despite compelling theoretical reasons and early supporting evidence in Fama and French (1988, 1989) and Ferson and Harvey (1991), several recent papers have cast some doubts on statistical robustness of the return predictability (see the citations in footnote 5). While it is outside the scope of this paper to reexamine the issue of time series predictability, we wish to present some evidence on a countercyclical expected market risk premium within our sample.

We perform a first-order VAR in five variables: the market excess return, the dividend yield, the one-month Treasury-bill return relative to its previous 12-month moving average, the term premium, and the default premium. The sample period is from January 1928 to December 2001: we use the 12 monthly observations in 1927 to calculate the relative Treasury-bill rate in January 1928. Table 2 presents the results of the equation for the excess market return in the VAR. If returns are not predictable, all of the coefficients on the lagged variables in the return equation must be zero. The χ^2 is the Wald statistic on the null hypothesis that the coefficients of the four conditioning variables are jointly zero. We observe that the conditioning variables have reliable predictive power for the market excess return: the χ^2 statistic is 14 with a p-value of 1.8%. The predictability persists in the shorter sample from 1963 to 2001, but has diminished somewhat in the most recent sample from 1986 to 2001.

Is the variation in the expected market risk premium related to the business cycle? To

Table 2 : First-Order VAR for Market Excess Returns, Dividend Yield, Relative Treasury-Bill rate, Term Premium, and Default Premium

This table reports the results for the market excess return equation in a first-order VAR in the market excess return, the dividend yield, the relative Treasury-bill rate, the term premium, and the default premium. The $\chi^2_{(4)}$ test is for the null hypothesis that the coefficients of the four conditioning variables are jointly zero. The t-statistics are adjusted for heteroscedasticity and autocorrelation of up to 12 lags using the Newey and West (1987) method.

Constant	$\log(R_t) - \log(r_t^f)$	DIV_t	RB_t	TERM_t	DEF_t	$\chi^2_{(4)}$	p	R^2
Panel A: January 1928 to December 2001 (888 Observations)								
-0.011	0.111	0.289	0.359	0.351	0.008	14	0.018	0.024
(-1.42)	(1.67)	(1.93)	(0.32)	(1.28)	(0.01)			
Panel B: January 1963 to December 2001 (468 Observations)								
-0.008	0.018	0.448	-3.024	0.263	1.152	21	0.000	0.037
(-0.93)	(0.40)	(1.42)	(-1.90)	(1.28)	(1.67)			
Panel C: January 1986 to December 2001 (192 Observations)								
0.035	0.018	1.300	-11.508	-1.068	0.848	10	0.090	0.026
(1.574)	(0.21)	(1.81)	(-1.92)	(-1.92)	(0.52)			

shed light on this issue, we follow Chen (1991) and regress the realized market excess return on the lagged growth rates of real industrial production: $R^e_{mt+1} = a + b\,\text{IPG}_{t-12,t} + \epsilon_{t+1}$, where R^e_{mt+1} is the market excess return from month t to month $t+1$ and $\text{IPG}_{t-12,t}$ is the recent annual real growth rate of industrial production at time t. The index of real industrial production is from the monthly database of the Federal Reserve Bank of Saint Louis. The sample period is from February 1940 to December 2001. Since the regressor has overlapping observations, we adjust the standard errors of the coefficients for autocorrelation of up to 36 lags using the Newey-West (1987) method. We find that the slope coefficient is negative, -0.150, and significant with a t-statistic of -2.27. We have also used the lagged values of the log real industrial production filtered by the Hodrick and Prescott (1997) filter to measure recent economic conditions and obtained quantitatively very similar results.

The expected market risk premium is also related to expected future economic growth. We test this hypothesis by regressing the realized market excess return on the expected growth rate of industrial production: $R^e_{mt+1} = a + b\,\text{E}_t[\text{IPG}_{\text{t,t+12}}] + \epsilon_{t+1}$, where the expected future growth rate $\text{E}_t[\text{IPG}_{\text{t,t+12}}]$ is estimated as the fitted component from regressing the realized growth rate on the lagged growth rate and the four conditioning variables. We again use GMM to account for the generated regressor problem in the expected growth rate, and adjust the standard errors for heteroscedasticity and autocorrelation of up to 36 lags. We find that the slope coefficient b is positive, 0.247, and significant with a t-statistic of 2.65.

In summary, consistent with Chen (1991), we find that the expected market risk premium is negatively correlated with recent economic growth and positively correlated with expected future economic growth. This suggests that the expected market risk premium is countercyclical within our sample.

4.3 Cyclical Variation in Portfolio Betas

We now turn to the center of our inquiry, which is the cyclical variation of value and growth betas. We start by reporting directly the average conditional portfolio betas in different states of the world. This is perhaps the most straightforward, albeit informal, way to examine the time-variation of betas. We define four states of the world. State "Boom" is identified with the lowest ten percent observations of the expected market risk premium; state "−" is the remaining months with the expected market risk premium below its average; state "+" is the months with the expected market risk premium above its average but other than the ten percent highest; and state "Bust" is the months with the ten percent highest observations of the expected market risk premium.

