Market Fragility and International Market Crashes

by

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Abstract

We extend the Pukthuanthong and Roll (2009) measure of integration to provide an estimate of systemic risk within international equity markets. Our measure indicates an increasing likelihood of market crashes. The conditional probability of market crashes, especially across markets, increases substantially following increases of our risk measure. High levels of our risk measure indicate the probability of a global crash is greater than the probability of local crash. That is,

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conditional on high levels of systemic risk, the probability of a severe crash across multiple markets is larger than the probability of a crash within a smaller number of markets.

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1. Introduction

International systemic risk exposure varies across countries and through time. Consequently, periods in which aggregate systemic risk exposure is high across multiple countries will correspond to periods in which the risk of a negative shock propagating internationally, and of multiple markets jointly crashing, is the greatest. To develop a time-varying measure of systemic risk within international equity markets, we extend the integration analysis of Pukthuanthong and Roll (2009). Their focus is measuring time-varying integration, however, their setting provides a unique framework in which an underlying world market factor is identifiable, and average loadings across countries on this factor can vary through time. From this unique setting, we aggregate time-varying loadings on the world market factor across countries to create a measure of systemic risk through time. Intuitively, a negative shock to the underlying world factor is likely (unlikely) to lead to severe market declines across multiple countries if the shock occurs during a period in which average exposure to this factor is high (low). From this intuition, we name our risk measure the Fragility Index (henceforth, 'FI'), as periods in which our measure is high indicating periods in which international equity markets are much more susceptible to a negative shock to the world market factor. We find that increases in our measure of systemic risk lead periods in which the probabilities of market crashes, and of joint co-exceedances across markets, increase substantially. Further, conditional on high levels of risk, the probability of a global crash across multiple markets exceeds the probability of local crashes confined within a smaller number of markets. This finding is very consistent with the concept of our risk measure, and indicates that if a shock occurs during periods in which multiple countries share a high risk exposure to a common factor, then these multiple countries will experience simultaneous market declines.

This study relates to research that considers the international propagation of financial shocks. Given that financial shocks, as well as contagion, may have significant impacts on investor wealth, these topics have received significant attention within the literature. In general, studies of contagion test if a shock in one market spreads to other markets, with multiple studies providing mixed results. The mixed results within the existing literature suggest that certain crises propagate internationally, while others remain local. As examples, Forbes and Rigobon (2001) study several recent emerging market crises and find evidence of high levels of interdependence, but not contagion. On the other hand, Asgharian and Nossman (2011) provide evidence of risk spillovers from the U.S., to European countries. Interestingly, Longstaff (2010) finds evidence of contagion within the sub-prime asset backed derivatives market. Our study builds on the existing literature by identifying periods in which national stock markets exhibit a high degree of inter-relation, and consequently identifying periods in which a shock in one market may be more likely to spread internationally.

Existing research also considers the probability of poor returns across markets. For example, Christiansen and Ranaldo (2009) consider joint co-exceedances across EU member nations. Their results suggest that closer economic linkages following EU entry may increase the probability of co-exceedances. Our approach extends the existing research by specifying a flexible and parsimonious model for fragility, and also focusing on many international markets. Markwat, Kole and van Dijk (2009) investigate the probability of a crash in one market leading to crashes in other markets. They find support for a domino effect, in which local and regional crashes increase the probability of a subsequent global crash. Our approach, which focuses on exposure to the world factor, may indicate periods of high systemic risk prior to an initial crash in one market.[3] Kumar, Moorthy and Perraudin (2003) investigate the probability of emerging market currency crashes. They find that economic and financial data can predict an increasing likelihood of significant currency devaluation. Finally, Bartram, Brown and Hund (2007) study risk within the global banking system during international crises. We extend the existing literature by presenting a parsimonious risk measure, in which aggregate systemic risk is captured by loadings on the underlying world market factor, and this risk measure is based on the economic framework of Pukthuanthong and Roll (2009).

Kritzman et al (2011) also study market crashes by analyzing the predictive ability of their absorption ratio (AR). They find evidence that spikes in the AR precede large drawdowns. Specifically, they present a principal component analysis, largely focusing only on domestic industry portfolios, and argue that the proportion of return variance explained by principal components provides a measure of fragility. In their setting, when a number of industry principal components explains a large portion of return variance, they argue this represents risky periods. Our approach focuses on underlying factor loadings; a large portion of an asset's return may be explained by principal components, even if the asset has a small or negative exposure to the underlying economic factors (cf. Pukthuanthong and Roll (2009)). Relative to Kritzman et al (2011), by extending the Pukthuanthong and Roll (2009) framework, our paper provides stronger

[3] In fact, in our robustness analysis, we find that our FI contains significant predictive information regarding the occurrence of an initial, and not preceded, shock.

economic justification for our systemic risk measure. Further, Kritzman et al focus their results on five domestic markets and measures of systemic risk within each domestic market, and only briefly investigate international events by highlighting levels of their global AR (estimated across 42 countries) prior to four identified international events. Contrasting their focus, our study considers international risk dynamics across a lengthy sample with ex-ante identifiable risk states and a focus on joint co-exceedances across markets. For example, our results suggest that high levels of FI indicate an increasing likelihood of joint crashes across many countries, or market classification indexes, and that these global crashes are more likely than crashes confined within a small number of countries or indexes. These analyses have important implications for international investors and policy makers, and are not apparent from Kritzman et al (2011). Finally, we compare our results with a measure comparable to the absorption ratio in Section 4.3. Our analyses that include both FI and a measure of adjusted R-square comparable to the absorption ratio as explanatory variables, document a strong and significant relation between FI and market crashes, but fail to provide evidence of a relation between AR and subsequent crashes.

To analyze the relation of our FI with world markets, we estimate the conditional probability of joint market crashes. We find a strong and positive relation between the conditional probability of market crashes and our FI. As examples of our results, the probability of the return to our equal-weighted world index falling below its fifth percentile is 3.8% and 4.4%, conditional on FI falling below its 90^{th} and 98^{th} percentiles, respectively. However, these conditional probabilities increase to 15.8% and 32.4% when our FI exceeds the same thresholds in question, documenting that increase in FI leads significant increases in the likelihood of crashes. We also classify country market indexes into three cohorts that approximate levels of market development. Conditional on extreme high realizations of our FI, the probability of each of the three cohorts simultaneously exhibiting a return below their tenth percentile is 27%, while the corresponding probability is approximately equal to 4% when the FI is below the same threshold. In general, conditional on high levels of systemic risk, we find the probability of severe global market crashes (crashes across a majority of countries, or cohorts) increases dramatically, and is also significantly greater than the probability of minor or local market crashes (crashes across a small number of countries or cohorts). Continuing the above example, while the probability of a simultaneous crash within all three cohorts conditional on high levels of fragility is 27%, the conditional probabilities of just one or two cohorts crashing are 11%, and 9%, respectively. That is, conditional on high levels of systemic risk, a shock is more likely to propagate internationally, rather than be confined within a specific cohort or market. As further examples of our results, in a logistic regression setting, the odds of all three cohort indexes exhibiting a return that falls below their second percentile increases by three, and nine times, respectively, as our FI increases by one and two standard deviations. Overall, our results indicate that high levels of our FI precede dramatic increases in the conditional probability of severe international equity market declines

Our study makes several important contributions. First, we present an ex-ante measure that exhibits a strong and positive relation with the probability of extreme market crashes, and with the probability of crashes propagating across markets. This measure, and our results, have obvious implications for portfolio management, as well as for policy makers. Second, we extend the contagion literature by identifying an important factor that relates to the likelihood of a shock in one market propagating internationally. Third, we extend the systemic risk literature by presenting a generalizable measure. Existing research focuses on crises stemming from specific risks, while our index is flexible and able to capture any economic variable that increases loadings on the world market factor, which also allows inclusion of a large international sample of countries in our study.

2. Economic Framework

Our focus is creating a generalizable measure of average systemic risk across countries. To create this measure, we extend the integration analysis of Pukthuanthong and Roll (2009) who regress country returns on ten global factors. These factors are estimated by out-of-sample principle components based on the covariance matrix in the previous calendar year computed with the returns from 17 major countries, the "pre-1974 cohort" described in their paper. In their analysis, the R-square from the regression provides a measure of world market integration. Further, the first principal component explains the greatest proportion of return variance, and they argue convincingly that this principal component represents an underlying world market factor.[4] Consequently, loadings on the first principal component represent exposures to the

[4] Pukthuanthong and Roll (2009) examine the factor exposures; i.e., the patterns of the slope coefficients from regressions of individual countries on the ten factors. The first factor does indeed appear to be something like a world market index because the exposures on this factor are positive for 90% of all countries and calendar years. Only five countries have negative average loadings on factor #1 (Mauritius, Nigeria, Saudi Arabia, Ukraine, and the United Arab Emirates.) Splitting the globe into six regions, (Africa, Americas, Asia, Europe, Middle East, and Pacific), we find that all regions have positive average exposures to factor #1. Thus, the first principal component appears to be proxying for a world factor that applies to all but a handful of small (and poorly integrated) countries.

world market factor. As we explain, we extend their model to aggregate loadings on the world factor at a point in time as a measure of systemic risk. Arguably, periods in which exposure to the world factor across multiple markets is high, may precede crises or crashes, as a negative shock to the world factor would have relatively larger impacts across all of these country indexes, relative to periods in which average systematic risk exposure is low. In our setting, the occurrence of negative shocks to the world factor may be unpredictable, but the impact and spillover effect of a given shock will vary with levels of systemic risk. Specifically, we assume that given forward looking market participants, significant negative market shocks will be unexpected, and will be based on new information that is revealed to the market. In this context, shocks will occur randomly through time, but our approach will identify periods in which a shock of a given magnitude will have a greater impact, and greater likelihood of propagating across multiple countries.

We explain the economic framework of our risk measure, and differentiate our risk measure from measures of general levels of integration. Pukthuanthong and Roll describe a model in which 'Salt' and 'Water' are two underlying economic factors. In this setting, two countries could exhibit high integration if both share a high exposure to one factor, Salt, for example. Alternatively, two countries could also exhibit high integration if one exhibited a high exposure to Salt, and the other was exposed to Water, and even potentially negatively related to Salt. In the first example, systemic risk is high because both countries have a high exposure to a

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In contrast, they apply three separate pieces of evidence and find that higher-order factors are rather dispersed globally.

common risk factor (Salt), and a negative shock to this risk factor would be expected to propagate across both countries, leading to simultaneous market declines. In the second example, the negative shock to Salt would impact only the first country, and may benefit the second country in the case that the second country was negatively exposed to Salt.[5] From this example it is clear that the R-square measure of integration would not distinguish between the varying levels of systemic risk across the two cases. However, a focus on the country by country exposure to the underlying economic factors would distinguish between levels of systemic risk across the examples. Our study generalizes the above example by focusing on the most important underlying factor, the world market factor identified by Pukthuanthong and Roll (2009), and then creating a risk measure by aggregating exposure to this factor across many markets.

