Essays in Financial Economics

By

David G Berger

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Chair

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ESSAYS IN FINACIAL ECONOMICS

Abstract

By David G Berger, Ph. D.
Washington State University
December 2008

Chair: Harry J. Turtle

‘Essays in Financial Economics’ consists of two separate manuscripts related to financial asset pricing. In the first manuscript of the dissertation, ‘Time variability in market risk aversion,’ I adopt realized covariances to estimate the coefficient of risk aversion across portfolios and through time. This approach yields second moments that are not influenced by a specified model for expected returns. Supporting the permanent income hypothesis, I find risk aversion responds to consumption smoothing behavior. As income increases, or as the ratio of consumption to income falls, relative risk aversion decreases. I also document variation in risk aversion across portfolios: risk aversion is highest for small and value portfolios.

In the second manuscript, ‘Emerging market contagion,’ I analyze hypotheses regarding the impact of emerging market crises on domestic portfolios. Based on liquidity shock and flight from risk hypotheses, I test for contagion effects from recent emerging market crises to domestic portfolios. From the hypotheses, contagion effects may vary across portfolios based on portfolio characteristics such as risk and liquidity. With size and book to market value as proxies for both risk and liquidity, I find support for the flight from risk hypothesis. Small stocks exhibit negative abnormal returns and

mid to high book to market stocks exhibit increased sensitivity to world and emerging market stocks during crises. Safer stocks exhibit positive abnormal returns. I find little evidence of contagion at the market level, indicating studies that focus on national aggregates may miss important dynamics during crises.

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GENERAL INTRODUCTION

The dissertation, ‘Essays in Financial Economics’ consists of two separate manuscripts, ‘Time variability in market risk aversion’ and ‘Emerging market contagion,’ respectively. The two manuscripts have been targeted towards different journals; therefore the formatting of each manuscript represents the formatting for the specific outlet. Both manuscripts consider the general topic of asset pricing in financial economics and specifically measure asset pricing dynamics across several portfolios. However, within the general area, the two essays differ in terms of the specific focus. The former essay considers the dynamics of risk aversion in the US market across portfolios and with respect to economic cycles. Risk Aversion relates to the reward for bearing a given level of market risk. The latter essay measures the impact of emerging market crises on separate domestic portfolios, rather than national aggregates.

TIME VARIABILITY IN MARKET RISK AVERSION

I. Introduction

We add to the extant empirical asset pricing literature with an examination of the evolution of risk aversion that varies over economic states and across multiple asset types. By adopting the realized volatility approach of Andersen et al (2003) to consider time varying conditional covariances, we are able to examine the evolution of risk aversion in relation to economic aggregates including income and consumption to wealth ratios. We find strong evidence in support of the permanent income hypothesis – as income increases, or as the consumption to wealth ratio falls, aggregate risk aversion falls.

The conditional CAPM holds that an asset's expected return is determined by its covariance with the market portfolio and the coefficient of relative risk aversion. Andersen et al (2003) show that summed high frequency squared returns produce second moments that are free from measurement error and that do not require a model for expected returns. Using this result to construct conditional covariances, we estimate the risk-return tradeoff in a multivariate setting. Consistent with Ghysels et al (2005), Bali (2008) and others, we find positive estimates of a static risk-return tradeoff. We then extend these findings to examine variation in risk aversion across portfolios and through time. Using realized covariances allows us to focus our analysis regarding the evolution of the risk aversion parameter. This approach has ample power to specify a risk aversion parameter that is a direct function of economic conditions. In this way, we extend existing research that provides indirect analysis of risk aversion through time.[1] In particular, we examine how risk aversion changes with economic conditions. We find counter cyclical variation in risk aversion relative to gross domestic product growth and the consumption to wealth ratio. We also consider a risk aversion specification that incorporates a flexible decay function for lagged economic conditions allowing for lagged relations between economic states and risk aversion.

Much of the extant literature has focused on constant estimates of risk aversion, with recent papers documenting a positive risk-return tradeoff based on the conditional CAPM (cf. Ghysels et al 2005; Bali 2008; Ludvigson and Ng 2007; Lundblad 2007). These authors estimate a constant risk-return trade-off through time in a univariate

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[1] For example, Rosenberg and Engle (2001) analyze variation in risk aversion with generated regressions.

context. As an example, Ghysels et al (2005) consider the risk-return using a mixed data sampling (MIDAS) approach for the market variance. Their MIDAS approach estimates variances for lengthy horizons by fitting a flexible weighting function to previous daily squared returns. In their specification, excess market returns are regressed on conditional market variance. They provide convincing evidence that constant estimates of risk aversion are significant and that the CAPM retains value for multiple variance specifications. Ludvigson and Ng (2007) use a factor analysis approach to estimate expected market returns and expected market variance. Including their estimated factors and conditional on lagged market mean and market volatility, they find a positive risk-return tradeoff for the market portfolio. Lundblad (2007) also finds a positive risk-return tradeoff in the market portfolio. He provides simulation evidence that a lengthy sample is required to estimate the risk-return tradeoff. Consequently, he looks at almost two centuries of returns in estimation. Our multivariate sample may provide the power to document the risk-return tradeoff with a shorter data set.

In an early study of the market portfolio, French et al (1987) employ daily returns to estimate monthly volatility. They then consider standard univariate time series models to provide evidence of a positive risk-return tradeoff, as suggested by a negative relation between returns and unpredictable volatility. Bollerslev et al (1988) specify a multivariate GARCH in mean process using quarterly data and estimate the constant coefficient of risk aversion, δ, to be approximately 0.5. Guo and Whitelaw's (2006) static risk aversion estimate increases with the sampling frequency, from an estimate of 2.1 for monthly returns to 7.8 for quarterly return data.[2] Harrison and Zhang (1999) only find evidence of a positive risk-return relation across lengthy time horizons. They conclude that the noise present in shorter time horizons may obscure the true economic relation. In contrast, implementing intra-day data to model market volatility, Bali and Peng (2006) find a significant risk-return relation between current daily volatility and the one-day ahead return. They argue that macroeconomic control variables should be included to mitigate noise that may obscure the risk-return relation, even when these variables are statistically insignificant. Finally, Bali et al (2007) recently provide evidence of a positive risk-return tradeoff by focusing only on downside risk.

The assumption of a constant risk-return tradeoff may miss important variation in risk aversion in relation to economic states. Fama and French (1989) examine the predictability of excess returns in relation to the business cycle. They find that lower excess returns follow strong economic periods and higher excess returns follow periods of poor economic conditions. Countercyclical variation in risk aversion may capture much of the predictable variation in excess returns. Lettau and Ludvigson (2001b) and Campbell and Cochrane (1999) also suggest that risk aversion should vary in a countercyclical manner. Campbell and Cochrane use their model to generate data that exhibits empirically documented patterns. Harrison and Zhang (1999) regress their estimates of the Sharpe ratio against business-cycle proxy variables and find variation in the price of risk across business cycles. Brandt and Kang (2004) model market excess returns and market variance as a vector autoregressive process. Plotting their estimates of

[2] Mehra and Prescott (1985) suggest plausible values of δ should fall in the range of zero to ten.

the dynamic Sharpe ratio against identified business cycles, they also find evidence of countercyclical risk aversion. In a univariate analysis of the market portfolio that is based on habit persistence models, Rosenberg and Engle (2002) also hypothesize countercyclical variation in risk aversion. They regress their estimates of risk aversion on business cycle indicators and find a positive relation between the credit spread and risk aversion. We expand these results by directly specifying our risk aversion parameter as a function of economic indicator variables.

The permanent income hypothesis suggests countercyclical variation in risk aversion. That is, current consumption decisions are based on estimates of potential long run consumption (cf. Hall 1978). A key implication of the hypothesis is that agents will smooth consumption over time in response to income shocks. We therefore use estimates of the consumption to wealth ratio as a measure of consumption smoothing behavior. According to the permanent income hypothesis, consumption as a fraction of wealth will increase following a negative income shock, as individuals try to maintain a consistent level of consumption. In this case, we expect to observe an increase in aggregate risk aversion. Following a quarter in which the consumption to wealth ratio is one standard deviation above the trend, we find that risk aversion increases from 1.2 to 3.3. Annually, risk aversion increases from 1.7 to 4.7 following a year in which the consumption to wealth ratio is one standard deviation above the trend. Alternatively, consumption as a fraction of wealth decreases following a positive income shock, as individuals increase current consumption, but also plan to increase their lifetime consumption stream. Here we document a significant decrease in risk aversion. In general, we show that levels of risk aversion respond to consumption smoothing in a manner that is consistent with the permanent income hypothesis. We also consider gross domestic product (GDP) growth as a measure of changes in income and find risk aversion increases following periods of poor GDP growth. With our multivariate sample, we estimate risk aversion to be 2.9 following a quarter of median GDP growth; with estimates increasing to 4.9 following a quarter in which GDP growth is one standard deviation below the median.

Although our results are consistent with the extant literature regarding constant estimates of risk aversion, and we find variablility in risk aversion consistent with the permanent income hypothesis; we also find evidence that even our extended risk aversion specification does not salvage the conditional CAPM. In particular, we find evidence that is consistent with Blackburn et al (2007) who suggest that risk aversion is higher for value, versus growth, investors. Our results are also consistent with Zhang's (2005) model in which value stocks, characterized by assets in place, are riskier than growth stocks during economic downturns. Given a countercyclical price of risk and costly reversibility, the model explains the spread in expected returns from value to growth stocks, despite comparable market betas. In this framework, a given level of market covariance implies greater risk for value, relative to growth stocks. Our results indicate small and value portfolios provide higher expected returns for a given level of market risk and that market risk is priced differently across portfolios.

II. The Model and Data

We begin with a general model partitioning returns into a conditional expectation and unexpected disturbance component,

$$R_{j,t} = \mu_{j,t} + \varepsilon_{j,t}, \tag{1}$$

in which $R_{j,t}$, the excess return for asset *j* during period *t*, is equal to its conditional expectation $\mu_{j,t}$, plus an error term, $\varepsilon_{j,t}$, for $j = 1,2,...\mathrm{N}$ and $t = 1,2,...\mathrm{T}$. For notational simplicity we treat the market portfolio as the $N+1^{st}$ asset, with conditional expected excess return $\mu_{m,t}$. We denote the $(N+1)$ by $(N+1)$ conditional covariance matrix as $\mathbf{H_t}$, with arbitrary element $h_{ij,t}$ representing the conditional covariance between assets *i* and *j* during period *t*. Arbitrary element $h_{jm,t}$ in the last column of $\mathbf{H_t}$ represents the conditional covariance between asset *j* and the market portfolio during time *t*, and $h_{mm,t}$ represents the conditional market variance. Following Bollerslev et al (1988), among others, we employ a conditional form of the CAPM to describe conditional asset expected returns,

$$\mu_{j,t} = \mu_{m,t} \frac{h_{jm,t}}{h_{mm,t}}. \tag{2}$$

In this specification, the ratio of the conditional expected excess market return to conditional market variance may be defined as the coefficient of risk aversion, δ_t, such that,

$$\delta_t = \frac{\mu_{m,t}}{h_{mm,t}}. \tag{3}$$

Substituting δ_t into equation (2) yields our primary specification,

$$\mu_{j,t} = \delta_t h_{jm,t}, \tag{4}$$

showing that the conditional expected excess return of asset *j* is determined by the product of its conditional covariance with the market, and the aggregate coefficient of risk aversion.

From equation (4), it is apparent that estimates of δ_t depend upon the covariance specification $\mathbf{H_t}$, and $h_{mm,t}$ in particular. We measure the covariance matrix, $\mathbf{H_t}$, using the realized volatility approach of Andersen et al (2001) based on the period immediately preceeding the return interval *t*. Anderson et al (2001, 2003) demonstrate that high frequency return data provide an excellent model-free measure of true volatility.

Our primary interest is in the relationship between conditional asset means as they relate to underlying economic aggregates. To link conditional asset returns to underlying economic aggregates, we model asset returns on a quarterly and annual basis, where the related covariance matrix is constructed using daily squared returns over the previous period. The theoretical underpinnings of the realized variances suggested by Andersen et al (2001) are based on the return interval for squared returns approaching zero. In their empirical work they consider a five-minute interval to estimate their realized volatility measure for Dow stocks. There is; however, some evidence that intraday data may induce problems that countervail the theoretical benefits of ultra-high-frequency data. Engle and Gallo (2006) discuss how intraday realized volatility measures are sensitive to the observation interval and are subject to microstructure biases. Voev and Lunde (2007) show that realized covariance calculations can include severe biases in the presence of non-synchronous trading and other noise, if the observation interval is too short. As a practical application of the realized volatility approach we choose daily squares and crossproducts of returns to balance the asymptotic properties underlying the theory with potential microstructure biases that occur with short return intervals. In addition, daily observations are available for a wide range of assets over a lengthy calendar period allowing us to consider economic relationships over many business cycles and across a broad range of assets.