Table 3 reports the results of sorting rolling betas on the expected market risk premium. The sample starts from January 1932 because we use the previous five years of data to estimate the first observations of conditional betas in a 60-month rolling window. Several interesting patterns emerge from Table 3. First, Panel A shows that the market beta of HML is clearly countercyclical: it is positive and significant in bad times (Bust) and negative and marginally significant in good times (Boom). Second, Panel B shows that in bad times, when the expected market risk premium is at its peak, the rolling beta difference between portfolios High and Low is about 0.90, and about zero in good times, when the expected market risk premium is at its bottom.[7] This evidence is consistent with the prediction in Zhang (2003) that the beta dispersion between value and growth is asymmetric across business cycles.

[7] The results from using 36- and 48-month rolling windows are very similar and are omitted to save space.

Table 3 : Average Rolling Betas Sorted on the Expected Market Risk Premium (January 1932 to December 2001, 840 Monthly Observations)

This table reports average rolling betas for Fama-French 25 portfolios, ten book-to-market portfolios, and ten size portfolios, in good and bad times, defined by sorting on the expected market risk premium. Four states of the world are defined: "Boom" is identified with the lowest ten percent expected market risk premium months; "−" is the remaining below average risk premium months other than the ten percent lowest; "+" is the above average risk premium months other than the ten percent highest; and "Bust" is the ten percent highest months of expected market risk premium in the sample. HML denotes the return spread between value and growth while controlling for size, and SMB denotes the return spread between Small and Big while controlling for book-to-market. The t-statistics are for testing the hypothesis that the HML and SMB betas are zero and are adjusted for heteroscedasticity and autocorrelation of up to 60 lags using the Newey-West (1987) method.

Panel A: HML and SMB

	Boom	−	+	Bust		Boom	−	+	Bust
HML	-0.15	-0.11	0.08	0.33	SMB	0.27	0.13	0.20	0.28
t-stat	-1.84	-1.34	0.62	12.64	t-stat	6.34	1.83	5.43	4.64

Panel B: 10 B/M Portfolios; Panel C: 10 Size Portfolios

Panel B	Boom	−	+	Bust	Panel C	Boom	−	+	Bust
Low	1.08	1.11	1.02	0.93	Small	1.22	1.08	1.39	1.75
2	1.01	1.02	1.01	1.00	2	1.25	1.12	1.34	1.62
3	0.97	1.00	1.00	0.95	3	1.27	1.14	1.28	1.46
4	0.96	0.95	1.04	1.08	4	1.24	1.12	1.23	1.37
5	0.89	0.89	0.94	0.97	5	1.18	1.10	1.21	1.37
6	0.92	0.93	1.04	1.08	6	1.15	1.08	1.19	1.29
7	0.92	0.94	1.06	1.27	7	1.10	1.06	1.17	1.23
8	0.97	0.98	1.05	1.28	8	1.08	1.05	1.11	1.12
9	1.00	0.99	1.19	1.59	9	1.00	1.00	1.07	1.11
High	1.09	1.09	1.35	1.81	Big	0.92	0.96	0.92	0.93

Panel D: Fama-French 25 Portfolios

	Low	2	3	4	High		Low	2	3	4	High
	Boom						−				
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
	+						Bust				
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

Third, Panel C of Table 3 reports a similar, but weaker, pattern of beta asymmetry for small and large firms. This result by itself is not new, as Chan and Chen (1988) and Perez-Quiros and Timmermann (2000) report similar cyclical patterns of small and large portfolio betas. We note that, however, HML and SMB in Panel A are constructed so that the former controls for the size effect, while the latter controls for the value effect, e.g., Fama and French (1993). The reason is that size and B/M are negatively correlated in the data, e.g., Fama and French (1992). In Panels B and C, no such controls are imposed on B/M or size portfolios. Thus, a comparison between Panels A and C indicates that, after the value effect is controlled for, there is no trace of beta asymmetry in SMB, but beta asymmetry persists in HML even after the size effect is controlled for. This evidence implies that the cyclical pattern in size portfolio betas documented in the current literature us to a large extent driven by that in B/M portfolio betas.

These three patterns of time-varying betas persist in Table 4, which reports the average fitted betas across the different states of the business cycle. In some aspects, the pattern is even stronger with the fitted betas than that with the rolling betas in Table 3. Panel A shows that the average HML beta in good times is now negative, -0.32, and significant with a t-statistic of -4.62; the average HML beta in bad times continues to be positive and highly significant. In Panel B, the beta dispersion between portfolios High and Low remains at about 0.75 in bad times but becomes negative, -0.26, in good times, displaying a higher degree of asymmetry.

Is the asymmetric beta dispersion between value and growth across the business cycles reported in Tables 3 and 4 statistically significant? Using conditional betas estimated from the 60-month rolling window, Table 5 reports the results for the cross-sectional variation of beta-premium sensitivities for HML, SMB, ten B/M portfolios, ten size portfolios, and Fama-French 25 size and B/M portfolios.