Our approach builds on existing research that considers systemic risk. For example, Kritzman et al (2011) effectively consider the R-square from a principal component analysis with a focus on domestic industries. Specifically, they consider the variance explained by industries and in some cases national indexes with respect to several principal components. However, in the context of Pukthuanthong and Roll (2009) R-square provides a measure of integration, and we argue that integration may be a necessary, although not a sufficient criteria to identify periods of high systemic risk. To explain, with low levels of integration in the world market, we would not expect shocks to propagate internationally as country markets would largely be insulated from world events. When integration is high, then the potential for shocks to

[5] Oil producing and oil consuming economies could provide an additional example of integration relative to factor exposures, in which integration may be high as shocks to the price of oil have significant impacts on both oil producing and oil consuming countries, but systemic risk is low as a shock to the price of oil has an opposite impact on the different economies.

spillover exists. However, in the case that integration is high, but countries exhibit varying exposure to underlying factors, we still would not expect a shock to an underlying factor to manifest across many markets. Arguably, only when integration is high, and when many countries exhibit a similar exposure to an underlying factor, would we then expect a shock to that underlying factor to impact many markets. Our approach, utilizing time-varying loadings is also similar to international asset-pricing studies of contagion (cf. Bekaert, Harvey and Ng (2005)).

As discussed above, our focus is a risk measure which aggregates country by country exposure to an underlying world market factor. To estimate factor loadings on the world market factor, we start with the Pukthuanthong and Roll (2009) measure of integration, in which country returns are regressed on ten principal components. Particularly, we specify

$$R_{j,t} = \sum_{i=1}^{10} \beta_{j,i} PC_{i,t} + e_{j,t}, \tag{1}$$

in which $R_{j,t}$ represents the US Dollar-denominated return for country or index *j* during day *t*, and $PC_{i,t}$ represents the *i*th principal component during day *t*. $PC_{i,t}$ is estimated based on Pukthuanthong and Roll (2009).

Conceptually, our risk measure is a direct extension of the Pukthuanthong and Roll (2009) framework; however, implementing the measure requires some degree of specification and parameterization. We now discuss how we specify our risk measure with respect to important parameters that define the FI, including estimation of factor loadings, factor loading aggregation, and definition of co-exceedances. Importantly, in Section 4.3, we show that results of our study, and the related inferences, are robust to multiple alternative specifications for each of the parameters discussed.

To aggregate the estimated factor loadings, we take the cross-sectional average of loadings on the world market factor across countries at each point in time; we argue that the average factor loading across countries provides the measure of systemic risk that is most intuitive and consistent with the economic framework of Pukthuanthong and Roll (2009). Initially, one may question our approach which aggregates systemic risk exposure across countries by estimating the average factor loading through time. Specifically, the international CAPM could be considered a special case of our international framework in which the underlying world market factor from Pukthuanthong and Roll (2009) was constrained to be equal to the aggregate world market portfolio. If this aggregate world market portfolio had been equally weighted, then, by construction, the average exposure on the factor (the EW index) would be exactly 1.0 in every period. Instead, if the index were value weighted, then the value-weighted exposure would be exactly 1.0. In either case, we could not use time-variation in average betas to measure systemic risk. The difference across the restrictive international CAPM approach and the flexible Pukthuanthong and Roll (2009) principal component analysis is that the market approach restricts the weights placed on the component indexes of the market portfolio to one specific value for each index, while the PC approach does not restrict the weights placed on component portfolios, and consequently can "select" a sub-set of component portfolios, or even place extra weight on some portfolios. The market approach would not allow time-variation in average beta. However, as the first PC is not restricted to equal the overall market portfolio, but rather a factor that drives the greatest proportion of world stock returns, average loadings on the first PC may then vary though time, given the less-restrictive weighting scheme. All in all, we argue that the framework of Pukthuanthong and Roll provides the flexible setting that is necessary to allow time-variation in average factor loadings as a means of measuring international systemic risk, which would not be possible in the more restrictive international CAPM setting. Therefore, we proceed by aggregating systemic risk exposure through average loadings. Importantly, in Section 4.3 we discuss results from alternative approaches to construction of our risk measure. Two of these alternative approaches are to aggregate factor loadings based on the 75th percentile (rather than the average), and to measure dispersion of factor loadings based on cross-sectional standard deviation. Both of these approaches contain significant predictive information and provide results that are similar to our original FI, but would be possible to construct even within the restrictive international CAPM, in which average factor loadings must equal one across all assets. Ultimately, we focus our study on FI constructed from average loadings as this seems most consistent with the concept of average cross-sectional systemic risk, but we highlight that inferences from our study would be robust to alternative specifications to aggregate factor loadings.

To estimate equation (1) and calculate average loadings, we use a 500 day rolling window for each country and place a decaying weighting scheme on previous daily observations such that the weight placed on daily observation t-x is equal to 0.995^{x-1}. This approach allows the impact of lagged days to decay through time, and places an approximate 50% weight on the observation halfway through the rolling window, relative to the weight placed on the most recent observation Countries are excluded from the analysis at a given point if we have less than 100 usable daily observations for the country within the specific rolling window. For a given day t, we calculate the average of the loading on the first principal component, $\beta_{j,1,t-1}$, which is estimated across days t-500 through day t-1, across all relevant countries, and define this variable as $\mu_{PC1,t}$, which we call the "Fragility Index." Consequently FI, is measured as the average coefficient on the first principal component based on Pukthuanthong and Roll's (2009) approach, and lagged one day, such that daily observations from day t-500 through day t-1 are used to calculate FI for day t.[6] Given our measure of fragility, we define a day as fragile or not, based on whether FI calculated through the previous day exceeds a given threshold percentile (80th, 90th, 95th, and 98th percentiles, for example).[7] For notation, we define fragility based on $\mu_{PC1,t} > Pk(\mu_{PC1})$ in which $Pk(\mu_{PC1,t})$ represents the kth percentile of μ_{PC1}. Later analyses consider results across market classification levels of development (developed, developing, emerging and frontier), and in these analyses, we define $\mu_{PC1,t}$ and $Pk(\mu_{PC1,t})$ for specific cohort indexes such that these variables measure average exposure to the world factor within a specific market classification.

Our focus is the conditional probability of a simultaneous crash across nations. Therefore, for any index j we identify a crash sub-sample as all days in which $R_{j,t} \leq Pk(R_j)$ for arbitrary return percentile threshold k. Within this setting $R_{j,t}$ represents the return to index j during day t and $Pk(R_j)$ represents a specified threshold percentile of full-sample returns for index j. Our

[6] While loadings on the additional principal components may contain predictive information regarding negative co-exceedances, the Pukthuanthong and Roll (2009) framework does not provide guidance as to how these additional factor loadings could be incorporated into a risk measure. Given this discussion, we focus our analysis on FI that is derived from loadings on the first principal component, as this captures common exposures to world market risk. Unreported analyses suggest that several of the remaining nine principal components contain some predictive information regarding co-exceedances. We leave the question of incorporating additional principal component loadings in a generalized risk measure to future research.

[7] The later analyses that implement logistic regressions do not require knowledge of full-sample percentiles.

'bad return' day is thus defined as the day that the index return falls below a given threshold percentile (fifth percentile, for example). This approach is consistent with Bae, Karolyi and Stulz (2005) who identify contagion based on returns falling below full-sample percentile thresholds. We then compare the probability of crashes across levels of fragility and examine the co-frequency of extreme fragility and large losses. We also focus on negative co-exceedances, defined as days in which multiple countries or cohorts each experience a return below the threshold in question.

A final consideration for the construction of our FI is trading day synchronicity. In the international context, non-synchronous trading in markets across time-zones creates a potential concern. By matching returns based on calendar days, we take a conservative approach to the non-synchronous trading issue. In our analysis, the potential impact of non-synchronous trading would bias our results against the predictive ability of FI. To illustrate, if a shock occurs during trading hours early in the day (before western hemisphere markets open), and this shock propagates internationally, then we would expect the shock to manifest in the western markets when they open, and therefore our methodology would capture this spillover. If a shock occurs later in the day (after eastern hemisphere market close) then we would expect the shock to manifest during the next trading day within those markets, and therefore if that shock propagated, our approach would not capture that as a spillover. However, potential lead/lag approaches attempting to capture these types of spillovers could also potentially lead to a spurious relation across FI and market crashes. Therefore, our approach and results present a conservative measure, and may understate the true predictive ability of FI. Our analyses of our equal-weighted all country index, as well as across cohort groups, which include countries across the globe and trade throughout the calendar day, further mitigate non-synchronous trading concerns, as a given shock may manifest within the markets open at the time of the shock and consequently be incorporated into the cohort return for the given calendar day. Finally, with respect to non-synchronous trading, our filter for usable daily returns described below ensures that we consider only valid return observations.

3. Data

We study the joint occurrence of severe market declines across countries; therefore, we consider a broad selection of national equity market indexes. Daily data are extracted for 82 countries from DataStream, a division of Thomson Financial. The data consist of broad country indexes converted into a common currency (the US dollar). Appendix 1 lists the countries, identifies the indexes, reports the time span of daily data availability, and provides the DataStream mnemonic indicator (which could help in any replication.) If the mnemonic contains the symbol "RI", the index includes reinvested dividends; otherwise, the index represents an average daily price. Similar to Pukthuanthong and Roll (2009) we assign countries to three specific cohorts based on each country's initial appearance in the database. We define countries appearing prior to 1984 as Cohort 1, countries appearing between 1984 and 1993 as Cohort 2, and the remaining countries as Cohort 3.[8] This classification assigns countries into cohorts approximating levels of market development with Cohort 1, Cohort 2 and Cohort 3 representing developed, developing, and emerging/frontier markets, respectively. (cf. Pukthuanthong and Roll

[8] Our cohort classification is similar in approach as Pukthuanthong and Roll (2009), but combines Cohorts 1 and 2 from their study into our Cohort 1. Consequently, our study considers three cohorts, while their paper uses four.

(2009), Berger et al (2011)). Throughout the study we aggregate country index returns into an all country index and into cohort specific indexes, and compute equal-weighted returns. Conceptually, FI identifies periods in which average loadings on the world factor are high across all countries, or all countries within a specific cohort. Therefore, the focus on equal-weighted returns provides a cleaner measure of crashes, as equal-weighted indexes are more likely to detect crashes that occur across multiple countries. A focus on value-weighted indexes would lead to results that are driven by the largest markets within the sample. For example, considering the all country index, a value-weighted approach would be driven by the largest developed markets and would virtually ignore returns to the emerging/frontier markets.