Related work by Ghysels et al (2006) provides evidence comparing the mean-squared-error of volatility estimates created with daily data and five-minute intraday sampling frequencies. They find evidence suggesting that daily data performs comparably to intraday data when constructing estimates of volatility over three or four week periods, and may outperform the intraday benchmark. By adopting a simple covariance specification we are able to model a multivariate specification that admits a flexible nonlinear decay pattern for our state dependent risk aversion parameter.[3]

We construct conditional covariances for period *t*, based on information that is available prior to the start of the period. In particular, the conditional covariance between any asset and the market during period *t* is determined during the previous period, denoted $t-1$. The covariance between asset *j* and the market portfolio during period *t*, $h_{jm,t}$, is defined as

$$h_{jm,t} = \frac{n}{L}\sum_{l=1}^{L}(r_{j,l})(r_{m,l}) , \tag{5}$$

where $r_{j,l}$ and $r_{m,l}$ are the return to asset *j* and the market portfolio, during day *l* during period $t-1$. Trading days during period $t-1$ are indexed with $l = 1,2,...\mathrm{L}$, and the scaling factor n/L adjusts for period lengths in different time periods. For example, the quarterly covariance matrix for the second quarter, April through June, 2005, is

[3] Our quarterly model is very comparable to the lag length suggested by Ghysels et al (2005). Our approach is also intuitively similar to the seminal work of French et al (1987) who use daily squared returns to determine market variance in a univariate context.

constructed with data from January through March 2005 with L equal to the number of trading days within the January through March period of 2005 and n equal to the number of trading days between April 1, and June 31. For annual covariances, we assume that the number of trading days per year is constant from year $t-1$ to year t.

Our primary empirical specification may be written as

$$R_{j,t} = \alpha_{j,t} + \delta_{j,t} h_{jm,t} + e_{j,t} \text{ for } j = 1,2,...25\,, \tag{6}$$

where $R_{j,t}$ represents the excess returns to 25 portfolios formed from the intersection of size and book to market quintiles over the sample period from January 1964 through December 2005.[4] Our estimation strategy begins with a simplified specification with constant estimates for $\delta_{j,t} = \delta_0$. We pool observations across our sample, leading to potential contemporaneous correlation across residuals in our model. Consequently we present OLS estimates using Rogers' (1983, 1993) clustered standard errors approach as well as the Feasible Generalized Least Squares (FGLS) of Parks (1967). From our initial specification with constant risk aversion, we then admit variation in the intercept and slope parameter over time and across portfolios. In our final empirical specifications, we consider variation in risk aversion related to the value of predetermined economic indicators.

Our economic state variables include a measure of aggregate income and the ratio of consumption to wealth. We use gross domestic product growth as a measure of aggregate income and obtain data from the Bureau of Economic Analysis. Seasonally adjusted percent change in real gross domestic product relative to period $t-1$ is given by

[4] We thank Kenneth French for supplying size and book-to-market quintile data.

Δgdp_t. We also consider an estimate of the aggregate consumption to wealth ratio, cay_t, introduced by Lettau and Ludvigson (2001).[5] In the current context, this variable provides a measure of consumption smoothing behavior.

Table 1 reports summary statistics for our data set, when all series are pooled across portfolios and over time. Quarterly and annual data are presented in Panels A and B, respectively. We observe substantial intertemporal variability in $R_{m,t} / h_{mm,t}$, as evidenced by the large standard deviations. With quarterly observations, the standard deviation of 26.9 is more than seven times the sample mean of 3.8. From equation (3), risk aversion during period *t*, is equal to the ratio of conditional market expected excess return to conditional market variance. Assuming that realized market excess return, $R_{m,t}$, provides an estimate of expected market excess return, $\mu_{m,t}$, then the ratio $R_{m,t} / h_{mm,t}$ provides an initial, albeit noisy, measure of realized risk aversion. At the mean, this ratio is approximately equal to four for both quarterly and annual observations. The intertemporal variation in this realized ratio suggests that risk aversion varies substantially through time.

III. Static Risk Aversion Estimates

In this section, we provide constant estimates of risk aversion by imposing the restriction that risk aversion is stable throughout the sample period. In general, our intertemporal multivariate approach allows us to test for differences in risk aversion over time and to examine differences across portfolios.

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[5] We thank Martin Lettau for this variable.

TABLE 1. Quarterly and Annual Summary Statistics for 25 Portfolios Formed from the Intersection of Book to Market and Size Quintiles.

	Mean	Median	St. Dev	N
Panel A: Quarterly Data				
$R_{j,t}$ $(\times 10^2)$	2.323	2.669	11.315	4175
$h_{jm,t}$ $(\times 10^2)$	0.427	0.283	0.545	4175
$h_{jj,t}$ $(\times 10^2)$	0.523	0.343	0.661	4175
$b_{jm,t}$	0.895	0.887	0.282	4175
$R_{m,t}$ $(\times 10^2)$	1.437	2.257	8.623	167
$h_{mm,t}$ $(\times 10^2)$	0.500	0.327	0.620	167
$R_{m,t} / h_{mm,t}$	3.767	6.445	26.861	167
Δgdp_{t-1}	3.345	3.200	3.496	167
cay_{t-1} $(\times 10^3)$	-0.098	0.362	12.917	167
Panel B: Annual Data				
$R_{j,t}$ $(\times 10^2)$	9.704	10.600	23.761	1025
$h_{jm,t}$ $(\times 10^2)$	1.723	1.295	1.432	1025
$h_{jj,t}$ $(\times 10^2)$	2.105	1.542	1.859	1025
$b_{jm,t}$	0.895	0.895	0.249	1025
$R_{m,t}$ $(\times 10^2)$	5.811	9.890	17.407	41
$h_{mm,t}$ $(\times 10^2)$	2.023	1.458	1.668	41
$R_{m,t} / h_{mm,t}$	3.886	5.053	15.599	41
Δgdp_{t-1}	3.320	3.500	2.088	41
cay_{t-1} $(\times 10^3)$	-1.929	4.291	16.000	38

Note: Observations are pooled across portfolios and over time. Summary statistics are also reported for the ratio $R_{m,t} / h_{mm,t}$, the-percent change in gross domestic product relative to the previous period Δgdp_{t-1} and the aggregate consumption/weath ratio, cay_{t-1}. Quarterly Δgdp_{t-1} observations are seasonally adjusted. Quarterly return variables, $R_{j,t}$ and $R_{m,t}$ begin April, 1964 and end December 2005. The sample period for all other quarterly variables is from January 1964 through September, 2005. Annual cay_{t-1} observations cover the period 1964 through 2001. Annual return variables, $R_{j,t}$ and $R_{m,t}$, begin January, 1965 and end December 2005. The sample period for all other annual variables is from January 1964 through December, 2004. The sample period for the ratio, $R_{m,t} / h_{mm,t}$, uses the sample for each separate variable.

We begin with consideration of the simplified model

$$R_{j,t} = \alpha_j + \delta_0 h_{jm,t} + e_{j,t}\text{, for } j = 1,2,...25\,. \tag{7}$$

Equation (7) is a special case of our primary empirical specification, equation (6), in which the risk aversion parameter is restricted to be equal across portfolios and constant through time, such that, $\delta_{j,t} = \delta_0$. Estimation results are presented in Table 2. In Panel A, we present univariate results based on the market portfolio, such that the market excess return is regressed on its own variance. We find significant estimates of risk aversion approximately equal to two in several specifications. Our approach and results are comparable to those of Ghysels et al (2005) who estimate risk aversion parameters of 2.0, 2.9 and 2.6.

We expand the univariate setting to include 25 portfolios in Panel B. We report our cross-sectional results using OLS with Roger's (1983, 1993) clustered standard errors and using FGLS with the Parks (1967) correction. Based on pooled OLS regressions with Roger's clustered standard errors, we find significant estimates of risk aversion equal to 3.0, 3.2 and 3.9 using quarterly returns, with various intercept specifications.[6] Omitting the intercept term, we find a significant estimate or risk aversion equal to 4.2 based on annual returns. As an alternate control for contemporaneous correlation, we also estimate equation (7) using FGLS and the Parks correction. Estimates from FGLS tend to be lower than the OLS counterparts, but retain significance in five of six cases. For example, based

[6] To obtain portfolio specific intercept terms in our pooled OLS regressions we include portfolio dummy-variables taking the value of one for a specific portfolio and zero otherwise. We specify 24 portfolio dummy variables, omitting the dummy variable for the small size and low book to market portfolio.

on annual returns, our estimates are 1.1, 1.7 and 3.4, and are significant at the one percent level.

TABLE 2. Constant Risk Aversion Estimates (δ_0).

	Intercept	OLS (*p*-value)	FGLS (*p*-value)
Panel A. Market Portfolio			
Quarterly	0.005	1.876	-
	(0.559)	(0.082)	
Quarterly	-	2.271	-
		(0.007)	
Annual	0.045	0.661	-
	(0.310)	(0.694)	
Annual	-	1.991	-
		(0.066)	
Panel B. Multivariate Estimation			
Quarterly	Portfolio	3.246	1.003
		(0.000)	(0.025)
Quarterly	Constant	3.018	0.657
		(0.000)	(0.129)
Quarterly	Omitted	3.939	1.354
		(0.000)	(0.001)
Annual	Portfolio	2.729	1.680
		(0.000)	(0.001)
Annual	Constant	2.138	1.131
		(0.000)	(0.020)
Annual	Omitted	4.206	3.402
		(0.000)	(0.000)

Note: We present risk aversion estimates for the pooled system

$$R_{j,t} = \alpha_j + \delta_0 h_{jm,t} + e_{j,t} \text{ for } j = 1,2,...25,$$

where the excess return of portfolio *j* during period *t* is defined as $R_{j,t}$ and $h_{jm,t}$ is the conditional covariance between portfolio *j* and the market portfolio. In Panel A, we report OLS estimates and p-values for the CRSP value-weighted market portfolio, with regressor $h_{mm,t}$. In Panel B, we report results for 25 portfolios formed from the intersection of size and book to market quintiles. The sample period is 1964:2 through 2005:4 for quarterly data and 1965 through 2005 for annual data. We present estimates of a general model in which the intercept term varies across portfolios, but is constant through time for any given portfolio (portfolio), estimates in which the intercept term is constant through time and equal across all portfolios (constant) and estimates in which the intercept is restricted to equal zero across all portfolios (omitted). For portfolio intercepts, we include 24 portfolio dummy variables taking the value of zero or one. We report parameter estimates and associated *p*-values from OLS regressions using Rogers' clustered methodology and Feasible Generalized Least Squares using Parks correction.

We next consider how risk aversion parameters may vary across portfolios with respect to the risk characteristics of the portfolios in our sample, as suggested by Zhang (2005). In Table 3 we estimate risk aversion parameters for each portfolio independently via univariate OLS by imposing the intertemporal restriction $\delta_{j,t} = \delta_j$, in equation (6) for each portfolio. For quarterly returns, the point estimates of risk aversion vary from 1.3 for the large size and low book to market portfolio to 6.5 for the small size and high book to market portfolio. These estimates are consistent with the 2.1 to 7.8 range from Guo and Whitelaw (2006). Using annual returns, we are limited to 41 observations for each portfolio and obtain fewer significant estimates of δ_j. Annual estimates range from 0.1 for the large size and low book to market portfolio to 9.0 for the small size and high book to market portfolio. For both return frequencies, we find that estimates appear to decrease with size and increase with book to market value.

To further examine variation in risk aversion estimates across portfolios and test for equality, we extend our specification to consider,

$$R_{j,t} = \alpha_0 + \sum_{j=2}^{25} \alpha_j Port_j + (\delta_0 + \sum_{j=2}^{25} \delta_j Port_j) h_{jm,t} + e_{j,t}, \text{ for } j = 1,2,...25, \quad (8)$$

where $Port_j$ represents 24 portfolio specific dummy variables defined for $j = 2,3...25$; the dummy is omitted for $j = 1$, corresponding to the small size and low book to market portfolio. To control for contemporaneous correlation across residuals, we estimate equation (8) via FGLS and the Parks correction. We then test the equality of portfolio specific risk aversion estimates across all 25 portfolios with the joint hypothesis that $\delta_j = 0$ for all $j = 2,3...25$; F-statistics and associated p-values are reported in the lower right hand entry in Panels A and B of Table 3.

TABLE 3. Risk Aversion Estimates by Portfolio(δ_j).