Table 5 indicates that there exists a strong relation between the beta-premium sensitivity and firm characteristics. In Panel A, HML has a rolling beta that is positively correlated with the expected market risk premium and the correlation is significant with a t-statistic of 1.99. The same is true for SMB but the effect there is not significant. In Panels B and C,

Table 4 : Average Fitted Betas Sorted on the Expected Market Risk Premium (January 1927 to December 2001, 900 Monthly Observations)

This table reports average fitted betas for Fama-French 25 portfolios, ten book-to-market portfolios, and ten size portfolios, in good and bad times, defined by sorting on the expected market risk premium. Four states of the world are defined: "Boom" is identified with the lowest ten percent expected market risk premium months; "−" is the remaining below average risk premium months other than the ten percent lowest; "+" is the above average risk premium months other than the ten percent highest; and "Bust" is the ten percent highest months of expected market risk premium in the sample. HML denotes the return spread between value and growth while controlling for size, and SMB denotes the return spread between Small and Big while controlling for book-to-market. The t-statistics are for testing the hypothesis that the HML and SMB betas are zero and are adjusted for heteroscedasticity and autocorrelation of up to 60 lags using the Newey-West (1987) method.

Panel A: HML and SMB

	Boom	−	+	Bust		Boom	−	+	Bust
HML	-0.32	-0.15	0.05	0.40	SMB	0.22	0.21	0.16	0.15
t-stat	-4.62	-2.74	0.70	19.82	t-stat	9.10	7.90	3.47	3.08

Panel B: 10 B/M Portfolios					Panel C: 10 Size Portfolios				
	Boom	−	+	Bust		Boom	−	+	Bust
Low	1.13	1.08	1.04	0.95	Small	1.08	1.18	1.27	1.60
2	1.00	1.02	1.03	0.98	2	1.16	1.25	1.29	1.46
3	1.01	1.01	1.00	0.92	3	1.13	1.17	1.22	1.37
4	0.94	0.93	0.97	1.09	4	1.10	1.15	1.17	1.28
5	0.89	0.88	0.90	0.99	5	1.08	1.13	1.17	1.29
6	0.86	0.90	0.97	1.15	6	1.08	1.11	1.14	1.25
7	0.79	0.88	1.02	1.28	7	1.09	1.11	1.12	1.17
8	0.75	0.89	1.06	1.33	8	1.04	1.06	1.08	1.13
9	0.77	0.98	1.20	1.58	9	0.98	1.01	1.05	1.12
High	0.87	1.09	1.31	1.70	Big	0.94	0.94	0.94	0.93

Panel D: Fama-French 25 Portfolios

	Low	2	3	4	High		Low	2	3	4	High
			Boom						−		
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
			+						Bust		
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

we report that the conditional rolling betas of value and small stocks covary positively with the expected market risk premium, while those of growth and large stocks covary negatively with the expected market risk premium. Moreover, the Wald test on the null hypothesis that the beta-premium sensitivity is equal across extreme B/M or size portfolios is rejected at the 5% significance level.

Using fitted betas, Table 6 reports that the cyclical patterns for value and growth portfolio betas continue to be significant, but the patterns for small and large portfolio betas cease to be so. A caveat is in order for Panel D of Table 6, concerning the cross-sectional variation of fitted beta-premium sensitivity for the 25 size and book-to-market portfolios. The first row of Panel D shows that, in the smallest quintile in which the value effect is strongest, the beta-premium sensitivity of growth stocks is actually higher than that of value stocks. In particular, the beta-premium sensitivity of the small-growth portfolio is 33.11, the highest in the smallest quintile. Moreover, in the largest quintile in which the value premium is weakest, the spread in beta-premium sensitivity between value and growth is huge.

Further diagnostic tests suggest that this pattern is mainly driven by the observations during the Great Depression. Table 7 repeats the analysis in Table 6 for the sample from January 1935 to December 2001. Panel D now reports a drastically different beta-premium sensitivity of the small-growth portfolio, -8.52. A comparison between Tables 6 and 7 also reveals that the conditional effect is more important during recessions. Once we exclude the Great Depression from the sample, the spread in beta-premium sensitivity between portfolios High and Low shrinks by about one quarter, and that between portfolios Small and Big goes down by more than 60%.

It is intriguing that the Great Depression has such a huge impact on the behavior of the small firms in general, and the small-growth firms in particular, but not as much on the value firms. We have done similar exercises by excluding other recessions in the sample and found that this feature is unique to the Great Depression: other recessions affect small and value firms more or less equally.[8] We speculate that other economic mechanism, possibly that of financial friction, rather than the technological friction of asymmetric adjustment

[8] The results are not reported here to save space but are available upon request.

Table 5 : Cross-Sectional Variation of Rolling Beta-Premium Sensitivity (January 1932 to December 2001, 840 Monthly Observations)

This table reports the cross-sectional variation of beta-premium sensitivity φ_i and its t-statistics across Fama-French 25 portfolios, ten book-to-market portfolios, ten size portfolios, and HML and SMB. Conditional betas are estimated using 60-month rolling-window regressions and the expected market risk premium is assumed to be a linear function of conditioning variables, including a constant, dividend yield, term premium, default premium, and 1-month Treasury bill rate. The 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 heteroscedasticity and autocorrelation using the Newey-West (1987) method with 60 lags. The Wald test statistic and its p-value on the equality of φ_i across two extreme portfolios are also reported.