The primary focus of our study is joint co-exceedances across countries and across cohort groups in particular. By definition, data for Cohort 3 countries are not available prior to 1994. Given data availability and our requirements for FI estimation, December 29, 1994 is the first available date for which we can estimate FI for Cohort 3. The latest available date, when all the data were downloaded, is November 30, 2010.[9] Throughout the study we present results based on daily returns to country indexes and cohort groups within the December 29, 1994 to November 30, 2010 sample period. Although results are based on the sample above, calculation of FI for the initial part of this sample utilizes observations that are prior to the start of the return analysis. Daily returns are calculated as log index relatives from valid index observations. An index observation is not used if it exactly matches the previous reported day's index. When an index is not available for a given trading day, DataStream inserts the previous day's value. This

[9] Zimbabwe is unique in our sample, in that it closed its stock market following October 2006. We include Zimbabwe in our analysis for the period in which we have data.

happens whenever a trading day is a holiday in a country and also, particularly for smaller countries, when the market is closed or the data are simply not available. Our daily returns are thus filtered to eliminate such invalid observations. This approach is consistent with Pukthuanthong and Roll (2009) and further mitigates concerns regarding non-synchronous trading.

We present a general picture of the relation between FI and returns of countries in different cohorts in Table 1. The mean, median, and standard deviation of equal-weighted stock returns of countries in all cohorts, Cohorts 1, 2, and 3 are shown across the full-sample, as well as across deciles of fragility. FI is measured for each cohort, such that the tenth decile of FI for Cohort 3 identifies the periods in which average factor loadings are highest across the Cohort 3 countries, for example. As FI increases from the first to the tenth decile, mean returns tend to decline. A plunge in returns is most drastic in Cohort 3 where the mean returns appear negative starting from the seventh decile to the tenth decile of FI. Finally, the analysis suggests an increase in standard deviation of returns as fragility increases. For example, the standard deviation of the all country index conditional on fragility above the 80^{th} or 90^{th} percentiles is over twice the standard deviation conditional on fragility falling in the first, second, or third deciles. This provides support for the concept of our FI. As risk exposure becomes concentrated on the underlying world factor, the diversification benefits of an equal-weighted portfolio will likely diminish, as returns to the portfolio largely reflect the common factor. Although not detailed in the Table, when measured across all countries, the time-series median of FI is $1.373 * 10^{-3}$ with a standard deviation of $8.167 * 10^{-2}$. FI thresholds based on the 80^{th}, 90^{th}, 95th, and 98th percentiles are $1.697 * 10^{-3}$, $3.456 * 10^{-3}$, $3.723 * 10^{-3}$, and $3.865 * 10^{-3}$, respectively.

Insert Table 1 about here

4. Fragility Index and Probabilities of Market Crashes.

4.1 Empirical crash probability conditional on FI

We analyze the conditional probability of market crashes across levels of FI. In the initial analysis, we consider equal-weighted returns to the world index, which is comprised of all countries within our sample. Considering the all country index, fragility may manifest because this index likely becomes more volatile and prone to extreme realizations as all component countries share similar risk-exposure, and consequently diversification benefits are dampened as FI increases. We consider various thresholds of FI and definitions of market crashes. Relatively low thresholds for FI provide a safety-first measure, which is likely to detect both major and minor events, while higher FI thresholds detect periods of extreme systemic risk. Similarly, various crash definitions consider the tradeoff between higher probability and lower impact events, with lower probability and higher impact events. In Table 2 we report the expected number of crashes under the assumption that crashes are independent from FI, $Ex(X \mid \mu_{PC1,t} > Pi\%(\mu_{PC1}))$, the actual number of occurrences, $f(X \mid \mu_{PC1,t} > Pi\%(\mu_{PC1}))$, and the empirical probability of a crash, $f/n(X \mid \mu_{PC1,t} > Pi\%(\mu_{PC1}))$, conditional on FI exceeding the *i*th percentile. We also report the same statistics conditional on FI falling below the given thresholds. Low levels of FI may indicate periods of decreasing risk. Finally, we report Z-scores testing that the probability of a crash is constant across levels of FI, $H_0: d = 0$.

Insert Table 2 about here

The results in Table 2 document a strong relation between FI and market crashes. Across all specifications there is a strong and significant relation between high values of FI and occurrences of market crashes. Reported Z-scores and associated p-values testing the equality of the probability of a market crash across FI risk states are significant in all cases considered. For example, as fragility increases from below the 80th percentile of FI to above this threshold, the empirical probability of crashes increases from 16.6% to 33.4% (representing a 201% increase), 7.1% to 21.5% (287%), 3% to 13% (433%) and 0.9% to 6.3% (700%) for crashes defined as returns below the 20th, tenth, fifth, and second percentiles, respectively. Our approach also documents that for all high (low) risk states the frequency of market crashes is higher (less) than the expected number of market crashes.[10] Highlighting the 95th percentile of FI as a measure of extreme periods of systemic risk, we observe 147 days in which the return falls below the fifth percentile and the preceding value of FI fell below the 95th percentile. This corresponds to an empirical frequency of 4.1%, and is slightly below the 177.7 observations we would expect if FI and crashes were independent. On the other hand, conditional on FI exceeding the 95th

[10] Even with the assumption that crashes are independent from FI, the expected number of crashes will still vary with the threshold of FI specified. For example, we have 3,744 daily observations, and by definition 74 daily returns will fall below the second percentile (3,744 * 0.02 = 74). If FI was independent from subsequent daily returns we would expect to have 7.4 (= 3,744 * 0.02 * 0.10) and 3.7 (= 3,744 * 0.02 * 0.05) observations in which the return during day *t* fell below the second percentile and FI calculated through day *t*-1 exceeded the 90th and 95th percentiles, respectively, simply due to chance. Showing that we actually have 27 and 18 of these observations, respectively, suggests a strong relation between FI and subsequent crashes.

percentile, we would only expect 9.3 days in which the subsequent return fell below the fifth percentile, but instead we observe 40 such occurrences, corresponding to an empirical frequency of 21.4%. Put alternatively, an event with odds of one in 20 unconditionally, becomes a one in 25 event conditional on low FI, but conditional on high FI, becomes a greater than one in five event.

To analyze the predictive content of FI across countries, as well as to consider the occurrences of co-exceedances, we conduct a similar analysis as above, but based on our cohort indexes described earlier. Conditional on FI falling above or below our thresholds, we present the empirical probabilities of the number of cohort index returns that fall below the return thresholds. The potential number of cohort index returns falling below our return thresholds ranges from zero, for a day in which no cohort group crashes, to three, representing a day in which all three cohorts jointly crash. In this analysis, return thresholds are defined separately for each cohort, such that only returns to Cohort *i* are used to calculate the return thresholds for that cohort. Table 3 presents the frequency and probability of market crashes for different thresholds of FI and bad returns. We maintain notation from Table 2 in which $Ex(X)$, $f(X)$, and $f/n(X)$, represent the expected number of occurrences, the empirical frequency, and the empirical probability, respectively, of a given number of cohorts crashing, *X*. We also report Chi-Squared statistics for each event, χ^2. Specifically, Chi-square tests may be conducted across all occurrences to test the null hypothesis that FI and crashes are independent. The entries for each outcome in the χ^2cell report that occurrence's contribution to the overall Chi-square statistic. We also report p-values from the Chi-square statistics in isolation. That is, the reported p-value represents the p-value based entirely on that event's contribution to the Chi-square statistic. Finally, given our focus on crashes and high levels of FI, we only report the expected number of crashes, and the Chi-square statistics for the high risk states.

*** Insert Table 3 about here ***

Consistent with the results in Table 2, the results in Table 3 show that the percentage of market crashes increases with high levels of FI. Further, high levels of FI precede increases in the probabilities of multiple cohorts jointly crashing, and frequently, conditional on high levels of FI, the probability of all three cohorts jointly crashing exceeds the probability of one or two cohorts crashing. For example, conditional on FI falling below the 95th percentile, the probability of one, two and three cohorts jointly exhibiting returns below their tenth percentile are 10%, 4% and 3%, respectively. The corresponding probabilities conditional on FI exceeding the 95th percentile are 11%, 7% and 19%.Comparing probabilities of crashes across levels of FI indicates that conditional on high levels of FI the probabilities of two or three cohorts jointly crashing increase substantially. Further, conditional on low levels of FI, the probability of just one cohort crashing (10%) exceeds the probability of two or three cohorts crashing combined (4% + 3%). However, conditional on high levels of FI, the probability of all three cohorts jointly crashing (19%) is greater than the probability of just one or two cohorts crashing (11% + 7%).[11,12]

[11] The FI calculation is purely ex-ante. However, our approach to identifying fragile periods in this section requires knowledge of the full-sample FI variable. In unreported results, we calculate a moving-average and standard deviation of long run FI, and compare this to a short run moving average of FI. When the short run average FI is greater than one standard deviation above the long run moving average, we continue to find predictive information contained within our risk measure. In short, our FI is robust to a ex-ante classification of risk.

[12] We conduct a similar analyses as above based on the proportion of country indexes that jointly crash, and continue to find similar results. For example, during our sample there are 22 days in which more than 50% of Cohort 3 countries experience a return below their fifth percentile. Of these 22 days, 20 follow days in which FI exceeds the

4.2 Logistic regression models

Taken together, the results thus far show that high levels of FI lead increasing probabilities of market crashes. Next, applying logistic regression models, we create several dependent variables based on the occurrences of various market crashes. These dependent variables are regressed on levels of FI. This approach allows us to use FI without pre-specifying threshold percentiles of fragility. Existing research utilizes logistic models to estimate the likelihood of market crashes (cf., Markwat, Kole and van Dijk (2009); Christiansen and Ranaldo (2009)). In our initial logistic analysis, we define the dependent variable for various return thresholds and consider separate analyses across our equal-weighted world index, $Cohort_{all}$, which consists of all countries in our sample, as well as across our cohort specific indexes, in which $Cohort_i$ represents the equal-weighted return to all countries within Cohort i. In this analysis, the dependent variable takes the value of one for any day in which the return to the given index falls below the threshold in question, and takes the value of zero otherwise. In this setting, a positive coefficient on FI is indicative of a positive relation between fragility and the probability of a market crash. Table 4 reports coefficient estimates on FI, as well as odds ratios which indicate the increase in the odds of a market crash for a one and two standard deviation increase in FI. Importantly, FI and return percentiles are calculated separately for each cohort group. Therefore, logistic regression results for the all country world index (arbitrary Cohort i) are based on a dependent variable that is equal to one on a day in which the equal-weighted

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80^{th} percentile, and only 2 follow days in which FI is below this cutoff. Therefore, conditional on fragility falling above (below) the 80^{th} percentile, the probability of this level of severe joint crash across countries is 2.74% (0.07%). This equates to a difference of approximately 40 times in magnitude.

return to all countries within our sample (countries within Cohort *i*) falls below its specified threshold, and the independent variable represents the average of the loading on the first principal component for all countries (countries in Cohort *i*).