Panel A. Quarterly Returns

	Small	S_2	S_3	S_4	Large	F statistic (p-value)
Growth	4.384	3.800	2.373	1.774	1.271	1.52
	(0.051)	(0.032)	(0.129)	(0.184)	(0.222)	(0.194)
BM_2	5.632	5.265	3.414	3.621	1.762	2.74
	(0.014)	(0.004)	(0.031)	(0.008)	(0.086)	(0.027)
BM_3	5.643	4.388	3.472	2.945	1.489	1.11
	(0.018)	(0.021)	(0.035)	(0.026)	(0.121)	(0.349)
BM_4	5.230	4.106	4.151	3.832	2.175	1.85
	(0.031)	(0.031)	(0.016)	(0.010)	(0.033)	(0.117)
Value	6.459	4.501	3.420	4.094	1.686	0.85
	(0.025)	(0.022)	(0.027)	(0.007)	(0.150)	(0.496)
F statistic	0.64	2.22	0.64	1.00	0.56	1.48
(p-value)	(0.635)	(0.064)	(0.635)	(0.409)	(0.694)	(0.061)

Panel B. Annual Returns

	Small	S_2	S_3	S_4	Large	F statistic (p-value)
Growth	4.007	2.142	0.597	0.652	0.104	0.75
	(0.340)	(0.426)	(0.780)	(0.717)	(0.951)	(0.560)
BM_2	5.995	4.458	1.685	2.554	1.807	3.43
	(0.165)	(0.094)	(0.488)	(0.205)	(0.281)	(0.009)
BM_3	7.504	3.843	2.110	3.188	0.387	4.23
	(0.099)	(0.238)	(0.413)	(0.145)	(0.813)	(0.002)
BM_4	7.058	3.189	4.404	4.950	2.076	3.24
	(0.133)	(0.320)	(0.143)	(0.065)	(0.266)	(0.012)
Value	8.990	5.347	4.247	4.459	2.178	3.12
	(0.108)	(0.082)	(0.103)	(0.076)	(0.299)	(0.015)
F statistic	2.95	5.78	1.36	3.22	2.42	8.84
(p-value)	(0.019)	(0.000)	(0.246)	(0.012)	(0.047)	(0.000)

(Continued)

Note: For each portfolio, we present separate OLS estimates of the equation

$$R_{j,t} = \alpha_j + \delta_j h_{jm,t} + e_{j,t}, \text{ for } j = 1,2,...25,$$

representing 25 portfolios formed from the intersection of size and book to market quintiles. The excess return of portfolio *j* during period *t*, is defined as $R_{j,t}$ and $h_{jm,t}$ is the conditional covariance between portfolio *j* and the market portfolio created with information from the previous period. The market portfolio is the CRSP value-weighted portfolio. The sample period is 1964:2 through 2005:4 for quarterly data and 1965 through 2005 for annual data. Each entry in the table reports the parameter estimate of δ_j and associated *p*-value for the given portfolio. Panel A reports results based on quarterly returns while Panel B reports results for annual returns. To test the hypotheses regarding equality of risk aversion across portfolios, we pool observations across all 25 portfolios and use FGLS and the Parks correction to estimate the equation

$$R_{j,t} = \alpha_0 + \sum_{j=2}^{25} \alpha_j Port_j + (\delta_0 + \sum_{j=2}^{25} \delta_j Port_j) h_{jm,t} + e_{j,t} \text{ for } j = 1,2,...25,$$

where $Port_j$ is a portfolio dummy variable taking the value of one for portfolio *j* and zero otherwise. We do not specify a portfolio dummy variable for the small /growth portfolio. Reported F-statistics and *p*-values in the final row (column) test the hypothesis that risk aversion is equal within size (book to market) quintiles. The entry in the bottom right corner tests equality of risk aversion across all portfolios ($\delta_j = 0$ for all *j*). Tests involving the small/value portfolio test the hypothesis that $\delta_j = 0$ for the remaining portfolios within the grouping. The remaining tests statistics report results testing the hypothesis that $\delta_i = \delta_j$ for all *I* and *j* within the portfolio grouping.

F-statistics with associated *p*-values in parentheses for quarterly and annual returns are 1.48 (0.061) and 8.84 (0.000) respectively. These values may be interpreted as rejections of the CAPM restriction that the coefficient of risk aversion is constant across all portfolios.

Having rejected the equality of risk aversion estimates across all 25 portfolios considered, we then consider if risk aversion parameters vary within size or book to market classifications. Within size (book to market) quintiles, we test for differences across book to market (size) quintiles. We maintain the specification in equation (8) and estimate the system across all 25 portfolios. Within the 25 portfolio system, we then test multiple restrictions across five portfolio groupings. Tests that include the small size and low book to market portfolio evaluate the joint restriction that $\delta_j = 0$ for all of the remaining portfolios in the grouping. Testing equality of the risk aversion parameter across portfolio groupings that do not include our default portfolio test the restriction that $\delta_j = \delta_i$ for all *I* and *j* within the grouping. F-statistics and *p*-values based on tests within size quintiles (across book to market portfolios) are reported in the final row of each panel; results based on tests within book to market portfolios are reported in the final column. For example, the last entry in the third row of Panel B reports the F-statistic of 4.23 and the corresponding *p*-value of 0.002. This entry and all but the growth portfolios reject the constancy of the market risk aversion parameter across size quintiles. Further, with the exception of the middle size quintile, we reject equality of risk aversion across book to market portfolios in Panel B. Reported risk aversion estimates in Table 3 show a consistent patterns across portfolio groupings – risk aversion appears to decrease with size and increase with book to market value. For example, with quarterly returns the risk aversion estimate for the small, value portfolio is 6.5 and the related estimate for the large, growth portfolio is only 1.3. This evidence is consistent with the motivation in Fama and French (1992) who find systematic mispricings in small value stocks relative to the CAPM.

Recently, Liu (2006) shows that liquidity may also be an important priced risk-factor. Relatively illiquid stocks such as small stocks and high book to market stocks may be more susceptible to market downturns and investors may require an additional reward not captured in the CAPM specification. Further, Zhang (2005) models value stocks as riskier relative to growth stocks for comparable levels of market covariance, especially during poor economic conditions. In general, the results from Table 3 provide evidence that risk aversion varies across portfolios and suggest that the required compensation for a given level of risk varies across portfolios, consistent with variation in risk across a given level of market covariance.

IV. Time Variation in Risk Aversion

We now examine how risk aversion parameters may vary over time and in relation to changes in economic states. The preliminary results presented in Section III impose the restriction that risk aversion is static throughout the sample period. We begin by testing the validity of this restriction using a time-dummy variable approach that admits a time-varying intercept and slope coefficient. In particular, we specialize our primary specification given by equation (6) to cross-sectionally estimate risk aversion through time,

$$R_{j,t} = \alpha_0 + \sum_{t=2}^{n} \alpha_t Time_t + (\delta_0 + \sum_{t=2}^{n} \delta_{0,t} Time_t) h_{jm,t} + e_{j,t}\text{, for } j = 1,2,...25\text{,} \quad (9)$$

where we define $Time_t$ as time-specific dummy variables for $t = 2,3...n$, with n equal to the number of periods in our sample and where $Time_t$ takes the value of one for the specific period t and zero otherwise.[7] With this specification, the risk aversion parameter is allowed to vary over time, but is equal across all portfolios for any given period. The dummy variable model does not impose a linear trend on risk aversion through time; rather, it allows unrestricted variation. We test for time variation in risk aversion by

[7] The specification of $Time_t$ is contingent upon the return frequency considered, such that $Time_t$ refers to specific quarter t or year t, when used with quarterly or annual return frequencies, respectively.

testing the joint hypothesis that $\delta_{0,t} = 0$ for all *t*, and we report F-test results for quarterly and annual return data in Table 4.

TABLE 4. Test Statistics from the Constant Risk Aversion Hypothesis ($\delta_{0,t} = \delta_0$ for all $t = 1,2,...T$).

	Intercept	F statistic (p-value)
Panel A. Quarterly Returns		
	Time-specific	7.42
		(0.000)
	Omitted	80.53
		(0.000)
Panel B. Annual Returns		
	Time-specific	9.68
		(0.000)
	Omitted	60.32
		(0.000)

Note: We estimate

$$R_{j,t} = \alpha_0 + \sum_{t=2}^{n} \alpha_t Time_t + (\delta_0 + \sum_{t=2}^{n} \delta_{0,t} Time_t) h_{jm,t} + e_{j,t} \text{ for } j = 1,2,...25,$$

representing 25 portfolios formed from the intersection of size and book to market quintiles. The excess return of portfolio *j* during period *t* is defined as $R_{j,t}$; $Time_t$ is a time-dummy variable taking the value of one for the specific period *t* and zero otherwise. We do not specify a time-dummy for the initial period in both quarterly and annual samples. We define $h_{jm,t}$ as the conditional covariance between portfolio *j* and the market portfolio created with information from the previous period. The market portfolio is the CRSP value-weighted portfolio. The sample period is 1964:2 through 2005:4 for quarterly data and 1965 through 2005 for annual data. Observations are pooled over time and across portfolios, and estimation is conducted via OLS. Time-specific intercepts correspond to the general model in which the intercept term varies through time, but is restricted to be equal across portfolios at any point. We test the null hypothesis that the parameter estimates of $\delta_{0,t} = 0$ for $t = 2,3...n$, and report F-statistics and associated *p*-values.

Results presented in Table 4 show that aggregate risk aversion exhibits significant temporal variation. The reported F-statistics of 7.4, 80.5, 9.7 and 60.3 all reject the null hypothesis of constant risk aversion at the one-percent level.[8] This result is robust to a number of intercept specifications. We include an intercept in our specification to control for possible nonlinearities or potential misspecification. In the first row of each panel, we allow a time-specific intercept term, but impose the restriction that the intercept is constant across portfolios at any given point in time. In the second and fourth row, we omit the intercept term entirely. For both data frequencies, we consistently reject the hypothesis of a constant risk aversion parameter over time.

Given evidence that risk aversion changes over time, we now consider possible links between risk aversion and underlying economic states. Fama and French (1989) find that the dividend yield, default spread and term spread, forecast low (high) returns during periods of strong (weak) economic conditions. We hypothesize that changing risk aversion can account for this predictable variation in excess returns. Specifically, we hypothesize that risk aversion will increase following periods of poor economic performance and decrease following periods of strong economic performance. We use the consumption to wealth ratio and gross domestic product growth as economic indicators. Our hypothesis of countercyclical variation in risk aversion may help to describe the documented pattern of excess returns. Consistent with the permanent income hypothesis, we hypothesize that individuals will attempt to smooth consumption in the context of income shocks. Following a negative income shock, individuals will attempt to maintain

[8] We obtain similar results utilizing period dummy variables as well. Specifically, we estimate (9) with five and ten-year period dummy variables in which the variable takes the value of one for any year within the range and zero otherwise. In these cases we again reject the hypothesis of constant risk aversion at the one percent level.

current consumption levels by borrowing from future consumption, resulting in an increase in risk aversion.

We estimate the relation between economic states and risk aversion by specifying

$$R_{j,t} = \alpha_j + (\delta_{j,0} + \delta_{j,gdp}\Delta gdp_{t-1} + \delta_{j,cay} cay_{t-1}) h_{jm,t} + e_{j,t} \text{ for } j = 1,2,...25. \quad (10)$$

In this context, our general risk aversion parameter from equation (6) may be written as $\delta_{j,t} = \delta_{j,0} + \delta_{j,gdp}\Delta gdp_{t-1} + \delta_{j,cay} cay_{t-1}$. The coefficient estimates $\delta_{j,gdp}$ and $\delta_{j,cay}$ measure the relation between the specific economic state variable and risk aversion. Panels A and B of Table 5 report our initial univariate results for equation (10) for the market portfolio in isolation. We observe that all estimates of $\delta_{j,cay}$ are positive and significant, indicating countercyclical variation in risk aversion. Parameter estimates from Table 5 may be used to calculate average risk aversion, as well as the impact of an economic shock on risk aversion. Considering the estimates that include δ_0 and the economic instrument, *cay*, we calculate risk aversion at the median realization of *cay*, δ , to be equal to 1.2 for quarterly market excess return data.[9] This estimate increases to 3.3 when *cay* is one standard deviation above the median in the previous quarter.[10] In a similar manner, annual risk aversion is estimated to be 1.7, evaluated at the median and increases to 4.7 when *cay* is one standard deviation above the median in the previous year.

[9] $\delta = 1.126 + 162.595 * (0.362 * 10^{-3})$

[10] $\delta = 1.121 + 162.595 * (0.362 * 10^{-3} + 12.917 * 10^{-3})$

TABLE 5. Conditional Risk Aversion Estimates Utilizing Economic Indicators Δgdp (Change in Gross Domestic Product Growth) and *cay* (Aggregate Consumption to Wealth Ratio).

Panel A. Quarterly Market Portfolio

Intercept (*p*-values)	δ_0 (*p*-values)	δ_{gdp} (*p*-values)	δ_{cay} (*p*-values)
0.007	2.493	-0.301	175.270
(0.429)	(0.118)	(0.230)	(0.016)
0.003	2.879	-0.212	
(0.732)	(0.074)	(0.400)	
0.009	1.126		162.595
(0.275)	(0.312)		(0.024)

Panel B. Annual Market Portfolio

Intercept (*p*-values)	δ_0 (*p*-values)	δ_{gdp} (*p*-values)	δ_{cay} (*p*-values)
0.045	0.596	0.174	195.658
(0.304)	(0.783)	(0.775)	(0.011)
0.062	0.823	-0.516	
(0.184)	(0.726)	(0.390)	
0.047	0.948		186.731
(0.271)	(0.589)		(0.007)

Panel C. Quarterly Returns Pooled Across 25 Size and Book to Market Portfolios

Parameter estimates (*p*-values)			F-statistics (*p*-values)		
δ_0	δ_{gdp}	δ_{cay}	$\delta_{j,0} = 0$;for all j	$\delta_{j,gdp} = 0$;for all j	$\delta_{j,cay} = 0$;for all j
4.620	-0.502	126.914	1.67	1.24	1.77
(0.002)	(0.079)	(0.099)	(0.021)	(0.191)	(0.012)
4.772	-0.546		1.70	1.28	
(0.001)	(0.055)		(0.078)	(0.160)	
2.400		118.956	1.58		1.82
(0.023)		(0.116)	(0.036)		(0.008)

(Continued)

Table 5. Continued.