Panel A: HML and SMB

	φ_i	t_{φ_i}		φ_i	t_{φ_i}
HML	20.42	1.99	SMB	2.84	1.07

Panel B: 10 B/M Portfolios					Panel C: 10 Size Portfolios				
	φ_i	t_{φ_i}	Wald	p		φ_i	t_{φ_i}	Wald	p
Low	-6.81	-1.95	4.46	0.035	Small	25.52	2.08	4.35	0.037
2	-1.77	-1.36			2	17.28	1.97		
3	-2.08	-1.14			3	10.70	2.12		
4	6.46	2.28			4	7.55	1.80		
5	5.04	2.48			5	8.99	1.98		
6	8.50	2.19			6	7.50	2.02		
7	14.32	2.09			7	6.06	1.55		
8	13.29	2.16			8	2.75	1.81		
9	24.15	2.14			9	4.80	1.83		
High	27.53	1.92			Big	-1.23	-1.47		

Panel D: 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

cost analyzed by Zhang (2003), is the dominating force during the Great Depression. As Bernanke (1983) argues, the Great Depression manifests many unique features not shared by other recessions. During 1930–1933, the U.S. financial system experienced waves of bank failures which culminated in the shutdown of the banking industry in March 1933. As a result, exceedingly high rates of default and bankruptcy affected almost every class of borrowers. The exceptionally adverse financial conditions are likely to impact more on small firms, and small-growth firms in particular, since these firms invest more, grow faster, and have higher demands of but less collateral for external financing, than large and value firms.

4.4 Is the Beta-Premium Sensitivity Priced?

We have shown that value is riskier than growth, especially in bad times when the expected market risk premium is high. A natural question is whether this covariation of the conditional beta and the expected market risk premium is priced and, if yes, whether it is sufficiently large to account for the value premium.

We investigate this issue using the Fama-MacBeth (1973) cross-sectional regressions. Equation (3) says that the unconditional average return on an asset is a linear function of its average beta and its beta-premium sensitivity. We measure the average beta, $\bar{\beta}$, by the unconditional market beta of each asset, and we measure the beta-premium sensitivity, φ, by regressing each portfolio's fitted beta on the expected market risk premium. For each month t in the cross-section, we measure the average betas and beta-premium sensitivities using all the information up to that month, i.e., an expanding window. As an alternative measure of time-variation of risk, we follow Jagannathan and Wang (1996) and use the slope coefficient from regressing portfolio excess returns on the default premium. We denote this measure by ϑ and include it in the right hand side of the regressions.

Table 8 presents the regression results using the 25 size and B/M portfolios as the target assets. Panel A reports the results for the sample from July 1936 to December 2001.[9] The panel shows that the unconditional CAPM performs reasonably well: the intercept is positive but not significant. Ang and Chen (2003) make a similar point on the performance of the

[9] We use this sample because (i) portfolio 55 has missing data before July 1931; and (ii) we use the first five years of data from July 1931 to June 1936 to compute the average betas for July 1937.

Table 6 : Cross-Sectional Variation of Fitted Beta-Premium Sensitivity (January 1927 to December 2001, 900 Monthly Observations)

This Table reports the cross-sectional variation of beta-premium sensitivity and its t-statistics across Fama-French 25 portfolios, ten book-to-market portfolios, ten size portfolios, and HML and SMB. The beta-premium sensitivity is computed as the slope coefficient from regressing the fitted conditional beta on the expected market risk premium. The expected market risk premium is estimated as a linear function of a vector of state variables, including a constant, dividend yield, term premium, default premium, and 1-month Treasury bill rate. The conditional beta is estimated as the fitted beta series using the same vector of state variables as above. The t-statistics are corrected for heteroscedasticity and autocorrelation using the Newey-West (1987) estimator with 60 lags. The Wald test statistic and its p-value on the equality of φ_i across two extreme portfolios are also reported.

Panel A: HML and SMB

	φ_i	t_{φ_i}		φ_i	t_{φ_i}
HML	33.34	2.12	SMB	-3.78	-0.47

Panel B: 10 B/M Portfolios					Panel C: 10 Size Portfolios				
	φ_i	t_{φ_i}	Wald	p		φ_i	t_{φ_i}	Wald	p
Low	-7.67	-1.65	4.01	0.045	Small	22.43	1.25	1.40	0.237
2	-0.17	-0.04			2	12.47	0.92		
3	-3.61	-1.06			3	10.79	1.10		
4	7.63	1.51			4	7.64	0.80		
5	5.31	1.08			5	9.18	1.15		
6	13.55	2.07			6	7.36	1.22		
7	23.06	2.48			7	3.48	0.76		
8	27.50	2.39			8	4.26	1.37		
9	37.11	2.25			9	6.91	2.45		
High	37.86	2.05			Big	-0.06	-0.04		

Panel D: Fama-French 25 Portfolios

	Low	2	3	4	High		Low	2	3	4	High
			φ_i						t_{φ_i}		
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

Table 7 : Cross-Sectional Variation of Fitted Beta-Premium Sensitivity (January 1935 to December 2001, 804 Monthly Observations)

This Table reports the cross-sectional variation of beta-premium sensitivity and its t-statistics across Fama-French 25 portfolios, ten book-to-market portfolios, ten size portfolios, and HML and SMB. The beta-premium sensitivity is computed as the slope coefficient from regressing the fitted conditional beta on the expected market risk premium. The expected market risk premium is estimated as a linear function of a vector of state variables, including a constant, dividend yield, term premium, default premium, and 1-month Treasury bill rate. The conditional beta is estimated as the fitted beta series using the same vector of state variables as above. The t-statistics are corrected for heteroscedasticity and autocorrelation using the Newey-West (1987) estimator with 60 lags. The Wald test statistic and its p-value on the equality of φ_i across two extreme portfolios are also reported.