Insert Table 4 about here

The analysis in Table 4 presents how the risk state parameter impacts the probability of market crashes. The coefficients on the risk state parameter are all positive and highly significant in every case considered. For example, considering $Cohort_3$ and returns below the fifth percentile, the coefficient estimate of 8.7 and associated odds ratios of 2.0 and 4.2 indicate that the odds of Cohort 3 crashing double, and more than quadruple, as FI increases by one and two standard deviations, respectively. Although estimates are significant in every specification, the results suggest that the most dramatic relation between FI and market crashes exists for extreme crash definitions and emerging markets. That is, the increase in crashes conditional on an increase in FI is most dramatic for Cohort 3 and for returns lower than the second percentile.

The previous analysis shows the relation between FI and market crashes within our equal-weighted world index, or within specific cohort indexes. Next, we examine how FI impacts the probability of simultaneous market crashes across cohort indexes. Table 5 presents results from logistic regressions with a dependent variable equal to one for any day in which the number of market crashes across cohorts equals or exceeds the specified value, as well as results from expanded multinomial and ordered logistic specifications. For example, results in Panel B present logistic results based on a dependent variable, $Y_t = I_{\sum X_i \geq 2}$, that takes the value of one for every day in which two or more (out of three) cohort indexes exhibit returns below the thresholds specified in the column headings. For notation, $I_{\sum X_i \geq n}$, is an indicator variable taking the value of one for any day in which the number of cohort indexes jointly crashing is equal to or greater than the value of n that is specified. Panels A and C present similar analyses with n set equal to one and three, respectively, while Panel D presents an ordered logit model in which the dependent variable is set equal to the number of cohort indexes experiencing a return below the specified threshold on a given day, and Panel E presents a similar analysis in a generalized logistic setting. Column headings of Table 5 identify the considered return thresholds. In general, this analysis reveals the relation between FI and simultaneous crashes across cohort indexes.

Insert Table 5 about here

Logistic regressions in Table 5 indicate a strong relation between FI and the likelihood of international crashes across multiple markets. Coefficient estimates are again all highly significant. The impact of FI is greatest when all three cohorts jointly crash. For example, defining crashes based on returns falling below the fifth percentile, coefficient estimates on FI monotonically increase from 6.6 to 10.3 as the dependent variable takes the value of one on a day in which at least one cohort crashes (Panel A), to Panel C in which the dependent variable takes the value of one on a day in which all three cohorts crash. Therefore, the impact of FI on the likelihood of market crashes is highest when crashes are defined as days in which all three cohorts fall together. Ordinal logistic regression results in Panel D further detail the strong relation between FI and multiple cohorts jointly crashing. Finally, Panel E presents generalized logistic regressions which compare the probability of i cohort indexes crashing, each relative to the state of the world in which no cohorts crash. For this analysis, we introduce the subscript ‘si’

in which i represents the sum of the cohorts that crash on a specific day. As an example, $Coef_{\mu_{PC1,s3}}$ represents the coefficient related to the chance of three cohorts jointly crashing, relative to the chance of no cohorts crashing. The results indicate that high levels of FI dramatically increase the chance of all three cohorts crashing, and either marginally increase, or in some cases even decreases, the chance of just one cohort crashing. For example, defining crashes as returns falling below the 20^{th} percentile, the coefficient of 7.441 for s3 indicates the likelihood of all three cohorts jointly crashing *increases* dramatically with FI, while the estimate of -1.846 for s1 indicates that high FI actually *decreases* the chance that just one cohort will crash. In other words, when fragility is high, either no markets crash, or if a shock occurs, then it propagates across a majority of markets. Specifications in which the threshold for returns is lower do indicate that high levels of FI indicate an increasing risk of just one cohort crashing. For example, a one standard deviation increase in FI leads to a 1.783 times increase in the odds of one cohort exhibiting returns below the second percentile, while also leading to a 3.105 times increase in the odds of all three cohorts crashing. In the final three rows of Panel E, we present statistical tests, $\emptyset_i = \emptyset_j$, comparing coefficient estimates across levels of market crashes, testing that the impact of FI on i number of markets crashing is equal to the impact of FI on j number of markets crashing. For example, defining crashes based on the second percentile of returns, the statistic of 9.569 indicates that an increase in FI has a larger impact on the probability of all three cohorts jointly crashing, compared to its impact on the probability of just one cohort crashing. These tests indicate that in all cases the increased probability of all three cohorts crashing together is greater than the increased probability of one or two cohorts crashing. This analysis supports the earlier results in that high levels of FI increase the probability of severe crashes.[13]

4.3 Alternative specifications

In general, the results presented in Sections 4.1 and 4.2 detail a strong relation between FI and subsequent market crashes. However, it is well-known that volatility is persistent, and volatility may also influence the principal component coefficient estimates used to construct FI. Therefore it is crucial that we compare FI to standard volatility estimates to ensure that FI contains predictive information beyond the information that is contained within measures of conditional volatility. For this comparison we create three measures of conditional volatility. First, we estimate a GARCH model of conditional volatility for our all country index return, and we use these estimates to calculate a forecasted value of volatility for day *t*. Second, using the same rolling window and weighting scheme as the FI calculation, we calculate the cross-sectional average of country index return standard deviations across all countries through day *t*-1, as well as the rolling window standard deviation of the all country index return through day *t*-1. As a final comparison, we also consider the predictive ability of FI relative to levels of international integration. Specifically, Pukthuanthong and Roll (2009) show that the R-square from their principal component regressions provides a measure of integration. We take the cross-

[13] In unreported analyses, we conduct similar logistic regressions across country indexes, rather than aggregate cohort indexes. The results are consistent with the two central previous findings. First, increases in FI lead increasing probabilities of market crashes. For example, defining crashes as returns below the tenth percentile, a one standard deviation increase in FI leads to a 3.98 times increase in the chance that over 75% of all countries will simultaneously crash. Second, we continue to find that conditional on high FI, global crashes are more likely than smaller crashes. Continuing the above example, a one standard deviation increase in FI only leads to an increase of 1.60 times in the odds that between 25% and 50% of all countries will simultaneously crash, and an increase of 2.16 times in the odds that between 50% and 75% of all countries simultaneously crashing.

sectional average of the adjusted R-square from each principal component regression used to calculate FI, and contrast this measure with the FI. As discussed earlier, Kritzman et al (2011) use a similar variable as their Absorption Ratio. To conduct the comparison of FI relative to these alternative measures, we conduct logistic regressions using the dependent variables defined in Table 5 with the fifth percentile of returns as the crash threshold. We then regress these dependent variables on FI and the alternative independent variables described above.[14] We present coefficient estimates and odds ratios in Table 6, with each panel containing an alternative control variable.

*** Insert Table 6 about here***

Results in Table 6 reveal a strong relation between FI and subsequent market crashes even after controlling for conditional volatility. That is, FI contains significant predictive information beyond conditional volatility. With only one exception in which the coefficient estimate on FI is significant at the five percent level (Row Two, Panel C), all remaining coefficient estimates on FI are significant at the one percent level. For example, the estimate of 5.9 and associated odds ratio of 1.6 in Panel A indicates that, after controlling for forecasted volatility from the GARCH specification, a one standard deviation increase in FI leads a 1.6 times increase in the odds that one or more cohort indexes will exhibit a subsequent return below the fifth percentile. For comparison, a one standard deviation increase in the GARCH forecast

[14] FI exhibits relatively large correlations with the measures of volatility as well as the time-series of average adjusted R-square, indicating that multi-collinearity may be a potential concern. However, the VIFs between FI and the alternative variables are 1.1, 1.5, 2.9 and 4.1 for the GARCH volatility forecast, the rolling-window cross-sectional average standard deviation, the rolling-window all country index standard deviation, and the cross-sectional average adjusted R-square, respectively. These values all fall well below the acceptable benchmark of 10, indicating multi-collinearity is not a concern.

leads to a 1.2 times increase in the odds of one or more cohorts crashing. Interestingly, the comparison of FI relative to the volatility measures is most dramatic with the dependent variable that takes the value of one only on days in which all three cohorts jointly crash. In Panel A, the odds ratio of 2.2 indicates a one standard deviation increase in FI more than doubles the odds that all three cohorts will jointly crash, while a one standard deviation increase in conditional volatility only increases the odds by 1.3 times. Further, in Panels B and C the odds ratios from FI remain approximately equal to 2.0, while the corresponding coefficient estimates for the alternative volatility measures are insignificant. This is very consistent with our concept of FI as high volatility may precede market crashes, but FI reveals periods in which risk is concentrated and if a shock occurs it would be expected to propagate across all markets. Finally, in all specifications considered with both FI and the adjusted R-square measure, the R-square coefficients are insignificant and small in magnitude, while the FI coefficients remain positive and highly significant.

Overall, we have shown a strong predictive relation between FI and subsequent market crashes, or international negative co-exceedances. However, several potential concerns regarding the implementation of our measure exist. These concerns include, FI construction, the unique sample period, whether FI only captures crashes following an initial shock, and others. In this section we show that the central results of our study are very robust to multiple alternative specifications that address the above concerns. The main result of the study is that high levels of FI indicate an increasing likelihood of market crashes, and of joint negative co-exceedances. The results of Panel D of Table 5 with negative co-exceedances defined based on the fifth percentile of returns provides a good example of these main results. Therefore, we focus our robustness analysis on this specification. We note that in unreported analyses, we find that the results throughout the paper are also robust to the alternative specifications considered. As a baseline specification and as presented in Panel D of Table 5, we define a dependent variable that is equal to the number of cohort returns that fall below their fifth percentile of returns for each day. This variable takes a value of zero, indicating a day in which no market crashes, to three, indicating a day in which all three cohort groups jointly crash. In Table 7 we present logistic regression results with this baseline specification as an initial case. We then alter one aspect of the approach from the baseline, and report results from this specification. Each row in Table 7 describes how the approach differs from the baseline specification, and presents the coefficient estimate, and associated p-value, for the independent variable, as well as the odds ratios, which indicate the increase in likelihood of one additional cohort group crashing, conditional on the independent variable increasing by one and two standard deviations.