Panel D. Annual Returns Pooled Across 25 Size and Book to Market Portfolios

Parameter estimates (*p*-values)			F-statistics (*p*-values)		
δ_0	δ_{gdp}	δ_{cay}	$\delta_{j,0} = 0$;for all j	$\delta_{j,gdp} = 0$;for all j	$\delta_{j,cay} = 0$;for all j
0.590	1.999	512.476	5.61	5.94	6.35
(0.777)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
-0.398	0.093		7.76	6.67	
(0.857)	(0.881)		(0.000)	(0.000)	
3.823		388.531	5.82		7.87
(0.033)		(0.000)	(0.000)		(0.000)

Note: We present estimates of the general model

$$R_{j,t} = \alpha_j + (\delta_{j,0} + \delta_{j,gdp}\Delta gdp_{t-1} + \delta_{j,cay} cay_{t-1})h_{jm,t} + e_{j,t} \text{ for } j = 1,2,...25,$$

where the excess return of portfolio *j* during period *t* is defined as $R_{j,t}$ and $h_{jm,t}$ is the conditional covariance between portfolio *j* and the market portfolio created with information from the previous period; Δgdp_{t-1} represents real-percent GDP growth and cay_{t-1} is the estimate of aggregate consumption/wealth, both measured over the period prior to the return interval. In Panels A and B we report univariate OLS estimates and *p*-values for the CRSP value-weighted market portfolio. In Panels C and D, we pool observations across the 25 portfolios formed from the intersection of size and book to market quintiles and present FGLS parameter estimates of the general model. We allow portfolio specific intercepts by including 24 portfolio specific dummy variables taking the value of zero or one. The sample period is 1964:2 through 2005:4 for quarterly data and 1965 through 2002 for annual data. To test equality of coefficients across portfolios, we specify

$$R_{j,t} = \alpha_0 + \sum_{j=2}^{25}\alpha_j Port_j + [\delta_0 + \sum_{j=2}^{25}\delta_{j,0} Port_j + (\delta_{gdp} + \sum_{j=2}^{25}\delta_{j,gdp} Port_j)\Delta gdp_{t-1} + (\delta_{cay} + \sum_{j=2}^{25}\delta_{j,cay} Port_j) cay_{t-1}]h_{jm,t} + e_{j,t}$$

where $Port_j$ is a portfolio dummy variable taking the value of one for portfolio *j* and zero otherwise. We do not specify a portfolio dummy variable for the small /value portfolio. We report F-statistics and *p*-values under the given null hypotheses that the specific risk aversion parameter is equal across all portfolios.

In Panels C and D of Table 5 we present multivariate estimates of our dynamic risk aversion specification based on our 25 portfolio sample. We observe strong evidence of countercyclical variation in aggregate risk aversion estimates. We admit portfolio specific intercepts with 24 dummy variables and estimate equation (10) using FGLS, imposing the restrictions that each specific risk aversion parameter is equal across all portfolios $(\delta_{j,0} = \delta_0; \delta_{j,gdp} = \delta_{gdp}; \delta_{j,cay} = \delta_{cay})$. In Panel C we find significantly negative parameter estimates for δ_{gdp} and significantly positive estimates for δ_{cay}. Our annual empirical results largely support these countercyclical risk aversion findings (when parameters are significant). Our estimates of risk aversion following a period in which *cay* is equal to the median are 2.4 and 5.5 based on quarterly and annual observations, respectively. These estimates increase to 4.0 and 11.7 following a period in which *cay* is one standard deviation above the median, for quarterly and annual observations, respectively. Our estimates suggest that annual shocks have a larger impact on risk aversion relative to quarterly shocks. Intuitively, a longer period of poor economic performance produces a larger corresponding increase in risk aversion.

Lettau and Ludvigson (2001) document that changes in the shared trend in *cay* are "better described as transitory movements in asset wealth than as transitory movements in consumption or labor income." This is indicative of consumption smoothing behavior. Following a negative income or wealth shock, the adjustment in current consumption is only a fraction of the innovation. Therefore, the total decrease in income is not offset by an equal decrease in consumption, and the consumption to wealth ratio increases. Conversely, an increase in income or wealth does not cause a proportional increase in current consumption, causing the consumption to wealth ratio to fall, following a positive income innovation. Our results indicate a clear relation between consumption smoothing behavior and risk aversion. Following a negative income shock, individuals largely maintain current levels of consumption by borrowing from future income, which leads to an increase in risk aversion.

Figure I provides a plot of the temporal evolution in conditional risk aversion based on the estimates in Table 5. As an example of the implied risk aversion from our model, we consider a three year moving average of the change in gross domestic product as a regressor in the following specification

$$\delta_t = \delta_0 + \delta_{gdp} * \Delta gdp_t \,. \tag{11}$$

We use the parameter estimates from the second row of Panel C $(\delta_0 = 4.772; \delta_{gdp} = -0.546)$ and plot the resultant conditional risk aversion estimates over time.

A cursory inspection of Figure I reveals several interesting features regarding the temporal dynamics in risk aversion. We observe substantial variation through time in the forecasted series – the series frequently dips below two and reaches a peak of near five over the sample. This variation is consistent with the range of constant estimates provided in the extant literature (cf., Ghysels et al 2005). Interestingly, the generated series also displays support our earlier findings of counter-cyclical variation in risk aversion.

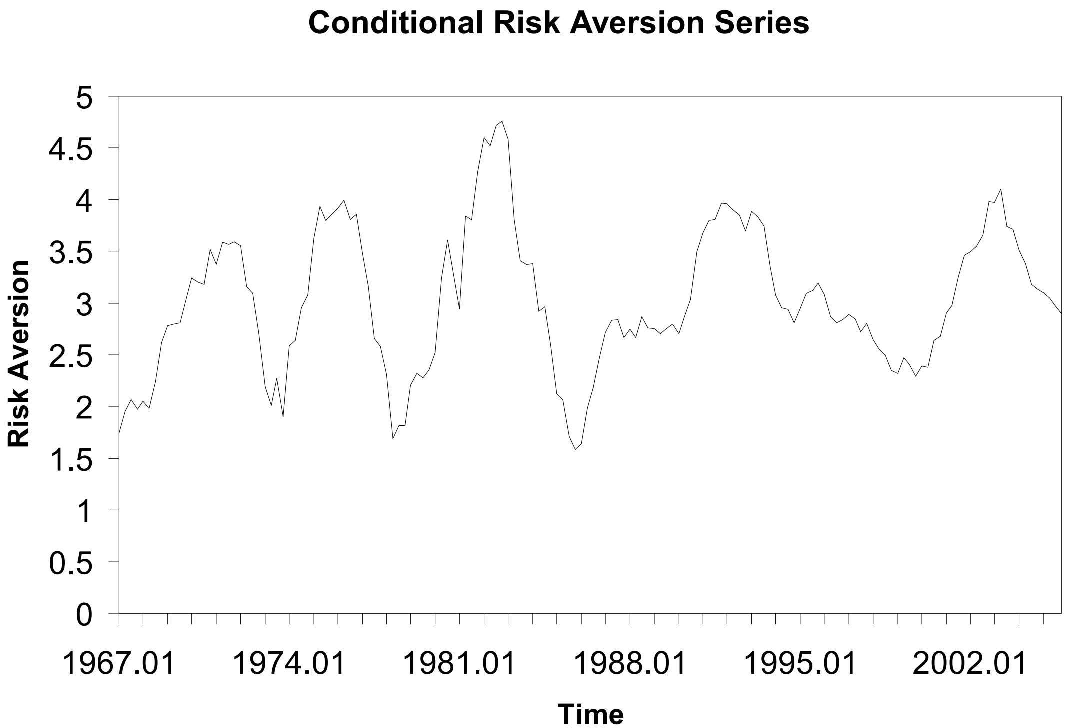

Figure I. Conditional Risk Aversion Series. We plot the three-year moving average of our quarterly conditional risk aversion parameter estimates from 1967.01 through 2005.04. Quarterly risk aversion is defined as,

$$\delta_t = \delta_0 + \delta_{gdp} \Delta gdp_t ,$$

and estimates of δ_0 and δ_{gdp} are obtained from Panel C in Table 5.

For example, we observe a steady decline in estimated risk aversion during the bull market of the late 1990s, followed by a steady increase in risk aversion following the subsequent market decline.

The relation between economic states and risk aversion may also vary across portfolios. Fama and French (1989) regress excess returns on the lagged default premium and find variation in their estimates dependent upon the asset class. Perhaps as expected, they find a small sensitivity in default slopes on high grade bond returns. In general, default sensitivities increase "from high-grade to low-grade bonds, from bonds to stocks and from big stocks to small stocks." A similar pattern exists for sensitivities to dividend yields, related to business condition risk. Assets that are more sensitive to the business cycle provide higher returns following periods of poor economic performance. We hypothesize that the sensitivity of risk aversion in relation to economic conditions varies across portfolios. To examine this hypothesis we specify

$$\begin{aligned} R_{j,t} &= \alpha_0 + \sum_{j=2}^{25} \alpha_j Port_j + [\delta_0 + \sum_{j=2}^{25} \delta_{j,0} Port_j + (\delta_{gdp} + \sum_{j=2}^{25} \delta_{j,gdp} Port_j) \Delta gdp_{t-1} \\ &+ (\delta_{cay} + \sum_{j=2}^{25} \delta_{j,cay} Port_j) cay_{t-1}] h_{jm,t} + e_{j,t} \end{aligned}, \qquad (12)$$

for $j = 1,2,...25$, where all variables are as previously defined. From this specification, we test the equality of each risk aversion parameter across all 25 portfolios by imposing dummy variable restrictions. We report F-statistics and associated *p*-values for the separate hypotheses $\delta_{j,0} = 0; \delta_{j,gdp} = 0; \delta_{j,cay} = 0$ for all $j = 2,3,...25$. Each null hypothesis then examines a restriction that the component of risk aversion is equal across all 25 portfolios. The last three columns of Table 5 report the relevant F-statistics and p-values for quarterly and annual returns in Panels C and D. The reported quarterly return data indicate that both the constant component of risk aversion and the sensitivities to *cay* vary across the 25 test portfolios. Annual return data provides even stronger evidence that all components of our linear risk aversion specification vary across the 25 test portfolios. The reported dummy variable restrictions are all highly significant suggesting that the linear specification for risk aversion is different for the 25 portfolios.[11]

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[11] As a robustness check we also estimated equation (10) across size and book to market portfolios. For each size (book to market) quintile we estimate equation (10), pooling across book to market (size) portfolios. This approach yields estimates of equation (10) for each size and book to market quintile based on five cross-sectional observations.

To examine if previous economic conditions impact risk aversion, we now consider the evolution of risk aversion in relation to a lengthier economic cycle. Our prior analysis demonstrates that risk aversion varies countercyclically based on last period's economic state. We now focus on annual returns and consider economic conditions prior to the previous period. We begin by extending equation (10) to incorporate a previous lag of one of our economic state variables,

$$R_{j,t} = \alpha_j + (\delta_0 + \delta_1 Econ_{t-1} + \delta_n Econ_{t-n}) h_{jm,t} + e_{j,t} \text{ for } j = 1,2,\ldots 25, \qquad (13)$$

where *Econ* represents either *cay* or Δgdp. We present results in Table 6.

Panels A and B present results for previous lags of *cay* and Δgdp, respectively. In Panel A, we again find evidence of countercyclical variation in risk aversion. Estimates of δ_1 range from 184.5 to 248.9 and are significant at the one-percent level in every instance. Further, estimates related to previous lags of *cay* are uniformly positive (but only significant for lags two and five). These estimates indicate that economic shocks may impact risk aversion for up to five years. Panel B shows a similar result for GDP growth, Δgdp. Estimates of δ_1 range from -1.2 to -1.4, and are significant at the one-percent level in every case. In addition, all significant earlier lags are also negative. From Panels A and B, we conclude that there is persistence in the impact of previous economic lags on current levels of risk aversion, with impacts lasting as long as five years.

Unreported results show that significant estimates of δ_{gdp} are negative and significant estimates of δ_{cay} are positive.

TABLE 6. Risk Aversion and Economic Cycles Based on Indicators Δgdp (Change in Gross Domestic Product Growth) and cay (Aggregate Consumption to Wealth Ratio) with Lag Parameters (δ_n).

Panel A. *cay*					
δ_0	δ_1	δ_2	δ_3	δ_4	δ_5
2.109	244.327				
(0.000)	(0.000)				
3.696	184.482	85.645			
(0.000)	(0.000)	(0.000)			
2.456	232.851		27.042		
(0.000)	(0.000)		(0.128)		
2.107	241.444			14.672	
(0.000)	(0.000)			(0.521)	
-0.347	248.923				266.461
(0.477)	(0.000)				(0.000)
Panel B. Δgdp					
δ_0	δ_1	δ_2	δ_3	δ_4	δ_5
4.346	-1.334				
(0.000)	(0.000)				
6.609	-1.222	-0.759			
(0.000)	(0.000)	(0.001)			
4.237	-1.313		0.019		
(0.004)	(0.000)		(0.948)		
3.496	-1.357			0.152	
(0.003)	(0.000)			(0.476)	
10.105	-1.342				-1.276
(0.000)	(0.000)				(0.000)
Panel C. Decay Function					
Econ	n	δ	β	λ	
cay	3	3.972	193.800	0.278	
		(0.000)	(0.000)	(0.005)	
cay	5	3.976	193.400	0.278	
		(0.000)	(0.000)	(0.001)	
cay	10	2.455	159.600	0.178	
		(0.001)	(0.000)	(0.112)	
Δgdp	3	8.415	-1.252	0.444	
		(0.000)	(0.000)	(0.000)	
Δgdp	5	18.269	-0.965	0.912	
		(0.000)	(0.000)	(0.000)	
Δgdp	10	12.409	-0.878	0.729	
		(0.007)	(0.000)	(0.000)	

(Continued)