Panel A: HML and SMB

	φ_i	t_{φ_i}		φ_i	t_{φ_i}
HML	24.97	1.99	SMB	-3.78	-0.47

Panel B: 10 B/M Portfolios and Panel C: 10 Size Portfolios

Panel B	φ_i	t_{φ_i}	Wald	p	Panel C	φ_i	t_{φ_i}	Wald	p
Low	-3.99	-0.91	3.80	0.051	Small	9.67	0.62	0.22	0.639
2	5.12	1.44			2	3.68	0.34		
3	1.19	0.39			3	0.58	0.08		
4	5.11	1.13			4	0.76	0.11		
5	2.96	0.75			5	2.95	0.52		
6	6.47	1.43			6	1.44	0.34		
7	16.75	2.29			7	2.63	0.73		
8	14.79	2.01			8	0.58	0.28		
9	24.39	2.21			9	5.64	2.60		
High	30.43	2.20			Big	1.78	1.03		

Panel D: Fama-French 25 Portfolios

	Low	2	3	4	High		Low	2	3	4	High
			φ_i						t_{φ_i}		
Small	-8.52	2.93	13.48	8.21	16.11	Small	-0.51	0.27	1.12	0.76	1.11
2	-10.84	-0.30	4.53	9.20	19.19	2	-1.07	-0.04	0.63	1.18	1.62
3	-14.49	3.18	6.90	11.92	25.14	3	-1.65	0.68	1.02	1.50	2.13
4	-12.94	1.88	9.92	15.77	24.20	4	-2.04	0.46	1.76	2.29	2.08
Big	2.91	4.31	4.56	19.08	30.33	Big	0.79	1.15	1.04	2.36	2.22

Table 8 : Cross-Sectional Regressions

This table presents the results of monthly cross-sectional regressions, including the regression coefficients expressed as percentage per month, and their corresponding t-statistics. Panel A uses the sample from July 1936 to December 2001 and Panel B uses the sample from July 1963 to December 2001. The dependent variables are the excess returns on Fama and French 25 portfolios sorted by book-to-market and size. The regressors include a constant, α, the average betas with respect to the market excess return, $\bar{\beta}$, the average betas with respect to the default premium, ϑ, and the beta-premium sensitivity for each portfolio, φ, which is the slope from regressing of each portfolio's fitted beta on expected market risk premium. All the regressors except the intercept at month t are calculated using all the information up to that month, i.e., an expanding window. $\bar{R}^2$ is the adjusted goodness-of-fit and is in percent.

Panel A: July 1936 to December 2001					Panel B: January 1963 to December 2001				
α	$\bar{\beta}$	ϑ	φ	$\bar{R}^2$	α	$\bar{\beta}$	ϑ	φ	$\bar{R}^2$
0.41	0.33			0.167	1.16	-0.48			0.180
(1.74)	(1.62)				(2.32)	(-0.91)			
0.57	0.12	0.10		0.193	1.11	-0.80	0.24		0.554
(2.24)	(0.45)	(1.57)			(2.22)	(-1.47)	(1.81)		
0.45	0.30		0.01	0.188	0.75	-0.06		0.03	0.344
(1.33)	(0.88)		(0.24)		(1.72)	(-0.13)		(2.86)	

uncondition CAPM in the long run. Adding the beta on the default premium, ϑ, as a regressor actually worsens the performance of the model. The inclusion of the beta-premium sensitivity, φ, raises the intercept slightly relative to that with the unconditional CAPM, but cuts its t-statistic by about one quarter.

Panel B of Table 8 reports the results for the subsample from July 1963 to December 2001. We consider this post-Compustat sample to facilitate comparison of our work to previous studies, e.g., Fama and French (1992) and Lakonishok, Shleifer, and Vishny (1994). The panel shows that the average market beta has a negative premium, and it leaves a significantly positive intercept unexplained. Adding the beta on the default premium shrinks α by five basis points per month but α is still significant; it also increases the magnitude of the negative coefficient on the average beta. The benefit of including the beta-premium sensitivity, φ, is very clear, as φ cuts the intercept by about a third and it is no longer significant. Moreover, the risk premium associated with φ is a positive three basis point per month and significant with a t-statistic of 2.86. The adjusted R^2 is lower when we replace the beta on the default premium with the beta-premium sensitivity. But Ferson and Harvey

(1999) argue that the adjusted R^2 is not a reliable statistic for explanatory power in this setting. So we focus on the significant t-statistic of φ instead.

Is the risk premium of 0.03% per month associated with the beta-premium sensitivity economically significant? We provide some simple calculations here. The largest return spread within the Fama-French 25 portfolios is that between portfolios 11 and 15, the small-growth and the small-value portfolios. This return spread is 0.84% per month in the sample from July 1963 to December 2001. This seems extremely troublesome for the unconditional CAPM since the small-growth portfolio has an average beta of 1.44, higher than 1.02, the average beta of the small-value portfolio. However, the small-growth portfolio also has a negative beta-premium sensitivity of -16.40, while the small-value portfolio has a positive beta-premium sensitivity of 5.86. So the amount of unconditional return spread between these two portfolios due to their spread in the beta-premium sensitivity equals $(5.86+16.40)\times 0.03\% = 0.67\%$, which is about 80% of the total average return spread.