Insert Table 7 about here

Results in Table 7 indicate that the earlier results are robust to all alternative specifications considered. We initially consider results relating to calendar periods and rolling window estimation. First, our specific sample period may be of concern for two reasons. The global financial crisis beginning in 2008 could be one unique instance that is driving our results. Alternatively, data for our third cohort group are added to the sample as the data are available, therefore data are relatively thin for Cohort 3 early in our sample period. However, the coefficient estimates of 15.3 and 7.6 for a subsample that ends 12/31/2007 and a subsample that begins 12/01/2000, respectively, alleviate these concerns, and show that relation between FI and subsequent crashes is robust to alternative samples. The significant coefficient estimates of 6.3, 3.8 and 4.0 indicate that FI is robust to a shorter 60 day rolling window calculation which measures FI as a short-run, rather than long run measure, robust to comparing short run relative to long run FI which captures increases in short run relative to long run risk, and to creating FI such that the composition of the principal components, which is updated annually, is constant for each rolling window used to estimate FI, respectively.[15]

The robustness results in Table 7 also address concerns relating to aggregation of factor loadings. Throughout the study, we have aggregated factor loadings based on the cross-sectional average. However, as discussed earlier, this approach would not be feasible in the more restrictive international CAPM setting. As one alternative, we define FI as the cross-sectional 75th percentile of loadings on the world factor at each point in time. This alternative identifies periods in which 25% of the countries within our sample exhibit high loadings on the world factor, and provides an approach that would be feasible within the restrictive international CAPM. The coefficient estimate of 4.1 indicates that high levels of this FI measure precede market crashes. Interestingly, we also find a positive coefficient estimate on dispersion of factor loadings, measured by cross-sectional standard deviation, which is equal to 6.4. Overall, the combined results based on the 75th percentile of loadings, and the standard deviation of loadings suggest that periods in which a number of countries exhibit extreme loadings on the underlying

[15] In the 60 day rolling window specification we maintain our decaying weighting structure such that the observation halfway through the rolling window is weighted approximately 50%.

world factor, in addition to periods in which countries exhibit high average loadings, also reveal periods of high risk.[16]

Results in Table 7 also address concerns relating to persistent volatility and specification of negative co-exceedances. The coefficient estimate of 13.2 from the specification in which crashes are defined based on absolute returns falling below negative five percent indicates that FI is robust to specifying crash thresholds ex-ante, rather than requiring knowledge of full sample returns. A final concern is that FI does not capture any initial market shock. Rather, an initial unpredicted shock leads to an increase in volatility as well as an increase in FI. Table 7 presents results conditional on no cohort return falling below its fifth percentile in the previous ten, 20 and 50 trading days. In this way, we measure the relation between FI and co-exceedances that are not preceded by an initial crash. The coefficient estimates conditional on no preceding crash within the previous ten and 20 trading days of 5.9 and 6.8, respectively, are highly significant and similar to the full-sample benchmark of 6.8. Unconditionally, we would expect a cohort return to fall below the fifth percentile in one of every 20 trading days. Therefore, conditioning our results on no cohort experiencing a return below its fifth percentile in the preceding 50 trading days reduces the sample to only 821 trading days, but the coefficient estimate of 11.0, which is significant at the five percent level, indicates the predictive ability of FI does not require an initial shock.

[16] In unreported results we regress the dependent variable on the average of factor loadings, the standard deviation of factor loadings and an interaction term. The interaction term enters with a negative loading, indicating that when average exposure is already high, then high dispersion actually reduces the likelihood of a crash.

5. Conclusions and Discussion

In this paper we argue that the probability of financial interdependence is highest during periods in which many countries share a high exposure to the world market factor. Specifically, we extend the Pukthuanthong and Roll (2009) integration analysis to develop the FI. This risk measure is defined as the average loading on the world factor across countries at a point in time.

We examine daily data for broad equity indexes from 82 countries and adopt several tests. Our FI identifies periods of systematic risk. When a country has a high loading on the first principal component from Pukthuanthong and Roll (2009), it is heavily exposed to the world factor and thus may not offer diversification. As the world becomes volatile or is subject to negative shocks, countries with high exposure to this factor will experience a drawdown. Our FI is a strong predictor of market crashes. The results are robust across countries in different cohorts where cohorts approximate levels of market development. When the FI is low, the probability of joint crashes between cohorts decreases with their severity. In other words, conditional on low systemic risk, crashes within one or two cohorts occur more frequently than crashes across all cohorts. In contrast, when the FI is high, the probability of a crash in all three cohorts increases, and the probability of all cohorts crashing exceeds the probability of only one or two cohorts crashing. We also apply logistic regression models which allow consideration of the relation between the FI and market crashes without specification of thresholds for FI. The probability of market crashes increases substantially as fragility increases especially for emerging and frontier markets and during the extreme crash definition.

Our study lays down a fundamental for future studies. Policy makers should adopt our FI to predict the period during which the economy is most fragile and highly exposed to systematic risk. Future study can also investigate the interaction of PC estimation and beta and explore whether FI captures recent volatility. Other researchers can explore why our fragility index is an example of systematic risks. Can it be explained by frictions as other papers on crisis have argued? Greenwood and Thesmar (forthcoming) study institutional ownership and “fragility” of individual stocks while Jotikasthira, Lundblad, and Ramadorai (2010) define “capital at-risk” and relate it to fire sales. There should be more studies showing the underlying asset pricing model and explanations behind the results of our study.

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Table 1. Average Returns Across Risk States

The table presents summary statistics of equal-weighted returns, in percentage form, to the All Country index, as well as to the Cohort 1, 2, and 3 indexes. Cohorts 1, 2, and 3 are stock indexes of countries that appear in DataStream prior to 1984, 1994, and after 1994, respectively. Panel A presents statistics based on full-sample returns, while Panel B presents returns across levels of fragility. Fragility is based on the coefficient, $\beta_{j,i,t}$, on the first principal component according to Pukthuanthong and Roll (2009), in which country stock returns are regressed on 10 principal components using daily observations from day *t*-500 through day *t*-1. We restrict the analysis to countries with at least 100 usable observations during any particular period, and use weighted least squares in which the weight placed on daily observation *t*-x is equal to 0.995^{x-1}. Panel B present results across deciles of fragility formed from the mean of loadings on the first principal component across countries at a given point in time. In Panel B, average loadings, and subsequent deciles of fragility are specific to countries included within each cohort.

	$Cohort_{all}$			$Cohort_1$			$Cohort_2$			$Cohort_3$		
	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std	Mean	Median	Std
Panel A: Full-sample summary statistics												
	0.0254	0.0719	0.8046	0.0234	0.0875	1.1217	0.0210	0.0702	0.7731	0.0344	0.0569	1.1814
Panel B: Statistics across mean of $\beta_{j,i,t}$												
1^{st} decile	0.1075	0.1515	0.5164	0.0532	0.1343	0.9910	0.1208	0.1224	0.4605	0.0617	0.0591	0.5212
2^{nd}decile	0.0235	0.0538	0.5153	0.0520	0.0875	0.5651	0.0191	0.0060	0.3860	0.0978	0.0896	0.4669
3^{rd} decile	0.1052	0.1040	0.3931	0.0304	0.0686	0.6249	0.0286	0.0795	0.5357	0.2122	0.0689	2.2370
4^{th} decile	0.0991	0.0737	0.7785	0.0436	0.1199	0.7184	0.0625	0.0801	0.5019	0.0777	0.0703	0.4693
fifth decile	-0.0107	0.0404	0.4755	-0.0562	0.0235	0.9391	-0.0215	0.0012	0.6566	0.0669	0.0566	0.4900
6^{th} decile	-0.0006	0.0329	0.6113	-0.0209	-0.0134	0.9605	-0.0180	0.0288	0.6902	0.0749	0.0684	0.6476
7^{th} decile	0.0224	0.0725	0.6760	0.1093	0.1818	0.8595	0.0485	0.1441	0.8113	-0.0362	0.0541	0.6742
8^{th} decile	-0.0276	0.0578	0.9863	0.0752	0.1564	0.8160	0.0447	0.1314	0.8280	-0.1280	-0.0300	2.2038
9^{th} decile	-0.1170	0.0224	1.0872	-0.1291	-0.0442	1.7080	-0.0992	-0.0042	0.9887	-0.0697	0.0189	0.9673
tenth decile	0.0524	0.1538	1.3939	0.0771	0.1779	2.0568	0.0247	0.1352	1.3536	-0.0138	0.0553	1.1322

Table 2. Conditional Market Crash Probabilities

The table presents conditional probabilities of market crashes within the equal-weighted returns to all country indexes. Risk states are determined by the FI, which is the average of $\beta_{j,i,t}$ across all countries at a given point *t*, and defined as $\mu_{PC1,t}$. $\beta_{j,i,t}$ for each country j and each point in time *t* is the coefficient of the first component (PC1) and estimated from daily observations from day *t*-500 through day *t*-1. The coefficient of PC1 is estimated by regressing country stock returns on 10 principal components constructed according to Pukthuanthong and Roll (2009). We restrict the analysis to countries with at least 100 usable observations during any particular period, and use weighted least squares in which the weight placed on daily observation *t*-x is equal to 0.995^{x-1}. Market crashes are defined as a daily return falling below the percentile listed in the column heading. Table rows present the expected number of crashes, the frequency of crashes and the percentage of crashes. The final row in each sub-panel presents a Z-score and associated p-value testing that the probability of a crash is equal across risk states. The sample is daily from December 29, 1994 through November 30, 2010 and consists of equal-weighted daily returns to all countries within the data set.