Note: We estimate the relation between risk aversion and lagged economic states. In Panels A and B, we present results from the model

$$R_{j,t} = \alpha_j + (\delta_0 + \delta_1 Econ_{t-1} + \delta_n Econ_{t-n})h_{jm,t} + e_{j,t} \text{ for } j = 1,2,...25,$$

where the excess return of portfolio *j* during period *t* is defined as $R_{j,t}$ and $h_{jm,t}$ is the conditional covariance between portfolio *j* and the market portfolio created with information from the previous period; *Econ* is defined as the estimate of the consumption to wealth ratio (*cay*), in Panel A, and real-percent change in GDP (Δgdp), in Panel B, and *n* is equal to one of 2, 3, 4, or 5. The sample period is 1970 through 2002 and 1970 through 2005 for models with *cay*, and Δgdp, respectively. In Panels A and B, we pool observations across the 25 portfolios formed from the intersection of size and book to market quintiles and report FGLS estimates and associated *p*-values under the Parks correction. In Panel C we present estimates of δ, β, and λ, from the model

$$R_{j,t} = \alpha_j + [\delta + \beta(\sum_{i=1}^{n} \lambda^{i-1} Econ_{t-i})]h_{jm,t} + e_{m,t}.$$

Our final empirical specification allows lagged economic indicators to have a diminishing impact on risk aversion. Specifically, we minimize the sum of squared errors from the model

$$R_{j,t} = [\delta + \beta(\sum_{i=1}^{n} \lambda^{i-1} Econ_{t-i})]h_{jm,t} + e_{j,t}, \text{ for } j = 1,2,...25, \quad (14)$$

where *Econ* represents either *cay* or Δgdp in alternate specifications, and *n* equals three, five or ten. The decay process that determines the weight placed on previous economic states is given by $\lambda \in (0,1)$. Large values of λ indicate a slowly diminishing process. The initial three rows of Panel C report results for the *cay* decay function. Parameter estimates for β are equal to 159.6, 193.4 and 193.8 for models including three, five or ten lags. The estimated decay parameter λ, is significant for the three and five lag systems and suggests a relatively quick decay with parameter estimates declining by more than 70 percent per period. For example, for *n* equal to five, our indirect estimates of the declining coefficients on *cay* lags from $t-1$ through $t-5$ are 193.4, 52.2, 14.1, 3.8 and 1.0. The comparable results for Δgdp are less consistent across the three five and ten lag specifications. The β estimates of -1.3, -1.0, and -0.9 for models including three, five or ten lags, respectively, are all significant. The estimated decay parameter λ, is quite variable across the three lag lengths; however, the longer specifications suggest a relatively slow decay in parameter estimates with an estimated λ in excess of 0.7. For the n equal to five specification, our indirect estimates for the coefficients on lags of Δgdp from $t-1$ through $t-5$ are -1.0, -0.9, -0.8, -0.7, and -0.7.

V. Conclusion

We estimate the coefficient of relative risk aversion in a manner that admits variability over time and in relation to economic states. Our constant estimates of risk aversion are approximately equal to two based on the market portfolio in isolation. Cross-sectional tests suggest that constant risk aversion estimates vary through time and across size and book to market classifications. Risk aversion varies countercyclically based on measures of aggregate income and the ratio of consumption to income – individuals rationally smooth consumption in response to income shocks. In the process, economic agents require greater compensation in periods of reduced income.

Our methodology mitigates problems associated with estimation of the conditional covariance matrix by using realized covariances to measure the conditional covariance matrix and to provide robust estimates of the risk aversion parameter of interest. Our use of daily data to construct covariances minimizes measurement error in the second moment matrix and allows us to examine the long term economic relations posited by the permanent income hypothesis. Another benefit of the proposed estimation approach is that it is straightforward to consider a wide range of test assets over a lengthy calendar sample in our empirical research design.

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EMERGING MARKET CONTAGION

Introduction

We examine the impact of emerging market crises on developed market portfolio returns. Recent emerging market crises make the topic of contagion especially pertinent. Carrieri et al (2007) demonstrate that world integration has been increasing through time. Bekiros and Georgoutsos (2008) discuss a dramatic increase in private capital flows into emerging markets in recent years. As developing nations become increasingly integrated in the world market, the role of financial crises may become more important. For example, Broner et al (2006) argue that contagion may result from investors scaling back areas that were overweighted.[1] Consequently, analyses of contagion have clear implications for portfolio management.

Explanations for financial contagion often focus on portfolio rebalancing strategies.[2] Extending these hypotheses, we expect domestic portfolio responses to an emerging market shock to vary based on portfolio characteristics and consequently, we sort portfolios based on risk and liquidity.[3] Given these characteristics, we focus on flight from risk and liquidity shock hypotheses. The flight from risk hypothesis implies that riskier domestic stocks will perform poorly during emerging market crises, while safer stocks exhibit strong performance. Given our focus on returns, the liquidity shock hypothesis implies poor performance across all portfolios. We argue that size and book to market portfolios can proxy for levels of risk and liquidity, by focusing on these portfolios. we are able to describe how emerging market crises affect developed market stocks. We find highly variable responses across portfolios that may have been missed in previous work focusing upon national equity indices and the transmission of shocks.

Our results support the flight from risk hypothesis, indicating contagion from emerging markets to small or mid to high book to market portfolios and strong large and growth stock performance during crises. Focusing on alpha as a measure of abnormal performance, conditional on emerging market crises, we find positive alpha estimates for large and growth stocks. Alternatively, the emerging market specific adjustment to alpha is dramatically negative for small portfolios. In addition to conditional alpha, we consider conditional correlations and domestic portfolio performance conditional on emerging market performance. After controlling for world conditions, we find the negative emerging market performance results in poor small and value returns. We also find correlations between domestic portfolios and emerging markets are largest when emerging market returns are the smallest; the evidence is strongest within small stocks and mid book to market stocks. Measured as shifts in correlation, we find contagion from emerging market crises to mid and high book to market stocks.

Existing research on contagion focuses on both emerging and developed markets.[4] Patel and Sarker (1998) contrast characteristics of emerging market and developed market crises, and argue that emerging market crises may be much more severe. Consequently, the impact of an emerging market crisis on developed markets may differ from the impact of a developed market crisis. By construction many prior studies will be impacted by both important contagion effects and fundamental valuation shifts. For example, a large shock to the US market will clearly have a large fundamental impact on worldwide markets at both the macro level for real and financial markets, as well as at the micro level for individual firms.

We examine the impact of a variety of emerging market crises on broad based US size and value portfolios. We focus upon seven emerging market crises, as identified by Collins and Gavron (2004). Focusing upon multiple events in smaller emerging markets allows us to limit the fundamental impact of any one emerging market event on our US portfolios. Our primary interest is to measure the impact of emerging market events on US portfolios in times of crisis. Contagion is often defined as excess comovement; that is, an interdependency beyond what would be expected based on fundamentals or the level observed during tranquil periods. Yan and Bessler (2008) point out that analyzing contagion within a region, such as Latin America during the Argentine crisis, may be difficult as all Latin American countries may share similar fundamentals or risk exposures with Argentina, the country of origin. Consequently, the most useful tests of contagion will limit fundamental effects of a crisis from the follow-on effects, above and beyond fundamentals. Our focus on portfolios within one large country, in relation to a large number of emerging market shocks, mitigates this concern. Finding contagion for some portfolios, flight to quality for others, and no effect in the remaining portfolios within the large market, we are quite confident that our results are due to emerging market events, rather than weakened fundamentals.[5]

Hypothesis Development

Many authors consider contagion as an increase in the comovement between countries when a crisis occurs.[6] With this definition, contagion does not include interdependence (i.e., a strong relation across both crisis and normal periods).[7] A large body of literature discusses mechanisms by which a crisis can spread across assets.[8] Many authors consider that investor actions based on wealth effects or liquidity shocks can cause a crisis to spread and lead to contagion.[9] Following a shock, investors rationally adjust their exposure to risk factors and a crisis can then quickly spread across markets. Investors may also sell assets in multiple markets in response to a liquidity shock triggered by an event in one market, the correlated liquidity shock theory. This is especially relevant in our paper, as shocks to an emerging market may lead investors to sell developed market assets, which tend to be highly liquid. We therefore hypothesize that an emerging market crisis will spread to developed markets.[10]

Contagion effects may naturally arise due to portfolio rebalancing, or changes in risk appetite due to the impact of emerging market shocks on portfolio holdings.[11] A negative shock in one market may lead to an increase in overall investor risk aversion. With higher levels of risk aversion, riskier assets must provide higher expected returns and current prices must fall. In this way, a crisis may quickly spread across risky assets without common fundamentals or risk factors. Schinasi and Smith (2000) discuss contagion based on portfolio management, suggesting that a shock causes leveraged investors to scale back their positions in all risky assets.

With contagion defined as an increase in cross-market relations during crises, testing for contagion requires a measure of the baseline relation and often specification of expected returns based on fundamentals. Many studies of emerging market crises find a high level of interdependence across emerging market in all states of the world, as opposed to contagion.[12] Bekaert et al (2005) test for contagion based on residual correlations from an asset pricing model. In their specification, an asset's expected return is based on the US market return, a regional market return and local information variables. They find evidence of contagion during the 1997 Asian crisis, but little evidence of contagion during the 1994 Mexican crisis.[13]

In addition to contagion, researchers have considered the flight to quality phenomenon as well. In general, flight to quality occurs when one asset or market responds positively to a crisis or shock to another asset or another market. This definition of flight to quality encompasses two similar phenomenon. In one potential case, an increase in risk or uncertainty in one asset may lead investors to switch to a safer asset. As an example, Andersson et al (2008) consider the relation between stock and bond returns and find evidence of flight to quality. Specifically, during periods of increased stock market uncertainty, the correlation between stock and bond returns decreases. This is consistent with investors reallocating their portfolios in response to increased stock market uncertainty. Another potential example of flight to quality would occur when a negative shock improves the position of competitors. Jorion and Zhang (2007) consider contagion and flight to quality with an intra-industry analysis of the credit market. They find evidence of competition effects, or flight to quality, measured as a decrease in correlation of CDS spreads following Chapter 7 bankruptcies. The intuition is that a bankruptcy may improve the competitive position of rivals.

We examine the impact of emerging market crises on US portfolios, testing for contagion and flight to quality. We argue that contagion occurs if the relation between two assets increases during a crisis, or if one asset exhibits significantly lower returns concurrent with a crisis in a different market. Conversely, flight to quality occurs if the relation between assets decreases during a crisis, or if an asset exhibits significantly higher returns conditional on a crisis in another market.

We hypothesize that the impacts of emerging market crises vary across portfolios based on portfolio characteristics. Specifically, we consider volatility and liquidity as important portfolio characteristics that may determine a portfolio's response to an emerging market crisis. We use small and value stocks as proxies for risky and illiquid stocks, while big and growth stocks proxy for safe and liquid stocks.[14]

Considering the flight from risk hypothesis, that investors reduce risky positions in response to a shock to one specific asset, we expect contagion effects within US risky assets (small and value) and flight to quality within safer assets (large and growth). Alternatively, the correlated liquidity shock hypothesis holds that investors will sell assets in all markets, following a shock in one market. Preference may be given to sell assets that are the most liquid to minimize negative price impacts. However, if negative price impacts begin, then less liquid stocks will likely also be sold. With respect to the correlated liquidity shock hypothesis, we expect contagion measured as abnormally negative returns across developed market portfolios. Our hypotheses may interact: facing a liquidity requirement and a desire to scale back risky investments, an investor may choose to gain liquidity by trading risky assets. We also consider that emerging market assets historically offer higher expected returns with higher risk. Therefore, following a shock to emerging markets, investors may choose to allocate additional wealth into riskier domestic stocks for their higher expected returns This is analogous to the competitive flight to quality discussed by Jorion and Zhang (2007). In this case, during an emerging market crisis we would expect to see flight to quality within riskier US portfolios.

Data and Initial Empirical Analysis

Focusing on several recent emerging market episodes, we test our hypotheses regarding crises and developed market portfolios. The propagation of crises likely depends on the level of world integration. Recent research suggests net capital flows from developed to emerging markets have risen dramatically and that world market integration has increased dramatically over time.[15,16] Collins and Gavron (2004) identify seven recent emerging market crises. We choose a sample period from 1988 through 2007 that includes these seven emerging market crises and is also recent enough to provide evidence regarding the current international context. A benefit of our multiple crisis approach is that we mitigate the noise present in any given event, to increase the power of our later inferences.

We consider monthly returns to size and book to market quintiles obtained from Kenneth French. From this data set, we construct a small minus big portfolio, *SMB*, by subtracting the return to the big portfolio from the small portfolio return. In a similar fashion, we construct a high minus low book to market portfolio, *HML*.

We present summary statistics for the data in Table 1. A cursory inspection of the table reveals that our sample includes turbulent periods. The minimum monthly emerging market is less than -30%. Further, the smallest three US stock quintiles all have minimum returns below -20%. We find that both US small stock portfolios and the emerging market index appear to offer high expected returns and greater volatility. The mean emerging market index return is approximately 2.2% with a standard deviation of over 6.5%. Considering US size quintiles, we find that mean returns, standard deviations, and minimum returns all decrease in magnitude monotonically with size.

Table 1. Summary Statistics

We present summary statistics for returns to foreign exchange indices and stock portfolios for our monthly sample from January 1988 through August 2007. We define *R* as the percent return in excess of the US one month Tbill of stock indices, where subscripts *w*, *dm*, and *em* represent the MSCI world, developed market, and emerging market indices. The US market excess return is denoted *Mkt*. We include the percent excess returns to five size and book to market quintiles, represented by *S* and *BM*, respectively, and indexed accordingly. We construct a 'small minus big' portfolio, *SMB*, and a 'high minus low' portfolio, *HML*, from our data.