The good news for the conditional CAPM is specific to the cross-sectional regression framework, however. Table 9 reports the results of conditional market regressions for HML, SMB, ten B/M portfolios, ten size portfolios, and the 25 size and B/M portfolios. Under this framework, conditional betas seem to add little to explain the returns on size and B/M portfolios. The difference in Jensen's α's between the high and low B/M quintiles is 29 basis points per month for the size quintile 3, 60 basis points for size quintile 2, and a whopping 110 basis points for the smallest size quintile.

We wish to emphasize that our goal in this paper is not to search for a better conditional beta specification. We adopt the linear specification of conditional beta because of its simplicity and prominence in the literature, e.g., Shanken (1990) and Ferson and Harvey (1999). As we argue in the next section, our main point is that in drawing economic inferences on time-varying risk and return, it is imperative to sort conditional betas on the expected, as opposed to the realized, market excess returns. Our approach is tantamount to the instrumental-variable estimation, which only requires that the conditioning variables are correlated with the expected, but uncorrelated with the unexpected, market excess returns.

Table 9 : Jensen's α from Conditional Market Regressions (January 1927 to December 2001, 900 Monthly Observations)

This table reports Jensen's α from conditional market regression for ten B/M portfolios (Panel A), ten size portfolios (Panel B), and 25 size and B/M portfolios (Panel C). The α for portfolio i is defined as the intercept from the regression:

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

where r_{it+1} and r_{mt+1} are excess portfolio return and market return, respectively. The intercepts are in percent. All the t-statistics are calculated from standard errors adjusted using Newey-West (1987) method with lag 6. The α's of HML and SMB are also reported in Panels A and B, respectively.

	Panel A: 10 B/M Portfolios										
	Low	2	3	4	5	6	7	8	9	High	HML
α	-0.08	0.03	0.02	-0.03	0.15	0.09	0.12	0.21	0.22	0.13	-0.03
t_α	-1.11	0.49	0.41	-0.41	2.05	1.21	1.28	2.21	1.90	0.80	-0.25
	Panel B: 10 Size Portfolios										
	Small	2	3	4	5	6	7	8	9	Big	SMB
α	0.32	0.14	0.14	0.14	0.12	0.10	0.09	0.06	0.03	0.00	-0.21
t_α	1.67	0.95	1.20	1.33	1.34	1.43	1.37	1.10	0.76	0.07	-1.95

	Panel C: Fama-French 25 Portfolios									
	Low	2	3	4	High	Low	2	3	4	High
	α					t_α				
Small	-0.59	-0.03	0.18	0.44	0.51	-2.72	-0.15	1.06	2.69	2.98
2	-0.31	0.17	0.33	0.34	0.29	-2.27	1.46	2.79	2.76	2.02
3	-0.10	0.13	0.24	0.29	0.19	-0.91	1.50	2.62	2.83	1.43
4	-0.01	0.03	0.17	0.19	0.18	-0.18	0.40	2.11	1.82	1.29
Big	-0.02	-0.02	0.09	0.05	0.16	-0.35	-0.41	1.19	0.55	0.91

This seems a much weaker assumption than the linear specification in Table 9.[10]

5 Implications for Previous Work

Our paper is not the first to look at the relative risk of value and growth across business cycles. Several strands of the empirical finance literature have investigated this issue and reached very different conclusions from ours. In this section, we revisit some of the previous studies and seek to understand the sources of the discrepancy.

[10]It seems an intriguing future direction to allow for a more flexible econometric specification of beta in conditional market regression. Using a time-varying parameter framework, Ang and Chen (2003) make some progress in this direction.

5.1 Implications for the Overreaction Literature

One of the most important studies in the overreaction literature is Lakonishok, Shleifer, and Vishny (1994) and it reaches an exactly opposite conclusion to ours.

LSV contend that value stocks would be fundamentally riskier than growth stocks if, first, they underperform growth 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 two-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.

The Relative Performance of Value and Growth Strategies

We replicate LSV's analysis using a long sample ranging from January 1927 to December 2001. First, we find that value underperforms growth in 45% of monthly, 43% of annual, 33% of three-year holding period, and 27% of five-year holding period return observations. (Following LSV, we compute overlapping three-year and five-year holding period returns.) These numbers are much higher than their counterparts (27% in annual returns, 10% in three-year returns, and 0% in five-year returns) reported in LSV (Table VI, Panel 3), which are based on a much shorter sample from 1968 to 1989. In our data corresponding to LSV's sample period, value underperforms growth in 46% of monthly, 27% of annual, 15% of three-year, and 6% of five-year returns. These numbers are generally consistent with LSV's results, although they are slightly higher, possibly because of different portfolio construction methods.[11] In any event, the frequency of value underperforming growth is much higher in the long sample than that in the short sample. If anything, LSV greatly underestimate the frequency of underperformance of value strategies.

[11] To be specific, LSV form ten-decile portfolios at the end of April based on the ratio of the end-of-previous-year's book value of equity to end-of-April market value of equity. In contrast, Fama and French form portfolios on B/M 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 $t-1$. The market value is price times shares outstanding at the end of December of $t-1$.