	$R_{j,t} \leq P20\%$	$R_{j,t} \leq P10\%$	$R_{j,t} \leq P5\%$	$R_{j,t} \leq P2\%$
$Ex(X \mid \mu_{PC1,t} < P80\%(\mu_{PC1}))$	598.36	299.18	149.59	59.20
$f(X \mid \mu_{PC1,t} < 80\%(\mu_{PC1}))$	498	213	90	27
$f/n(X \mid \mu_{PC1,t} < P80\%(\mu_{PC1}))$	16.63	7.11	3.01	0.90
$Ex(X \mid \mu_{PC1,t} > P80\%(\mu_{PC1}))$	149.64	74.82	37.41	14.80
$f(X \mid \mu_{PC1,t} > P80\%(\mu_{PC1}))$	250	161	97	47
$f/n(X \mid \mu_{PC1,t} > P80\%(\mu_{PC1}))$	33.38	21.50	12.95	6.28
$H_0: d = 0$	9.042	9.145	7.857	5.952
	(0.000)	(0.000)	(0.000)	(0.000)
$Ex(X \mid \mu_{PC1,t} < P90\%(\mu_{PC1}))$	673.28	336.64	168.32	66.61
$f(X \mid \mu_{PC1,t} < 90\%(\mu_{PC1}))$	627	288	128	47
$f/n(X \mid \mu_{PC1,t} < P90\%(\mu_{PC1}))$	18.61	8.55	3.80	1.39
$Ex(X \mid \mu_{PC1,t} > P90\%(\mu_{PC1}))$	74.72	37.36	18.68	7.39
$f(X \mid \mu_{PC1,t} > P90\%(\mu_{PC1}))$	121	86	59	27
$f/n(X \mid \mu_{PC1,t} > P90\%(\mu_{PC1}))$	32.35	22.99	15.78	7.22
$H_0: d = 0$	5.477	6.483	6.260	4.304
	(0.000)	(0.000)	(0.000)	(0.000)
$Ex(X \mid \mu_{PC1,t} < P95\%(\mu_{PC1}))$	710.64	355.32	177.66	70.30
$f(X \mid \mu_{PC1,t} < 95\%(\mu_{PC1}))$	673	319	147	56
$f/n(X \mid \mu_{PC1,t} < P95\%(\mu_{PC1}))$	18.92	8.97	4.13	1.57
$Ex(X \mid \mu_{PC1,t} > P95\%(\mu_{PC1}))$	37.36	18.68	9.34	3.70
$f(X \mid \mu_{PC1,t} > P95\%(\mu_{PC1}))$	75	55	40	18
$f/n(X \mid \mu_{PC1,t} > P95\%(\mu_{PC1}))$	40.11	29.41	21.39	9.63
$H_0: d = 0$	5.815	6.073	5.720	3.716
	(0.000)	(0.000)	(0.000)	(0.000)

Table 2. Cont'd

$Ex(X \mid \mu_{PC1,t} < P98\%(\mu_{PC1}))$	733.22	366.61	183.30	72.54
$f(X \mid \mu_{PC1,t} < 98\%(\mu_{PC1}))$	715	345	163	64
$f/n(X \mid \mu_{PC1,t} < P98\%(\mu_{PC1}))$	19.48	9.40	4.44	1.74
$Ex(X \mid \mu_{PC1,t} > P98\%(\mu_{PC1}))$	14.78	7.39	3.70	1.46
$f(X \mid \mu_{PC1,t} > P98\%(\mu_{PC1}))$	33	29	24	10
$f/n(X \mid \mu_{PC1,t} > P98\%(\mu_{PC1}))$	44.59	39.19	32.43	13.51
$H_0: d = 0$	4.318	5.23	5.13	2.957
	(0.000)	(0.000)	(0.000)	(0.002)

Table 3. Conditional Probabilities of Joint Crashes
The table presents the conditional probability of joint market crashes across cohorts, conditional on market states. We consider equal weighted returns to the three cohorts within our sample. Risk states are indicated in the initial column, and return thresholds that define crashes are indicated in the panel headings. Risk states are determined by the FI, which is the average of $\beta_{j,i,t}$ across all countries at a given point *t*, and defined as $\mu_{PC1,t}$. $\beta_{j,i,t}$ for each country *j* and each point in time *t* is the coefficient of the first component (PC1) from Pukthuanthong and Roll (2009). Estimation of $\beta_{j,i,t}$ is described in Table 2. We present the frequency ($f(X)$) and empirical probabilities ($f/n(X)$) of *X* cohort indexes jointly crashing on a given day across risk states, with *X* labeled in the column headings. For the high risk states, we present the expected number of a given number of joint occurrences ($Ex(X)$), and the chi-squared statistic and associated p-value testing for independence between risk states and crashes. The sample is daily from December 29, 1994 through November 30, 2010 and consists of equal-weighted daily returns to all countries within the data set.

Panel A: Crash defined as $R_{j,t} \leq P20\%$					
Risk state	Statistic	$X = 0$	$X = 1$	$X = 2$	$X = 3$
$\mu_{PC1,t} \leq P80\%$	$f(X)$	2038	531	270	156
	$f/n(X)$	68.05	17.73	9.02	5.21
$\mu_{PC1,t} \geq P80\%$	$f(X)$	436	79	76	158
	$Ex(X)$	494.93	122.03	69.22	62.82
	$f/n(X)$	58.21	10.55	10.15	21.09
	χ^2	7.02	15.78	0.66	144.23
		(0.071)	(0.001)	(0.883)	(0.000)
$\mu_{PC1,t} \leq P90\%$	$f(X)$	2253	576	309	232
	$f/n(X)$	66.85	17.09	9.17	6.88
$\mu_{PC1,t} \geq P90\%$	$f(X)$	221	34	37	82
	$Ex(X)$	247.14	60.94	34.56	31.37
	$f/n(X)$	59.09	9.09	9.89	21.93
	χ^2	2.76	11.91	0.17	81.74
		(0.430)	(0.008)	(0.982)	(0.000)
$\mu_{PC1,t} \leq P95\%$	$f(X)$	2378	593	324	262
	$f/n(X)$	66.85	16.67	9.11	7.37
$\mu_{PC1,t} \geq P95\%$	$f(X)$	96	17	22	52
	$Ex(X)$	123.57	30.47	17.28	15.68
	$f/n(X)$	51.34	9.09	11.76	27.81
	χ^2	6.15	5.95	1.29	84.10
		(0.105)	(0.114)	(0.732)	(0.000)
$\mu_{PC1,t} \leq P98\%$	$f(X)$	2442	600	339	289
	$f/n(X)$	66.54	16.35	9.24	7.87
$\mu_{PC1,t} \geq P98\%$	$f(X)$	32	10	7	25
	$Ex(X)$	48.90	12.06	6.84	6.21
	$f/n(X)$	43.24	13.51	9.46	33.78
	χ^2	5.84	0.35	0.00	56.91
		(0.120)	(0.950)	(1.000)	(0.000)

Table 3. Cont'd

Panel B: Crash defined as $R_{j,t} \leq P10\%$					
Risk state	Statistic	$X = 0$	$X = 1$	$X = 2$	$X = 3$
$\mu_{PC1,t} \leq P80\%$	$f(X)$	2540	296	107	52
	$f/n(X)$	84.81	9.88	3.57	1.74
$\mu_{PC1,t} \geq P80\%$	$f(X)$	538	66	45	100
	$Ex(X)$	615.76	72.42	30.41	30.41
	$f/n(X)$	71.83	8.81	6.01	13.35
	χ^2	9.82	0.57	7.00	159.27
		(0.020)	(0.903)	(0.072)	(0.000)
$\mu_{PC1,t} \leq P90\%$	$f(X)$	2816	328	127	99
	$f/n(X)$	83.56	9.73	3.77	2.94
$\mu_{PC1,t} \geq P90\%$	$f(X)$	262	34	25	53
	$Ex(X)$	307.47	36.16	15.18	15.18
	$f/n(X)$	70.05	9.09	6.68	14.17
	χ^2	6.72	0.13	6.35	94.18
		(0.081)	(0.988)	(0.096)	(0.000)
$\mu_{PC1,t} \leq P95\%$	$f(X)$	2961	342	138	116
	$f/n(X)$	83.24	9.61	3.88	3.26
$\mu_{PC1,t} \geq P95\%$	$f(X)$	117	20	14	36
	$Ex(X)$	153.74	18.08	7.59	7.59
	$f/n(X)$	62.57	10.70	7.49	19.25
	χ^2	8.78	0.20	5.41	106.30
		(0.032)	(0.978)	(0.144)	(0.000)
$\mu_{PC1,t} \leq P98\%$	$f(X)$	3039	354	145	132
	$f/n(X)$	82.81	9.65	3.95	3.60
$\mu_{pC1,t} \geq P98\%$	$f(X)$	39	8	7	20
	$Ex(X)$	60.84	7.15	3.00	3.00
	$f/n(X)$	52.70	10.81	9.46	27.03
	χ^2	7.84	0.10	5.31	96.15
		(0.049)	(0.992)	(0.150)	(0.000)

Table 3. Cont'd

Panel C: Crash defined as $R_{j,t} \leq P5\%$					
Risk state	Statistic	$X = 0$	$X = 1$	$X = 2$	$X = 3$
$\mu_{PC1,t} \leq P80\%$	$f(X)$	2807	119	45	24
	$f/n(X)$	93.72	3.97	1.50	0.80
$\mu_{PC1,t} \geq P80\%$	$f(X)$	606	58	33	52
	$Ex(X)$	682.78	35.41	15.60	15.20
	$f/n(X)$	80.91	7.74	4.41	6.94
	χ^2	8.63	14.41	19.39	89.05
		(0.035)	(0.002)	(0.000)	(0.000)
$\mu_{PC1,t} \leq P90\%$	$f(X)$	3123	143	56	48
	$f/n(X)$	92.67	4.24	1.66	1.42
$\mu_{PC1,t} \geq P90\%$	$f(X)$	290	34	22	28
	$Ex(X)$	340.94	17.68	7.79	7.59
	$f/n(X)$	77.54	9.09	5.88	7.49
	χ^2	7.61	15.06	25.91	54.86
		(0.055)	(0.002)	(0.000)	(0.000)
$\mu_{PC1,t} \leq P95\%$	$f(X)$	3283	152	63	59
	$f/n(X)$	92.30	4.27	1.77	1.66
$\mu_{PC1,t} \geq P95\%$	$f(X)$	130	25	15	17
	$Ex(X)$	170.47	8.84	3.90	3.80
	$f/n(X)$	69.52	13.37	8.02	9.09
	χ^2	9.61	29.54	31.65	45.93
		(0.022)	(0.000)	(0.000)	(0.000)
$\mu_{PC1,t} \leq P98\%$	$f(X)$	3373	163	66	68
	$f/n(X)$	91.91	4.44	1.80	1.85
$\mu_{PC1,t} \geq P98\%$	$f(X)$	40	14	12	8
	$Ex(X)$	67.46	3.50	1.54	1.50
	$f/n(X)$	54.05	18.92	16.22	10.81
	χ^2	11.18	31.52	70.95	28.11
		(0.011)	(0.000)	(0.000)	(0.000)