	Mean	*Median*	σ	*Min*	*Max*
$R_{w,t}$	0.247	0.906	3.861	-16.080	9.127
$R_{dm,t}$	0.188	0.813	3.839	-15.419	9.006
$R_{em,t}$	2.234	2.689	6.540	-31.818	20.428
Mkt	0.664	1.065	3.979	-16.200	10.300
SMB	0.208	-0.135	4.745	-20.340	29.050
Small	0.866	1.135	5.797	-22.230	27.250
S_2	0.779	1.450	5.342	-20.720	17.220
S_3	0.778	1.315	4.837	-20.480	11.770
S_4	0.837	1.080	4.518	-18.110	12.870
Big	0.657	0.945	3.944	-14.920	11.290
HML	0.292	0.375	3.396	-9.850	14.590
Growth	0.627	0.540	4.463	-14.920	14.470
BM_2	0.792	1.070	4.021	-17.860	9.630
BM_3	0.775	1.235	3.782	-18.310	9.180
BM_4	0.822	1.270	3.668	-14.280	9.740
Value	0.919	1.255	4.068	-13.640	11.580

In our analysis of contagion, we compare returns across crisis and normal periods. Specifically, we test for structural breaks surrounding the onset of emerging market crises. We consider a number of alternative approaches to capture the variability in returns across crises. For each crises date identified by Collins and Gavron (2004), we consider a four-month crisis window that begins the month prior to the crisis month, includes the crisis month, and the following two months.[17] A relatively wide crisis window has the benefit of capturing much of the interesting run-up and follow-on behavior before and following various crises. For example, the devaluation of the Thai Baht is often used as the crisis date for the East Asian crisis (July 1997). Notwithstanding this choice, newspaper reports from May and June suggested that a devaluation and crisis was likely. Our approach should capture much of the variability around these seven crises, and also provide a reasonable number of crisis observations to provide good test power.[18] [19]

Table 2 presents mean returns for US domestic portfolios across a variety of aggregate market return scenarios. From this analysis, we can compare mean returns of US portfolios across emerging market states to assess whether mean returns for a specific portfolio differ conditional upon emerging markets. Panel A presents results for size portfolios and Panel B presents results for book to market portfolios. The first two columns of Table 2 reports mean returns conditional on an emerging market crisis period. For each reported portfolio mean in a normal or crisis period, we also present a p-value for the test that these values differ. We observe a smaller conditional mean in crisis states for all but the biggest size based portfolio. In addition, the crisis period returns monotonically increase across size portfolios. The normal period return for the smallest size portfolio of 1.1% is dramatically larger than the crisis period return of -1.27% (marginally significant at the 5.7% level). The *SMB* portfolio has a normal period return of 0.455% and a crisis period return of -1.97% (significant at the 1.7% level). We fail to reject the equality of means between normal and crisis periods for our remaining size portfolios in Panel A and across any of our book to market portfolios in Panel B. Therefore, conditional on our emerging market crisis windows, we observe significantly lower returns for the small portfolio and no effect across the other portfolios, providing initial evidence of contagion within risky assets and supporting our flight from risk hypothesis.[20]

Table 2. Conditional Means in Crisis and Normal Periods

We report mean excess monthly returns for size and book to market quintiles conditional on emerging market crises, and global stock indices for our monthly sample period from January 1988 through August 2007. We consider seven emerging market crises and define *crisis* months as the four month period beginning one month prior to, and ending two months after, the identified crisis month. We define the remaining months in our sample as *normal*. We define R_w and R_{em} as the excess return to the MSCI world and emerging market indexes. Superscripts '+' and '-' refer to a positive or negative return, respectively. Reported *p*-values test the hypothesis that the given portfolio mean return is equal across emerging market regimes, conditional on an emerging market crisis or a given world regime.

			R_w^+		R_w^-	
	Normal	*EM Crisis*	R_{em}^+	R_{em}^-	R_{em}^+	R_{em}^-
			Panel A: Size Portfolios			
SMB	0.455	-1.970	0.916	-3.559	0.624	-0.593
	(0.017)		(0.002)		(0.135)	
Small	1.107	-1.267	3.847	-1.002	-0.657	-3.473
	(0.057)		(0.001)		(0.006)	
S_2	0.988	-1.067	3.754	-0.009	-1.128	-3.531
	(0.210)		(0.001)		(0.012)	
S_3	0.961	-0.841	3.596	0.574	-1.016	-3.438
	(0.239)		(0.001)		(0.007)	
S_4	1.007	-0.667	3.533	1.103	-1.110	-3.142
	(0.216)		(0.006)		(0.008)	
Big	0.652	0.703	2.931	2.557	-1.280	-2.880
	(0.952)		(0.621)		(0.011)	
			Panel B: Book to Market Portfolios			
HML	0.411	-0.760	0.132	-1.511	0.667	0.758
	(0.110)		(0.077)		(0.898)	
Growth	0.603	0.843	2.988	2.936	-1.262	-3.208
	(0.858)		(0.956)		(0.006)	
BM_2	0.868	0.123	3.083	1.634	-1.117	-2.557
	(0.558)		(0.066)		(0.037)	
BM_3	0.892	-0.262	2.894	1.160	-0.960	-2.253
	(0.352)		(0.019)		(0.072)	
BM_4	0.929	-0.127	2.657	1.952	-0.951	-1.797
	(0.330)		(0.340)		(0.242)	
Value	1.014	0.083	3.121	1.426	-0.595	-2.450
	(0.289)		(0.036)		(0.017)	

The analysis above documents domestic performance conditional on identified emerging market crises. We also wish to consider domestic performance conditional on poor emerging market performance throughout our sample.[21] This analysis provides a robustness check of our crisis window specification. Finding comparable results across our crisis windows and periods of observed poor emerging market performance validates our crisis specification. Intuitively we wish to examine situations in which emerging market risk is realized after controlling for world market behavior. In particular, we wish to observe portfolio returns when emerging markets rise or fall when world markets perform positively. We therefore provide tests for differences in US portfolio mean returns across emerging market regimes, for a given world market regime. In this analysis, rejecting the equality of mean returns across emerging market states shows that the given portfolio performs differently conditional on emerging market states after controlling for world factors. Finding that a US based portfolio performs poorly during a state of world market increase and emerging market decline provides evidence of contagion. The final four columns of Table 2 report the mean returns for size and book to market portfolios conditional on the sign of the world (R_w^+ and R_w^-) and emerging market indices (R_{em}^+ and R_{em}^-).[22]

Columns three and four of Table 2 consider the situation where world markets increase.[23] Comparing the smallest and largest size portfolio returns across states shows the dramatic effect that poor emerging market behavior can have on small size portfolios. If the emerging market also increases, then the small and big stock portfolio increase 3.8% and 2.9%, respectively. In contrast, when the emerging market falls, the small and big portfolios earn -1.0% and 2.6%, respectively. The small stock portfolio appears dramatically impacted by the emerging market return after removing the impact of the world index. In fact, for all but the largest portfolio, smaller portfolios do relatively worse when emerging markets fall. The highly significant difference between the *SMB* portfolio when emerging markets rise or fall is 4.475% (= 0.916% + 3.559%). The comparable difference for value portfolios is 1.643% (= 0.132% + 1.511%). These results provide evidence of contagion from emerging markets to risky US stocks. We do not observe similar negative performance across safe US stocks.

In general, the results based on size portfolios support our flight from risk hypothesis, as small stocks and the *SMB* portfolio exhibit deteriorating returns during emerging market crises and emerging market downturns. Further, as this pattern is confined to specific portfolios, we support the idea that emerging market crises do not uniformly affect all US portfolios. The results in Table 2 based on identified crises and periods of poor emerging market performance both consistently support our flight from risk hypothesis

Defining contagion as increased comovement during crises, many researchers analyze contagion based on changing correlations around crises.[24] In Table 3, we report pairwise correlations (and associated p-values) between US portfolio returns and the emerging market index for our crisis window specification and for emerging market return quartiles. The analysis based on return quartiles provides another robustness check of our crisis window specification. The estimated correlations suggest an increased dependency between US portfolios and emerging markets during periods of poor emerging market performance. For example, focusing on size quintiles, our correlation estimates range from 0.67 to 0.77 conditional on emerging market crises. These estimates compare to a range of 0.49 to 0.55 during our normal sample period. Considering emerging market return quartiles and size portfolios, we find significant correlation estimates ranging from 0.58 to 0.68 conditional on emerging market returns falling in the lowest quartile. We do not obtain significant correlation estimates for any portfolio within any of the three remaining emerging market return quartiles.[25] Thus, considering emerging market return quartiles, we find large, significant correlation estimates between US portfolio returns and the emerging market index during periods in which the emerging market index exhibits the worst performance and we fail to find significant correlation estimates otherwise.

To compare correlations between our normal and emerging market sample periods as well as across quartiles of emerging market performance, we present z-scores and the associated *p*-values testing equality of correlations in Panel B of Table 3.[26] [27] Entries under the 'Normal' column in Panel B compare correlations across our normal and crisis sample periods. For example, the entry of 1.42 with the associated *p*-value of 0.039 rejects equality across normal and crisis periods for the value portfolio. With the exception of the growth portfolio, we marginally reject equality for the remaining book to market portfolios. These results indicate contagion from emerging markets to mid and high book to market stocks, as these stocks exhibit a larger correlation with emerging markets during emerging market crises. Considering size portfolios, we marginally reject equality across normal and crisis periods for the small stock portfolio, as well as the two largest stock portfolios.

Table 3. Conditional Correlations

We consider sample correlations between the MSCI emerging market US Dollar index and US size quintiles, and book to market quintiles. In Panel A we present sample correlations and the associated *p*-value conditional upon our emerging market crisis specification as well as the given emerging market return percentile. In Panel B we test for differences in correlations between a given US portfolio and the emerging market index across normal and crisis periods as well as across levels of emerging market performance. Entries in Panel B represent z-scores and *p*-values from the hypothesis that the correlation is equal across emerging market crisis and normal periods as well as under the given emerging market return quartile compared to the correlation under the lowest emerging market index return quartile. In Panel B we control for heteroskedasticity following Forbes and Rigobon (2002) in the instances in which we reject equality of variances across samples.

Panel A: Correlation Estimates

	Normal	*EM Crisis*	$x<25\%$	$25\%<x<50\%$	$50\%<x<75\%$	$75\%<x$
Small	0.490	0.669	0.623	0.091	0.049	0.026
	(0.000)	(0.000)	(0.000)	(0.491)	(0.714)	(0.845)
S_2	0.537	0.673	0.622	0.052	0.122	0.062
	(0.000)	(0.000)	(0.000)	(0.696)	(0.359)	(0.641)
S_3	0.551	0.731	0.677	0.082	0.121	0.056
	(0.000)	(0.000)	(0.000)	(0.535)	(0.360)	(0.673)
S_4	0.530	0.766	0.664	0.084	0.095	0.042
	(0.000)	(0.000)	(0.000)	(0.525)	(0.477)	(0.755)
Big	0.502	0.773	0.579	0.108	0.105	0.042
	(0.000)	(0.000)	(0.000)	(0.414)	(0.428)	(0.754)
Growth	0.496	0.715	0.541	0.087	0.121	0.085
	(0.000)	(0.000)	(0.000)	(0.513)	(0.361)	(0.523)
BM_2	0.480	0.829	0.667	0.054	0.095	-0.011
	(0.000)	(0.000)	(0.000)	(0.686)	(0.475)	(0.933)
BM_3	0.442	0.848	0.656	0.077	0.078	-0.006
	(0.000)	(0.000)	(0.000)	(0.561)	(0.557)	(0.967)
BM_4	0.404	0.738	0.528	-0.070	0.060	0.042
	(0.000)	(0.000)	(0.000)	(0.597)	(0.653)	(0.750)
Value	0.480	0.690	0.435	0.111	-0.049	0.037
	(0.000)	(0.000)	(0.001)	(0.401)	(0.714)	(0.779)

Panel B: Test Statistics						
	Normal	*EM Crisis*	x<25%	25%<x<50%	50%<x<75%	75%<x
Small	1.19			3.38	3.30	3.72
	(0.058)			(0.000)	(0.000)	(0.000)
S_2	0.41			3.58	2.12	3.53
	(0.170)			(0.000)	(0.008)	(0.000)
S_3	0.55			3.92	2.41	4.06
	(0.145)			(0.000)	(0.004)	(0.000)
S_4	0.85			3.79	2.83	4.01
	(0.099)			(0.000)	(0.001)	(0.000)
Big	0.88			1.87	1.95	3.28
	(0.095)			(0.015)	(0.013)	(0.000)
Growth	0.70			2.01	1.95	2.75
	(0.121)			(0.011)	(0.013)	(0.001)
BM_2	1.17			3.98	2.75	4.32
	(0.060)			(0.000)	(0.001)	(0.000)
BM_3	1.27			3.75	2.64	4.19
	(0.051)			(0.000)	(0.002)	(0.000)
BM_4	1.07			2.36	1.97	2.89
	(0.071)			(0.005)	(0.012)	(0.001)
Value	1.42			1.88	2.73	2.27
	(0.039)			(0.015)	(0.002)	(0.006)

The remaining entries in Panel B of Table 3 compare correlations within the given emerging market return quartile to the correlation within the lowest emerging market return quartile, for a given domestic portfolio. In this analysis, we reject equality in all instances, indicating an increase in the relations between domestic stock and emerging markets during periods of poor emerging market performance.

Controlling for International Risk Sources

Given that our focus is on domestic portfolios in relation to both domestic and international risks, we consider a variety of pricing specifications. We begin with a standard domestic CAPM and consider the level of alphas for various portfolios and how these alphas change during emerging market crises. Alpha is typically considered a measure of abnormal positive or negative performance. Estimates of alpha conditional on emerging market crises thus document abnormal performance for a given stock during emerging market crises. We also extend the asset pricing model to admit changes in risks in relation to emerging market crises, as well as in relation to developed market and emerging market returns. This allows us to detail abnormal performance during emerging market crises even after controlling for changing levels of risk. We find strong evidence that small stock portfolios display weak performance in times of emerging market crisis.