Second, LSV compare the performance of value and growth portfolios in the worst months of the stock market. We replicate the same exercise in Table 10. Panel A is identical to Panel 1B of Table VII in LSV, Panel B presents the average returns of value and growth portfolios using our data set corresponding to LSV's sample period from 1968 to 1989, and Panel C reports the results using the full sample from 1927 to 2001. Four states of the world are defined: (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, we also report the average value-minus-growth returns, defined as the equal-weighted returns of B/M portfolios 9 and 10 minus the equal-weighted returns of B/M portfolios 1 and 2, for each state along with the t-statistics for testing zero average returns.

Panel A of Table 10 reports that value outperforms growth by 1.10% per month in the worst months of the market. Value also beats growth by a significant 0.80% per month in other negative market months. Panel B largely confirms LSV's evidence using our data corresponding to their sample period.[12] Therefore, LSV's argument is very clear: how can the value strategy be risky if it does not expose investors to greater downside risk!?

We shall rebut shortly that, despite its intuitive appeal, sorting on the ex post market return is not a reliable way to measure downside risk. For now, we simply note that LSV's point from Panels A and B is sample-specific. Using the long sample, Panel C reports that in the worst times, portfolio Low lost 9.5% per month compared to 11.6% for portfolio High and value underperform growth by 2% per month with a t-statistic of -2.98. Moreover, value outperforms growth in the very best months of the market by 1.7% with a t-statistic of 3.13. In short, even using LSV's metric of time-varying risk, we find that the value strategy exposes investors to greater downside risk.

Discussion

We have now two methods for gauging downside risk, i.e., sorting on the expected market risk premium and sorting on the ex post realized market excess return. How are these two

[12]There exists one small difference between Panels A and B. In LSV data, value outperforms growth substantially in the very best months, while in our data value underperforms growth slightly in the very best months of market. But this difference actually helps LSV's argument.

Table 10 : Average Returns Sorted on the Ex Post Market Excess Returns

This table reports monthly returns of ten B/M portfolios and a value-minus-growth portfolio in monthly percent during good and bad times, defined by sorting on the ex post realized market excess return. Value-minus-growth, denoted V-G, is the spread between value (equally-weighted portfolios 9 and High) and growth (equally-weighted portfolios Low and 2). Four states of the world are defined: "Worst" is identified with the 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 A is borrowed from Panel 1B of Table VII in LSV (1994). Panel B reports the results using our data corresponding to LSV's sample period, and Panel C reports the results using our data for the full sample. The t-statistics are for testing the hypothesis that the V-G spreads are zero.

	Low	2	3	4	5	6	7	8	9	High	V-G	t-stat
Panel A: LSV Sample (January 1968 to December 1989), LSV Data												
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: LSV Sample (January 1968 to December 1989), Our Data												
	Low	2	3	4	5	6	7	8	9	High	V-G	t-stat
Worst	-9.04	-8.52	-8.15	-7.74	-7.31	-6.91	-6.32	-6.09	-6.88	-7.35	1.66	2.23
−	-2.04	-1.84	-1.67	-1.83	-1.38	-1.28	-1.05	-1.04	-0.95	-1.15	0.88	2.90
+	3.34	3.79	3.75	3.66	3.19	3.37	3.07	3.35	3.68	3.86	0.20	0.70
Best	9.19	9.13	8.91	9.04	8.61	8.60	8.51	7.93	8.40	9.45	-0.24	-0.20
Panel C: Long Sample (January 1927 to December 2001), Our Data												
	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

procedures related? Which one is more accurate?

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 difficulty in measuring the conditional beta can be greatly alleviated by using the beta-premium sensitivity, which, according to (3), gives a convenient *unconditional* measure of the effects that *conditional* betas have on unconditional average returns. Intuitively, value stocks could earn higher returns because the betas of value stocks are higher than those of growth stocks when the expected market risk premium is high.

From this perspective, LSV's procedure of sorting on the *ex post* market excess returns is only fit for identifying differences in *unconditional* betas that may line up with differences in average returns.[13] However, it seems that what LSV intend to do is to identify differences in *conditional* betas, since "to be fundamentally riskier, value stocks must underperform glamor stocks with some frequency, and particularly in the states of the world when the marginal utility of wealth is high (page 1543)," and "value stocks could be described as having higher up-market betas and lower down-market betas than glamor stocks with respect to economic conditions (page 1569)." Moreover, "performance in extreme bad states is often the last refuge of those claiming that a high return strategy *must* be riskier, even when conventional measures of risk such as beta and standard deviation do not show it (page 1569)."

The crux of our rebuttal to LSV is that the realized market excess return is at best a very noisy proxy for "marginal utility" or "economic conditions." It is well-known in the macroeconomics literature that the ex post market excess return does not have substantial predictive power for business cycles, e.g., Fama (1981), Harvey (1989), and Stock and Watson (1989, 1999). Intuitively, the realized market excess returns equal their rational expectations plus unexpected shocks. Since the shocks are relatively big, any correlations between portfolio betas and the expected market risk premium will be swamped by these ex post shocks. Moreover, LSV seem to identify good states with times of high market realized returns and bad states with times of low market realized returns. The danger is that if the ex post market return is positively correlated with its ex ante measure (this correlation is 0.11 in the long sample), then what LSV call good states are actually bad states, and bad states are actually good states, in terms of "economic conditions."