Table 3. Cont'd

Panel D: Crash defined as $R_{j,t} \leq P2\%$					
Risk state	Statistic	$X = 0$	$X = 1$	$X = 2$	$X = 3$
$\mu_{PC1,t} \leq P80\%$	$f(X)$	2933	39	18	5
	$f/n(X)$	97.93	1.30	0.60	0.17
$\mu_{PC1,t} \geq P80\%$	$f(X)$	677	35	14	23
	$Ex(X)$	722.19	14.80	6.40	5.60
	$f/n(X)$	90.39	4.67	1.87	3.07
	χ^2	2.83	27.55	9.02	54.04
		(0.419)	(0.000)	(0.029)	(0.000)
$\mu_{PC1,t} \leq P90\%$	$f(X)$	3277	54	25	14
	$f/n(X)$	97.24	1.60	0.74	0.42
$\mu_{PC1,t} \geq P90\%$	$f(X)$	333	20	7	14
	$Ex(X)$	360.61	7.39	3.20	2.80
	$f/n(X)$	89.04	5.35	1.87	3.74
	χ^2	2.11	21.50	4.53	44.87
		(0.550)	(0.000)	(0.210)	(0.000)
$\mu_{PC1,t} \leq P95\%$	$f(X)$	3452	59	28	18
	$f/n(X)$	97.05	1.66	0.79	0.51
$\mu_{PC1,t} \geq P95\%$	$f(X)$	158	15	4	10
	$Ex(X)$	180.31	3.70	1.60	1.40
	$f/n(X)$	84.49	8.02	2.14	5.35
	χ^2	2.76	34.57	3.61	52.90
		(0.430)	(0.000)	(0.307)	(0.000)
$\mu_{PC1,t} \leq P98\%$	$f(X)$	3554	64	30	22
	$f/n(X)$	96.84	1.74	0.82	0.60
$\mu_{PC1,t} \geq P98\%$	$f(X)$	56	10	2	6
	$Ex(X)$	71.35	1.46	0.63	0.55
	$f/n(X)$	75.68	13.51	2.70	8.11
	χ^2	3.30	49.83	2.96	53.60
		(0.348)	(0.000	(0.398)	(0.000)

Table 4. Logistic Regressions Within Cohort Indexes

This table presents logistic regression results. For each sub-panel, the dependent variable takes a value of 1 if the return to the given equal-weighted return index falls below the threshold identified in the panel heading. $Coef_{\mu_{PC1}}$ represents the coefficient estimate on the FI, and associated p-value. The FI is the average of $\beta_{j,i,t}$ across all countries within the given cohort at a given point *t*, and defined as $\mu_{PC1,t}$. $\beta_{j,i,t}$ for each country *j* and each point in time *t* is the coefficient of the first component (PC1) and estimated from daily observations from day *t*-500 through day *t*-1. The coefficient of PC1 is estimated by regressing country stock returns on 10 principal components constructed according to Pukthuanthong and Roll (2009). We restrict the analysis to countries with at least 100 usable observations during any particular period and use weighted least squares in which the weight placed on daily observation *t*-x is equal to 0.995^{x-1}. $OR_{1\sigma}$ and $OR_{2\sigma}$ represents the odds ratio of a crash when $\mu_{PC1,t}$ increases by one and two standard deviations, respectively. The independent variable is multiplied by 100 for scaling purposes. Cohort 1, Cohort 2, and Cohort 3 are formed from country indexes with available data beginning prior to 1984, 1994, and after 1994, respectively.

	$Cohort_{all}$	$Cohort_1$	$Cohort_2$	$Cohort_3$
		$R_{j,t} \leq P20\%$		
$Coef_{\mu_{PC1}}$	4.450	2.376	5.240	4.192
	(0.000)	(0.000)	(0.000)	(0.000)
$OR_{1\sigma}$	1.438	1.332	1.483	1.407
$OR_{2\sigma}$	2.069	1.775	2.198	1.980
		$R_{j,t} \leq P10\%$		
$Coef_{\mu_{PC1}}$	6.378	3.741	7.520	6.063
	(0.000)	(0.000)	(0.000)	(0.000)
$OR_{1\sigma}$	1.684	1.571	1.760	1.639
$OR_{2\sigma}$	2.835	2.468	3.096	2.687
		$R_{j,t} \leq P5\%$		
$Coef_{\mu_{PC1}}$	8.125	4.938	8.416	8.736
	(0.000)	(0.000)	(0.000)	(0.000)
$OR_{1\sigma}$	1.942	1.815	1.882	2.038
$OR_{2\sigma}$	3.771	3.294	3.542	4.153
		$R_{j,t} \leq P2\%$		
$Coef_{\mu_{PC1}}$	9.808	6.829	8.568	10.587
	(0.000)	(0.000)	(0.000)	(0.000)
$OR_{1\sigma}$	2.228	2.280	1.904	2.370
$OR_{2\sigma}$	4.964	5.200	3.624	5.617

Table 5. Logistic Regressions Across Cohorts

The table presents logistic regression results. Column heading define return thresholds that determine market crashes. In Panels A through C, the dependent variable takes the value of one for any day *t* in which the number of market crashes across the three cohorts exceeds the specified value. For example, in Panel B the dependent variable takes the value of one for any day in which at least two of the three cohort index returns fall below the percentile given in the column heading. Panel D presents ordinal logistic regressions in which the dependent variable is set equal to the number of cohorts experiencing a crash on the given day. Panel E presents generalized logistic results in which the dependent variable is as defined as in Panel D. The final three rows of Panel E present statistical tests of equality across coefficients. $Coef_{\mu_{PC1}}$ represents the coefficient estimate of FI, and the associated p-value is reported below. The FI and estimation of this measure are defined in Table 2. Row headings are as defined in the previous table. Finally, the subscript 's*i*' in Panel E refers to parameter estimates based on *i* cohorts jointly crashing.

	$R_{j,t} \leq P20\%$	$R_{j,t} \leq P10\%$	$R_{j,t} \leq P5\%$	$R_{j,t} \leq P2\%$
		Panel A: $\sum X_i \geq 1$		
$Coef_{\mu_{PC1}}$	2.192	4.256	6.623	8.159
	(0.000)	(0.000)	(0.000)	(0.000)
$OR_{1\sigma}$	1.196	1.416	1.718	1.947
$OR_{2\sigma}$	1.431	2.004	2.950	3.792
		Panel B: $\sum X_i \geq 2$		
$Coef_{\mu_{PC1}}$	4.979	7.186	8.525	9.244
	(0.000)	(0.000)	(0.000)	(0.000)
$OR_{1\sigma}$	1.502	1.798	2.006	2.128
$OR_{2\sigma}$	2.255	3.235	4.025	4.527
		Panel C: $\sum X_i = 3$		
$Coef_{\mu_{PC1}}$	7.569	9.942	10.364	13.543
	(0.000)	(0.000)	(0.000)	(0.000)
$OR_{1\sigma}$	1.856	2.252	2.331	3.023
$OR_{2\sigma}$	3.443	5.073	5.435	9.136
		Panel D: $\sum X_i$		
$Coef_{\mu_{PC1}}$	3.430	4.917	6.828	8.229
	(0.000)	(0.000)	(0.000)	(0.000)
$OR_{1\sigma}$	1.323	1.494	1.747	1.958
$OR_{2\sigma}$	1.751	2.233	3.051	3.835
χ^2	153.291	99.602	18.978	11.804
	(0.000)	(0.000)	(0.000)	(0.003)

Table 5. Cont'd

Panel E: Generalized Logistic Regression				
$Coef_{\mu_{PC1,s3}}$	7.441	10.250	10.908	13.873
	(0.000)	(0.000)	(0.000)	(0.000)
$OR_{1\sigma.s3}$	1.836	2.310	2.437	3.105
$Coef_{\mu_{PC1,s2}}$	1.352	3.891	6.812	6.023
	(0.051)	(0.000)	(0.000)	(0.000)
$OR_{1\sigma,s2}$	1.117	1.374	1.744	1.635
$Coef_{\mu_{PC1,s1}}$	-1.846	0.787	4.480	7.081
	(0.006)	(0.260)	(0.000)	(0.000)
$OR_{1\sigma,s1}$	0.860	1.066	1.442	1.783
$\emptyset_3 = \emptyset_1$	134.410	93.441	25.568	9.569
	(0.000)	(0.000)	(0.000)	(0.002)
$\emptyset_3 = \emptyset_2$	55.659	33.416	7.937	9.696
	(0.000)	(0.000)	(0.005)	(0.002)
$\emptyset_2 = \emptyset_1$	13.013	8.600	3.400	0.304
	(0.000)	(0.003)	(0.065)	(0.581)

Table 6. Logistic Regressions Controlling for Volatility

The table presents logistic regression results. The dependent variable is detailed in the initial column, and is based on $\sum X_i$, which represents the number of cohort indexes that experience a crash on day *t*. In the first three rows of each panel, the dependent variable is equal to an indicator variable that takes the value of one an any day *t* in which the number of cohort indexes that crash is greater than or equal to one, greater than or equal to two, or equal to three, respectively. In the final row of each panel the dependent variable equals the number of cohort indexes that crash on day *t*. For each cohort, a crash is defined as a return that falls below the fifth percentile of full-sample returns. The dependent variable in each specification is regressed on FI, calculated through day t-1, and a control variable. In Panel A the control variable represents forecasted volatility for day *t* of the all country index return from a GARCH specification. In Panels B and C the control variable is the cross-sectional average of country index standard deviations, and the standard deviation of the all country index, respectively, each calculated through day *t*-1 with the same 500 day rolling window and weighting scheme as FI. In Panel D the control variable is the cross-sectional average adjusted R-square from the FI regressions. Table entries represent coefficient estimates, and associated p-values, as well as odds ratios for a one standard deviation increase in the given variable.

Panel A: GARCH forecasted volatilty				
	$Coef_{\mu_{PC1}}$	$OR_{\mu_{PC1}}$	$Coef_{\sigma}$	OR_{σ}
$Y_t = I_{\sum X_i \geq 1}$	5.933	1.623	10.056	1.201
	(0.000)		(0.000)	
$Y_t = I_{\sum X_i \geq 2}$	7.759	1.885	10.445	1.210
	(0.000)		(0.000)	
$Y_t = I_{\sum X_i = 3}$	9.428	2.160	12.428	1.254
	(0.000)		(0.000)	
$Y_t = \sum X_i$	6.107	1.647	11.286	1.228
	(0.000)		(0.000)	

Panel B: Cross-sectional average standard deviation				
	$Coef_{\mu_{PC1}}$	$OR_{\mu_{PC1}}$	$Coef_{\sigma}$	OR_{σ}
$Y_t = I_{\sum X_i \geq 1}$	4.188	1.408	1.427	1.384
	(0.000)		(0.000)	
$Y_t = I_{\sum X_i \geq 2}$	5.688	1.591	1.599	1.440
	(0.000)		(0.001)	
$Y_t = I_{\sum X_i = 3}$	9.778	2.222	0.305	1.072
	(0.000)		(0.674)	
$Y_t = \sum X_i$	4.402	1.433	1.409	1.379
	(0.000)		(0.000)	

Panel C: World index standard deviation				
	$Coef_{\mu_{PC1}}$	$OR_{\mu_{PC1}}$	$Coef_{\sigma}$	OR_{σ}
$Y_t = I_{\sum X_i \geq 1}$	2.950	1.272	1.753	1.442
	(0.007)		(0.000)	
$Y_t = I_{\sum X_i \geq 2}$	3.467	1.327	2.397	1.650
	(0.024)		(0.000)	
$Y_t = I_{\sum X_i = 3}$	8.027	1.926	1.066	1.249
	(0.002)		(0.344)	
$Y_t = \sum X_i$	3.149	1.293	1.749	1.441
	(0.004)		(0.000)	

Panel D: Cross-sectional average adjusted R-square				
	$Coef_{\mu_{PC1}}$	$OR_{\mu_{PC1}}$	$Coef_{AR}$	OR_{AR}
$Y_t = I_{\sum X_i \geq 1}$	5.445	7.657	0.015	1.122
	(0.000)		(0.363)	
$Y_t = I_{\sum X_i \geq 2}$	5.972	1.629	0.033	1.290
	(0.003)		(0.184)	
$Y_t = I_{\sum X_i = 3}$	9.307	2.139	0.014	1.112
	(0.003)		(0.721)	
$Y_t = \sum X_i$	5.701	1.593	0.014	1.116
	(0.000)		(0.384)	

Table 7. Logistic Regressions for Robustness

The table presents logistic regression results. The dependent variable is based on the number of cohort indexes that exhibit a crash on the given day. The benchmark specification is detailed in Panel D of Table 5 with crashes defined based on the fifth percentile of returns. Results in each row are based on the benchmark specification, with the only difference in methodology described in the first column of each row.