We implement an empirical model in which structural breaks reveal changing returns and risk surrounding emerging market crises. Our empirical specification is as follows,

$$R_{j,t} = \alpha_j + \phi_{0,j} C_t + (\beta_{w,j} + \phi_{1,j} C_t) R_{w,t} + \varepsilon_{j,t}\,, \qquad (1)$$

for j=1,2…N; t=1,2,…T; $R_{j,t}$ and $R_{w,t}$ represent the excess return to asset j and the world portfolio, respectively; C_t is a crisis indicator variable taking the value of one for the four month period beginning one month prior to, and ending two months after, the identified crisis month, and 0 otherwise.[28] The coefficients, $\phi_{0,j}$ and $\phi_{1,j}$ for j=1,2…N represent structural breaks during identified emerging market crises for portfolio j. In general the alpha for any portfolio is given by $\alpha_j + \phi_{0,j} C_t$ where the normal period component is α_j and $\phi_{0,j} C_t$ represents the change in alpha during a crisis. Significant estimates of $\phi_{0,j}$ indicate a return shock during crises. Finding positive estimates of $\phi_{0,j}$ indicates that asset j exhibits positive alpha during an emerging market crisis, while negative estimates indicate a negative alpha concurrent with crises. Significant estimates of $\phi_{1,j}$ represent a change in an asset's sensitivity (or beta) to the world market during emerging market crises. Our initial results omit the $\phi_{1,j}$ term and estimate equation (1) for the US market portfolio, size quintiles, and book to market quintiles. We report parameter estimates of $\phi_{0,j}$ in Table 4.

We initially present estimation results for the market portfolio in Panel A. Given our specification, we fail to find a significant conditional alpha estimate, $\phi_{0,Market}$ for the market portfolio. This result indicates that we fail to find any abnormal performance within the US Market portfolio during emerging market crises. This supports the idea that emerging market shocks do not impact the aggregate domestic market.

Table 4. Alpha Conditional on Emerging Market Crises

We report parameter estimates and p-values from the following model

$$R_{j,t} = \alpha_j + \phi_{0,j} C_t + \beta_{w,j} R_{w,t} + \varepsilon_{j,t},$$

where $R_{j,t}$ represents the excess return of asset j during time t and $R_{w,t}$ represents the excess return to the MSCI world index. We consider seven emerging market crises and define crisis months, C_t, as the four month period beginning one month prior to, and ending two months after, the identified crisis month. We consider j=11 assets representing the US market portfolio, and US size and book to market quintiles separately. In Panel A we report parameter estimates for the market portfolio. Panels B and C report parameter estimates for individual size and book to market portfolios, respectively. In Panels B and C, we present F statistics for the hypotheses that the given parameter is equal across all portfolios within the panel and that the given parameter is jointly equal to zero across all portfolios within the panel.

	α_j	$\phi_{0,j}$	β_j
Panel A: Market Estimates			
Mkt	0.409	0.283	0.917
	(0.001)	(0.475)	(0.000)
Panel B: Size Portfolios			
SMB	0.446	-2.402	0.028
	(0.171)	(0.019)	(0.725)
Small	0.802	-1.619	0.926
	(0.011)	(0.099)	(0.000)
S_2	0.665	-1.255	0.981
	(0.011)	(0.121)	(0.000)
S_3	0.644	-1.018	0.962
	(0.003)	(0.126)	(0.000)
S_4	0.692	-0.895	0.956
	(0.000)	(0.109)	(0.000)
Big	0.356	0.784	0.898
	(0.007)	(0.057)	(0.000)
$\Phi_j = \Phi_i$: for all i and j	1.93	3.49	-
	(0.106)	(0.009)	
$\Phi_j = \Phi_i = 0$: for all i and j	3.72	3.10	-
	(0.003)	(0.010)	

(Continued)

Panel C: Book to Market Quintiles			
HML	0.464	-1.302	-0.161
	(0.045)	(0.072)	(0.005)
Growth	0.287	1.022	0.959
	(0.099)	(0.061)	(0.000)
BM_2	0.580	-0.033	0.873
	(0.000)	(0.945)	(0.000)
BM_3	0.633	-0.513	0.786
	(0.000)	(0.291)	(0.000)
BM_4	0.694	-0.474	0.714
	(0.000)	(0.364)	(0.000)
Value	0.751	-0.280	0.798
	(0.000)	(0.626)	(0.000)
$\Phi_j = \Phi_i$: for all *i* and *j*	1.05	1.59	-
	(0.384)	(0.177)	
$\Phi_j = \Phi_i = 0$: for all *i* and *j*	4.13	1.30	-
	(0.001)	(0.264)	

However, considering results based on size and book to market portfolios presented in Panels B and C, we find evidence that emerging market crises do impact certain portfolios. With our four month crisis window, we find a significant negative change in alpha during crises periods of 2.4% and 1.3% for our *SMB* and *HML*, respectively. The unconditional alphas α_j, presented in Table 4 provide evidence of strong performance across all US portfolios during our sample period. Excluding *SMB* and *HML*, all of our unconditional alpha estimates are positive and significant. Thus, excluding emerging market crisis observations from our sample, our remaining sample covers a period that is described by strong US stock performance.

We test joint restrictions across α_j as well as $\phi_{0,j}$ and present F-statistics in the final two rows of each panel. Using Φ_j to represent a general parameter, we test the hypotheses that $\Phi_j = \Phi_i$ and $\Phi_j = \Phi_i = 0$, for all *i* and *j*. Considering our estimates of unconditional alpha, we fail to reject equality across all portfolios for both size and book to market models. However, in both cases we do reject that all estimates are jointly equal to zero. These results based on unconditional alpha indicate that during our sample domestic portfolios exhibited some level of abnormal performance that was not captured by the world CAPM, however we do not find evidence that abnormal performance varies across portfolios.

Considering the hypothesis regarding conditional alpha estimates, we reject both hypotheses across size portfolios, but not across book/market portfolios. Rejecting the hypothesis that the $\phi_{0,j}$ terms are jointly equal to zero indicates that emerging market crises do impact domestic portfolios. Rejecting equality of the $\phi_{0,j}$ terms across all assets indicates that the impact of emerging market crises varies across portfolios. Thus, focusing on size portfolios, we find emerging market crises impact domestic stocks in terms of abnormal performance and the level of abnormal performance varies across assets. Considering point estimates of $\phi_{0,j}$ in Panels B and C, we find positive estimates equal to 1.0 for the growth portfolio and equal to 0.8 for the large portfolio. This provides evidence of flight from risk during emerging market crises, as these safer portfolios exhibit positive abnormal performance. Given our four month crisis window, we find an estimate of $\phi_{0,j}$ equal to -1.6 for the small stock portfolio.[29]

From Table 4, we find that emerging market crises do not impact the aggregate US market. However, based on our F-statistics, we find that emerging market crises do impact US portfolios and the effect varies across portfolios with positive returns to safe portfolios and negative returns to the small stock portfolio. In the above analysis, we omitted the slope-shift term, $\phi_{1,j}$. Consequently, our analysis did not include any potential change in the risk of our given portfolios. Next, we consider potential shifts in asset betas during emerging market crises. This analysis also determines if we still observe abnormal returns, measured as alpha, conditional on emerging market crises after we control for changing levels of risk. We present results based on the general model, equation (1), in Table 5.

Our hypotheses maintain that emerging market crises do not impact the aggregate US index, but do effect specific portfolio returns. In Panel A of Table 5 we present estimates of equation (1) based on the market portfolio. Consistent with our earlier results, we fail to find an impact from emerging markets, measured as either abnormal returns or changing risk, when we consider the US market portfolio. However, our hypotheses consider varying effects across size and book to market portfolios and we argue that the big and growth portfolios may serve as proxies for safer assets. Therefore, we estimate equation (1) based on our *SMB* and *HML* portfolios and based on individual size and book to market portfolios. In Panels B and C we find negative estimates of $\phi_{0,j}$ for the *SMB* and *HML* portfolios. This supports the results presented in Table 4, and shows that we still find abnormal performance, even after controlling for increased risk during emerging market crises. That is, we find significant underperformance of small stocks and value stocks, relative to large and growth stocks, respectively, during emerging market crises. Further, we find that this result is not sensitive to changing levels of risk.

Table 5. The International Capital Asset Pricing Model with Structural Breaks

We report parameter estimates and *p*-values from the following model

$$R_{j,t} = \alpha_j + \phi_{0,j} C_t + (\beta_{w,j} + \phi_{1,j} C_t) R_{w,t} + \varepsilon_{j,t},$$

where $R_{j,t}$ represents the excess return of asset j during time t and $R_{w,t}$ represents the excess return to the MSCI world index. We consider seven emerging market crises and define crisis months, C_t, as the four month period beginning one month prior to, and ending two months after, the identified crisis month. We consider j=11 assets representing the US market portfolio, and US size and book to market quintiles separately. In Panel A we report parameter estimates for the market portfolio. Panels B and C report parameter estimates for individual size and book to market portfolios, respectively. In Panels B and C, we present F statistics for the hypotheses that the given parameter is equal across all portfolios within the panel and that the given parameter is jointly equal to zero across all portfolios within the panel.

	α_j	$\phi_{0,j}$	$\beta_{w,j}$	$\phi_{1,j}$
Panel A: Market Estimates				
Mkt	0.414	0.307	0.902	0.073
	(0.001)	(0.440)	(0.000)	(0.341)
Panel B: Size Quintiles				
SMB	0.434	-2.456	0.062	-0.167
	(0.183)	(0.017)	(0.486)	(0.398)
Small	0.797	-1.639	0.939	-0.063
	(0.012)	(0.096)	(0.000)	(0.739)
S_2	0.665	-1.254	0.980	0.004
	(0.011)	(0.123)	(0.000)	(0.982)
S_3	0.649	-0.996	0.947	0.071
	(0.003)	(0.136)	(0.000)	(0.584)
S_4	0.693	-0.892	0.954	0.008
	(0.000)	(0.111)	(0.000)	(0.943)
Big	0.363	0.817	0.877	0.104
	(0.006)	(0.048)	(0.000)	(0.193)
$\Phi_j = \Phi_i$: for all *i* and *j*	1.87	3.60	-	1.06
	(0.117)	(0.007)		(0.379)
$\Phi_j = \Phi_i = 0$: for all *i* and *j*	3.69	3.22	-	1.05
	(0.003)	(0.008)		(0.387)

(Continued)

Panel C: Book to Market Quintiles				
HML	0.451	-1.362	-0.122	-0.187
	(0.051)	(0.060)	(0.054)	(0.182)
Growth	0.293	1.049	0.942	0.084
	(0.093)	(0.056)	(0.000)	(0.426)
BM_2	0.592	0.022	0.838	0.173
	(0.000)	(0.963)	(0.000)	(0.061)
BM_3	0.647	-0.449	0.745	0.201
	(0.000)	(0.352)	(0.000)	(0.033)
BM_4	0.701	-0.442	0.693	0.099
	(0.000)	(0.398)	(0.000)	(0.329)
Value	0.744	-0.313	0.819	-0.103
	(0.000)	(0.587)	(0.000)	(0.358)
$\Phi_j = \Phi_i$: for all *i* and *j*	1.02	1.51	-	3.33
	(0.400)	(0.201)		(0.011)
$\Phi_j = \Phi_i = 0$: for all *i* and *j*	4.18	1.24	-	2.98
	(0.001)	(0.290)		(0.013)

Estimates of equation (1) based on individual size and book to market portfolios presented in Panels B and C provide further evidence supporting our flight from risk hypothesis. We find positive estimates of $\phi_{0,j}$ for the big and growth portfolios. For example, with our four-month crisis window beginning one month prior to the onset of each crisis, our estimates of $\phi_{0,j}$ are 0.8 and 1.0 for the big and growth portfolios, respectively. This indicates a large positive return to these portfolios during emerging market crises. Small stocks may be riskier and high book to market stocks may be relatively distressed (cf. Fama and French (1993)). Therefore, these results indicate a flight from risk, towards safety during the initial onset of an emerging market crisis. Supporting the analysis in Table 4, we continue to observe a significant negative estimate of $\phi_{0,j}$ for the small portfolio with a four month crisis window, indicating that even after controlling for changing risk, we still find negative returns to the small stock portfolio. Positive estimates of $\phi_{1,j}$, for the middle book to market quintiles indicate an increased sensitivity, or risk, with respect to the world market during emerging market crises. Finally, based on book to market portfolios, we reject both hypotheses, $\phi_{1,j} = \phi_{1,i}$, for all *i* and *j* and $\phi_{1,j} = \phi_{1,i} = 0$, for all *i* and *j*. The rejections indicate that levels of risk within book to market portfolios experience a structural break during emerging market crises and that the structural break varies across portfolios.

Our focus is the impact of emerging market crises on US portfolios. With some degree of market segmentation there may be deviations from the international capital asset pricing model. For example, Bekaert et al (2005) find evidence that regional markets are priced, in addition to the world market. To specifically consider a model with potential segmentation, we specify

$$R_{j,t} = \alpha_j + \phi_{0,j} C_t + \beta_{dm,j} R_{dm,t} + (\beta_{em,j} + \phi_{1,j} C_t) R_{em,t} + \varepsilon_{j,t}, \qquad (2)$$

for *j*=1,2…*n* and *t*=1,2,…*T*. In this model $R_{em,t}$ and $R_{dm,t}$ represent excess returns to the emerging market and developed market index, respectively. Estimates of $\phi_{1,j}$ measure any changing sensitivity of asset *j* to the emerging market index during a crisis, allowing us to analyze changing levels of emerging market risk across US portfolios. We report parameter estimates in Table 6.