Statistically, LSV's informal procedure amounts to regressing portfolio betas on the ex post market excess return, as opposed to the expected market risk premium. Since the realized return is largely correlated with its unexpected component, LSV's estimates of the beta-premium sensitivities of value and growth portfolios are biased towards zero as a result of attenuation. In a table not reported here, we regress conditional betas on the ex post market excess returns and find the empirical magnitude of the attenuation to be extremely severe. This is not surprising since the unexpected return is much more volatile than its

[13] We are grateful to the referee for providing this insight to us.

expected counterpart. Intriguingly, our approach of using a set of conditioning variables is an exact application of the instrumental variable estimation, the standard cure of attenuation.

5.2 Implications for the Predictive Asymmetry Literature

Identifying possible asymmetry in conditional betas is also a central question in the time-varying volatility literature. In a well-known study, Braun, Nelson, and Sunier (1995) report that while predictive asymmetry is strong in volatility, it appears to be entirely absent in conditional betas. However, their Exponential-GARCH framework defines beta asymmetry with respect to innovations in the realized market returns. Specifically, they model the conditional beta for portfolio p, denoted β_{pt}, as:

$$\beta_{pt} = \alpha + \delta[\beta_{pt} - \alpha] + \lambda_p z_{pt} + \lambda_m z_{mt}$$

where $\alpha, \delta, \lambda_p$ and λ_m are parameters to be estimated, and 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 shocks to the market return. Bekaert and Wu (2000) also report weak evidence for beta asymmetry using a similar framework.

Cho and Engle (1999), on the other hand, find some evidence of asymmetric betas by applying the EGARCH framework to daily individual stock return data, and attribute their different results to the lack of cross-sectional variation in the data used by Braun, Nelson, and Sunier (1995). Our analysis agrees with Cho and Engle on this point. Since value and growth portfolio betas react differently to shocks to the expected market risk premium, a mixture of value and growth stocks, such as the industry portfolios used by Braun, Nelson, and Sunier (1995), will likely weaken the time-variation of betas.

Outside the GARCH framework, Ang and Chen (2002) and Ang, Chen, and Xing (2002) also examine downside and upside betas, but still conditional on falling and rising markets. Specifically, they define downside beta β^- and upside beta β^+, respectively, as:

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

where r_{it} and r_{mt} are the excess returns on asset i and the market, respectively, and $\overline{r}_m$ denotes the average market excess return. Upon finding that the conditional betas defined this way exhibit little asymmetry and that the conditional correlations show much stronger asymmetry across downside and upside market movements, they turn to asymmetric correlation as a measure of downside risk.

6 Conclusion

We have shown that, while there does not exist much difference in the unconditional betas between value and growth stocks, the dispersion in their conditional market betas displays intriguing business cycle patterns. The market betas of value stocks are higher than those of growth stocks in bad times when the expected market risk premium is high, and to a lesser extent, the betas of growth stocks are higher than those of value stocks in good times when the expected market risk premium is low. Our evidence, while casting doubt on the overreaction literature, lends support to the rational expectations explanation of the value premium proposed by Zhang (2003).

We also demonstrate that the previously documented weak, and even negative, evidence on beta asymmetry is effectively defined with respect to the realized market excess returns. A strong empirical presence of this form of beta asymmetry, while interesting in itself, is largely *irrelevant* for explaining the cross-section of average returns. The reason is that the part of the conditional beta that is correlated with the unexpected market excess return, but uncorrelated with the expected risk premium, which Jagannathan and Wang (1996) call "residual beta", has no effect on the unconditional average returns.

Our evidence is potentially interesting that the cyclical variation in size portfolio betas seems to be driven by that in B/M portfolio betas, at least during the periods other than the Great Depression. The reason is that the current literature has interpreted the cyclical variation in size portfolios as supporting the imperfect capital markets theories, e.g., Bernanke and Gertler (1989) and Kiyotaki and Moore (1997). The basic idea is that a decline in a borrower's net worth raises the agency cost on external finance. In a recession, the net worth and collateral of small firms will be lower than usual, and tighter credit conditions will have stronger adverse effects on small firms than on large firms. Fama and French (1992, 1993, 1996) also use this "flight-to-quality" story to interpret their size and value effects. However, subsequent research has only reported mixed evidence on the effects of financial distress on expected returns.[14] Our evidence suggests that the cyclical variation in B/M portfolio betas seems more fundamental than that in size portfolio betas, at least for periods without wide-spread financial system failure such as that in the Great Depression. Since the economic mechanism motivating the empirical analysis here relies on the asymmetric capital adjustment cost, a *technological*, not financial, friction, future empirical scrutiny on its asset pricing implications using firm-level data seems promising.

[14]For example, Lamont, Polk, and Saa-Requejo (2001) document that firms that are more likely to suffer from financing constraints actually earn on average lower returns than firms that are less constrained financially. Gomes, Yaron, and Zhang (2003) show that the role of financing constraints is negligible in explaining the cross-section of returns, unless the external financing premium is procyclical, a property at odds with the data. However, Vassalou and Xing (2002) show that the size and B/M effects are present only within portfolios with highest default probabilities.

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