Table 6. The Segmented International Capital Asset Pricing Model with Structural Breaks

We report parameter estimates and p-values from the following model

$$R_{j,t} = \alpha_j + \phi_{0,j} C_t + \beta_{dm,j} R_{dm,t} + (\beta_{em,j} + \phi_{1,j} C_t) R_{em,t} + \varepsilon_{j,t},$$

where $R_{j,t}$ represents the excess return of asset j during time t and $R_{dm,t}$ and $R_{em,t}$ represent the excess return to the MSCI developed and emerging market indices. We consider seven emerging market crises and define crisis months, C_t, as the four month period beginning one month prior to, and ending two months after, the identified crisis month. We consider j=11 assets representing the US market portfolio, and US size and book to market quintiles separately. In Panel A we report market estimates. Panels B and C report parameter estimates for individual size and book to market portfolios, respectively. In Panels B and C, we present F statistics for the hypotheses that the given parameter is equal across all portfolios within the panel and that the parameter is jointly equal to zero across all portfolios within the panel.

	α_j	$\phi_{0,j}$	$\beta_{dm,j}$	$\beta_{em,j}$	$\phi_{1,j}$
Panel A: Market Estimates					
Mkt	0.402	0.383	0.875	0.032	0.046
	(0.005)	(0.362)	(0.000)	(0.224)	(0.316)
Panel B: Size Portfolios					
SMB	-0.108	-1.655	-0.182	0.218	-0.116
	(0.764)	(0.119)	(0.076)	(0.001)	(0.319)
Small	0.345	-0.933	0.716	0.208	-0.057
	(0.324)	(0.364)	(0.000)	(0.001)	(0.615)
S_2	0.327	-0.650	0.806	0.164	-0.000
	(0.257)	(0.444)	(0.000)	(0.002)	(0.998)
S_3	0.408	-0.487	0.818	0.124	0.044
	(0.086)	(0.485)	(0.000)	(0.004)	(0.561)
S_4	0.608	-0.689	0.884	0.064	0.031
	(0.003)	(0.244)	(0.000)	(0.083)	(0.637)
Big	0.453	0.722	0.899	-0.010	0.059
	(0.002)	(0.095)	(0.000)	(0.718)	(0.212)
$\Phi_j = \Phi_i$: for all i and j	1.91	2.70	-	-	0.59
	(0.110)	(0.031)			(0.572)
$\Phi_j = \Phi_i = 0$: for all i and j	3.57	2.46	-	-	0.65
	(0.004)	(0.034)			(0.662)

(Continued)

Panel C: Book to Market Portfolios					
HML	0.365	-1.323	-0.173	0.032	-0.081
	(0.162)	(0.085)	(0.020)	(0.500)	(0.335)
Growth	0.327	0.960	0.946	0.014	0.019
	(0.096)	(0.096)	(0.000)	(0.704)	(0.762)
BM_2	0.650	0.146	0.837	0.003	0.130
	(0.000)	(0.771)	(0.000)	(0.934)	(0.018)
BM_3	0.733	-0.251	0.750	-0.010	0.182
	(0.000)	(0.619)	(0.000)	(0.737)	(0.001)
BM_4	0.812	-0.518	0.723	-0.023	0.078
	(0.000)	(0.346)	(0.000)	(0.495)	(0.195)
Value	0.692	-0.363	0.773	0.045	-0.062
	(0.001)	(0.551)	(0.000)	(0.228)	(0.355)
$\Phi_j = \Phi_i$: for all *i* and *j*	1.11	1.14	-	-	6.90
	(0.354)	(0.337)			(0.000)
$\Phi_j = \Phi_i = 0$: for all *i* and *j*	4.08	0.95	-	-	5.97
	(0.002)	(0.448)			(0.000)

Consistent with the analysis in Table 5, we find no impact of emerging market crises on the US market portfolio. However, results based on size and book to market portfolios provide evidence of contagion as well as flight to quality. We again find positive estimates of $\phi_{0,j}$ for the big and growth portfolios, indicating positive abnormal returns after controlling for changing levels of risk. We observe an increased sensitivity to the emerging market index among the middle book to market portfolios, measured as positive $\phi_{1,j}$ estimates. The final row of each panel reports F-statistics for the hypothesis that the given parameter is jointly equal to zero across all portfolios. With a value of 5.97, we reject that all $\phi_{1,j}$ estimates are equal to zero for our book to market portfolios.[30] This provides evidence that the sensitivity of domestic book to market portfolios to the emerging market index changes during a crisis. Finally, the penultimate row of each panel reports F statistics corresponding to the hypothesis that the given parameter is equal across all portfolios. The reported value of 6.90 in Panel C strongly rejects this hypothesis across book to market portfolios. These results indicate that the response to emerging market crises varies across domestic portfolios. From the final two rows of Panel C, we can see that the sensitivity of US book to market portfolios to emerging markets changes during crises and that the change is not constant across portfolios.

Conclusion

We find evidence that, despite having no impact on the aggregate US market, emerging market crises negatively impact small and value stocks, while having a positive impact on large and growth stocks. Our results largely support our flight from risk hypothesis. During emerging market crises we observe negative abnormal performance within small stocks. This result holds even after controlling for changing levels of risk. Specifically, we find larger emerging market betas within small portfolios. Nonetheless, the emerging market conditional crisis alpha adjustment remains significantly negative for small portfolios. Alternatively, our emerging market crisis alpha estimates document positive abnormal performance within large and growth stocks during crises.

Further supporting our flight from risk hypothesis, we find that after controlling for positive world market performance, negative emerging market returns lead to poor small and value portfolio returns. Based on our correlation analysis, we find contagion from emerging market stocks to mid and high book to market portfolios during emerging market crises. We also find that mid book to market portfolios show an increase in the emerging market index beta during crises. Both of these results show that, excluding the growth portfolio, the relation between emerging markets and book to market portfolios increases during crises. In sum, our results strongly support the flight from risk hypothesis and document that emerging market crises do impact the US stock market, with a varying impact across portfolios.

Endnotes

[1] Further, Bayoumi et al (2007) find that developed market investors herding into emerging markets may be an important precondition for a crisis to occur.

[2] Kodres and Pritsker (2001) model contagion via investors optimally rebalancing their exposure to multiple risk factors and consequently transmitting shocks across markets. Schinasi and Smith (2000) describe contagion based on portfolio management and Fazio (2007) argues that flight from risk could be a potential mechanism by which shocks are transmitted across markets.

[3] We use size and book to market to proxy for both risk and liquidity. Fama and French (1993) argue that small and high book to market stocks may be riskier. Liu (2006) documents that these stocks are also relatively illiquid.

[4] From the hypothesis, investors respond to liquidity needs triggered by a financial crisis by selling the most liquid assets in order to minimize the price impacts. Consequently, we would observe volume decreasing with book to market value, but negative price impacts equal across all portfolios or confined to the more liquid portfolios.

[5] For example, Sriananthakumar and Silvapulle (2008) study the impact of the 1997 Asian crisis on six East Asian stock markets and Boschi (2005) focuses on the impact of the Argentine crisis on five other emerging markets. Yang and Bessler (2008) study contagion surrounding the October 1987 US market crash, while King and Wadhwani (1990) study volatility between New York, Tokyo and London. More recently, Bonfiglioli and Favero (2005) find abnormal fluctuations within the US market spill over to Germany, and Hon et al (2004) find evidence of global contagion between developed and emerging markets following September 11, 2001.

[6] Arestis et al (2005) is similar to our study in that they consider the impact of the East Asian crisis upon France and United Kingdom markets. We expand on this literature by focusing on stock portfolios within a single developed market in relation to seven emerging market crises.

[7] Forbes and Rigobon (2002) compare cross market correlations during crises to normal periods and define contagion as a significant increase in correlation during crises.

[8] Fazio (2007) differentiates between discriminating contagion and flight from risk. Discriminating contagion occurs if a shock in one market spreads to other markets that investors perceive as similar. This similarity may be based on fundamentals, regional similarities or other factors. In contrast, a flight from risk or pure contagion may occur if a shock is spread as investors move away from risky assets in general.

[9] In an early study, King and Wadhwani (1990) consider a model in which investors must disentangle global and idiosyncratic shocks from a market's total return, which can lead to rational contagion.

[10] For example, Kodres and Pritsker (2002) model contagion via portfolio rebalancing due to liquidity, risk factors, and wealth shocks. Broner et al (2006) describe contagion based on investors scaling back investments in areas that are overweighted, following a shock.

[11] Kyle and Xiong (2001) present a related model of contagion based on wealth effects. In their model, a shock in one market causes financial intermediaries to scale back risky positions in multiple markets.

[12] Campbell and Cochrane (1999) present a model consistent with counter cyclical variation in risk aversion. Baek et al (2005) argue that a crisis in one country may alter the market's risk appetite and lead to contagion.

[13] See for example, Forbes and Rigobon (2001), Boschi (2005), or Candelon et al (2005).

[14] Yang and Bessler (2008) point out that testing for contagion among regional emerging markets may be difficult as these markets likely share similar fundamentals and trade linkages.

[15] Fama and French (1993) argue that size and book to market may proxy for risk factors. In particular, high book to market stocks may be relatively distressed. Berk (1995) argues that small stocks will be riskier relative to large stocks. Liu (2006) finds a positive correlation between book to market and illiquidity and a negative correlation between size and illiquidity. Li et al (2007) also finds that smaller stocks are relatively illiquid.

[16] For example, Bekiros and Georgoutsos (2008) document that net private capital flows from developed to emerging markets increased from approximately 15 billion over 1983 to 1988 compared to over 105 billion between 1989 through 1995.

[17] Carrieri et al (2007) document that, although there are periods in which integration decreases, world market integration has increased over time.

[18] We also considered a narrower crisis definition that only included the seven specific crisis months to define the crisis periods for analysis. As expected, these months have more dramatic negative return shocks, as well as more sampling variability. These results are omitted for brevity. We also considered multiple crisis window specifications beginning *M* months prior to, and ending *N* months after the identified date. Results

tended to be consistent for reasonable *M* and *N* specifications and are also omitted for brevity.

[19] Identifying crises based on relative event dates is common in existing research (e.g., Sriananthakumar and Silvapull 2008, or Forbes and Rigobon 2001).

[20] Our crisis dummy variable is not in the information set during the sample period. However, under the null hypothesis we expect no effect related to the emerging market shock. Finding an effect based on the crisis dummy variable leads us to support the alternative hypothesis.

[21] To admit potential non-normalities in portfolio excess returns we also performed a test of differences in Wilcoxon scores. Our *SMB* portfolio results are qualitatively unchanged.

[22] Peltomaki (2007) performs a similar analysis to consider mean hedge fund performance across market return and volatility regimes. Specifically, he compares mean returns for a given hedge fund across positive and negative S&P 500 return regimes.

[23] Bekaert et al (2005) also discuss how world market conditions will impact US returns.

[24] Bekaert et al (2005) also discuss how world market conditions will impact US returns.

[25] The final two columns of Table 2 are included for completeness.

[26] Forbes and Rigobon (2002) correct for heteroskedasticity and largely find evidence of interdependence, not contagion, following the 1987 US market crash, the 1994 Mexican crisis and the Asian crisis of 1997. Tests for significant differences across correlations are sensitive to the number of observations. With a brief episode, it is unlikely that the null hypothesis will be rejected. Bradley and Taqqu (2005) introduce a measure of spatial contagion. Their approach estimates and compares correlations in the normal and loss-tail areas of the distribution. They define contagion as an increase in dependency when one

market is doing poorly. Andersson et al (2008) compare correlations of stock and bond returns across quartiles of macroeconomic performance. As an example, they estimate a positive correlation between stock and bond returns following months in which stock market volatility was in the lowest quartile. Following months in which stock market volatility was in the highest quartile, they estimate a negative correlation between stock and bond returns. They interpret this as evidence of flight to quality, as the relation between stock and bond returns breaks down during periods of increased uncertainty.

[27] The quartile based correlations temper concerns regarding unbalanced sample sizes. By construction, these correlations are based on equal sample sizes within each quartile column. Finding strong significance only when we observe left-tail emerging market behavior suggests a potentially different economic relationship between portfolios when emerging markets falter. This finding also led us to consider the alternative paper title, "Emerging market diversification: A water soluble umbrella."

[28] Forbes and Rigobon (2002) show that heteroskedasticity across samples can bias correlation estimates and provide a correction for the bias. We initially test equality of variances across the relevant samples. In the cases in which we reject equality, we present results based on the correction provided by Forbes and Rigobon.

[29] Our initial hypotheses considered potential contagion, increasing correlation, and flight to quality, decreasing correlation, effects of a crisis. Consequently, we present results from two-sided tests.

[30] Our empirical specification is similar to Maroney et al (2004) who employ a benchmark ICAPM and find structural breaks for the relevant Asian markets during the 1997 Asian financial crisis.

[31] In systems with potential contemporaneous residual correlation, the seemingly unrelated regression approach is often used to improve efficiency of estimation. However, in the case when all equations contain identical regressors, the seemingly unrelated regression estimates and standard errors are identical to the OLS counterparts. Therefore, we report results based on multivariate OLS regressions.

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