Alteration	$Coef_{\mu_{PC1}}$	$OR_{1\sigma}$	$OR_{2\sigma}$
Benchmark Case: Table 5, Panel D, crashes defined based on fifth percentile of returns	6.828 (0.000)	1.747	3.051
Sample period: 12/29/1994-12/31/2007	15.284 (0.000)	1.311	1.720
Sample period: 12/01/2000 – 11/30/2010	7.635 (0.000)	2.115	4.471
FI estimation: 60 day rolling-window	6.302 (0.000)	1.822	3.321
FI specification: FI estimated from 60 day rolling-window subtract FI estimated from 500 day rolling window	3.773 (0.000)	1.220	1.488
FI estimation: 60 day rolling-window. Results analyzed only in months April through December	3.958 (0.000)	1.234	1.524
FI specification: 75th percentile of Beta	4.096 (0.000)	1.722	2.965
FI specification: Standard deviation of Beta	6.382 (0.000)	1.452	2.108
Crash definition: Absolute return below -5%	13.201 (0.000)	2.939	8.639
Only observations not preceded by a crash within any cohort in the previous 10 trading days	5.854 (0.000)	1.401	1.964
Only observations not preceded by a crash within any cohort in the previous 20 trading days	6.823 (0.001)	1.376	1.893
Only observations not preceded by a crash within any cohort in the previous 50 trading days	10.974 (0.017)	1.341	1.798

Appendix 1.

Country Index Sample Periods and Index Identification

Eighty-Two countries have index data availability from DataStream, a division of Thomson Financial. Some countries have several indexes and the index chosen has the longest period of data availability. All index values are converted into a common currency, the US dollar. An index with the designation "RI" is a total return index (with reinvested dividends.) The designation "PI" denotes a pure price index. When calculating log returns from the indexes, neither the beginning nor the ending index value can be identical to its immediately preceding index value; (this eliminates holidays, which vary across countries, and days with obviously stale prices.) Cohorts 1, 2, and 3 includes countries starting in DataStream in pre-1974 until 1983, 1984-1993, and post-1993.

	DataStream Availability				DataStream
Country	Begins	Ends	Cohort	Index Identification	Mnemonic
Argentina	2-Aug-93	30-Nov-10	2	ARGENTINA MERVAL	ARGMERV(PI)~U$
Australia	31-Dec-79	30-Nov-10	1	AUSTRALIA-DS MARKET	TOTMAU$(RI)
Austria	1-Jan-73	30-Nov-10	1	AUSTRIA-DS Market	TOTMKOE(RI)~U$
Bahrain	31-Dec-99	30-Nov-10	3	DOW JONES BAHRAIN	DJBAHR$(PI)
Bangladesh	1-Jan-90	30-Nov-10	2	BANGLADESH SE ALL SHARE	BDTALSH(PI)~U$
Belgium	31-Dec-79	30-Nov-10	1	BELGIUM-DS Market	TOTMKBG(RI)~U$
Botswana	29-Dec-95	30-Nov-10	3	S&P/IFCF M BOTSWA0.	IFFMBOL(PI)~U$
Brazil	7-Apr-83	30-Nov-10	1	BRAZIL BOVESPA	BRBOVES(PI)~U$
Bulgaria	20-Oct-00	30-Nov-10	3	BSE SOFIX	BSSOFIX(PI)~U$
Canada	31-Dec-79	30-Nov-10	1	S&P/TSX COMPOSITE INDEX	TTOCOMP(RI)~U$
Chile	2-Jan-87	30-Nov-10	2	CHILE GENERAL (IGPA)	IGPAGEN(PI)~U$
China	3-Apr-91	30-Nov-10	2	SHENZHEN SE COMPOSITE	CHZCOMP(PI)~U$
Colombia	10-Mar-92	30-Nov-10	2	COLOMBIA-DS Market	TOTMKCB(RI)~U$
Côte d'Ivoire	29-Dec-95	30-Nov-10	3	S&P/IFCF M COTE D'IVOIRE	IFFMCIL(RI)~U$
Croatia	2-Jan-97	30-Nov-10	3	CROATIA CROBEX	CTCROBE(PI)~U$
Cyprus	3-Sep-04	30-Nov-10	3	CYPRUS GENERAL	CYPMAPM(PI)~U$
Czech Republic	9-Nov-93	30-Nov-10	2	CZECH REP.-DS NON-FINCIAL	TOTLICZ(RI)~U$
Denmark	31-Dec-79	30-Nov-10	1	MSCI DENMARK	MSDNMKL(RI)~U$
Ecuador	2-Aug-93	30-Nov-10	2	ECUADOR ECU (U$)	ECUECUI(PI)
Egypt	2-Jan-95	30-Nov-10	3	EGYPT HERMES FINANCIAL	EGHFINC(PI)~U$
Estonia	3-Jun-96	30-Nov-10	3	OMX TALLINN (OMXT)	ESTALSE(PI)~U$
Finland	2-Jan-91	30-Nov-10	2	OMX HELSINKI (OMXH)	HEXINDX(RI)~U$
France	31-Dec-79	30-Nov-10	1	FRANCE-DS Market	TOTMKFR(RI)~U$

Germany	31-Dec-79	30-Nov-10	1	DAX 30 PERFORMANCE	DAXINDX(RI)~U$
Ghana	29-Dec-95	30-Nov-10	3	S&P/IFCF M GHA0.	IFFMGHL(PI)~U$
Greece	26-Jan-06	30-Nov-10	3	ATHEX COMPOSITE	GRAGENL(RI)~U$
Hong Kong	2-Jan-90	30-Nov-10	2	HANG SENG	HNGKNGI(RI)~U$
Hungary	2-Jan-91	30-Nov-10	2	BUDAPEST (BUX)	BUXINDX(PI)~U$
Iceland	31-Dec-92	30-Nov-10	2	OMX ICELAND ALLSHARE	ICEXALL(PI)~U$
India	2-Jan-87	30-Nov-10	2	INDIA BSE (100) NATIONAL	IBOMBSE(PI)~U$
Indonesia	2-Apr-90	30-Nov-10	2	INDONESIA-DS Market	TOTMKID(RI)~U$
Ireland	1-Jan-73	30-Nov-10	1	IRELAND-DS MARKET	TOTMIR$(RI)
Israel	23-Apr-87	30-Nov-10	2	ISRAEL TA 100	ISTA100(PI)~U$
Italy	31-Dec-79	30-Nov-10	1	ITALY-DS MARKET	TOTMIT$(RI)
Jamaica	29-Dec-95	30-Nov-10	3	S&P/IFCF M JAMAICA	IFFMJAL(PI)~U$
Japan	31-Dec-79	30-Nov-10	1	TOPIX	TOKYOSE(RI)~U$
Jordan	21-Nov-88	30-Nov-10	2	AMMAN SE FINANCIAL MARKET	AMMANFM(PI)~U$
Kenya	11-Jan-90	30-Nov-10	2	KENYA NAIROBI SE	NSEINDX(PI)~U$
Kuwait	28-Dec-94	30-Nov-10	3	KUWAIT KIC GENERAL	KWKICGN(PI)~U$
Latvia	3-Jan-00	30-Nov-10	3	OMX RIGA (OMXR)	RIGSEIN(RI)~U$
Lebanon	31-Jan-00	30-Nov-10	3	S&P/IFCF M LEBANON	IFFMLEL(PI)~U$
Lithuania	31-Dec-99	30-Nov-10	3	OMX VILNIUS (OMXV)	LNVILSE(RI)~U$
Luxembourg	2-Jan-92	30-Nov-10	2	LUXEMBURG-DS MARKET	LXTOTMK(RI)~U$
Malaysia	2-Jan-80	30-Nov-10	1	KLCI COMPOSITE	KLPCOMP(PI)~U$
Malta	27-Dec-95	30-Nov-10	3	MALTA SE MSE -	MALTAIX(PI)~U$
Mauritius	29-Dec-95	30-Nov-10	3	S&P/IFCF M MAURITIUS	IFFMMAL(PI)~U$
Mexico	4-Jan-88	30-Nov-10	2	MEXICO IPC (BOLSA)	MXIPC35(PI)~U$
Morocco	31-Dec-87	30-Nov-10	2	MOROCCO SE CFG25	MDCFG25(PI)~U$
Namibia	31-Jan-00	30-Nov-10	3	S&P/IFCF M NAMBIA	IFFMNAL(PI)~U$
Netherlands	31-Dec-79	30-Nov-10	1	NETHERLAND-DS Market	TOTMKNL(RI)~U$
New Zealand	4-Jan-88	30-Nov-10	2	NEW ZEALAND-DS MARKET	TOTMNZ$(RI)
Nigeria	30-June-95	30-Nov-10	3	S&P/IFCG D NIGERIA	IFGDNGL(PI)~U$
Norway	2-Jan-80	30-Nov-10	1	NORWAY-DS MARKET	TOTMNW$(RI)
Oman	22-Oct-96	30-Nov-10	3	OMAN MUSCAT SECURITIES MKT.	OMANMSM(PI)~U$
Pakistan	30-Dec-88	30-Nov-10	2	KARACHI SE 100	PKSE100(PI)~U$
Peru	2-Jan-91	30-Nov-10	2	LIMA SE GENERAL(IGBL)	PEGENRL(PI)~U$
Philippines	2-Jan-86	30-Nov-10	2	PHILIPPINE SE I(PSEi)	PSECOMP(PI)~U$
Poland	16-Apr-91	30-Nov-10	2	WARSAW GENERALINDEX	POLWIGI(PI)~U$
Portugal	5-Jan-88	30-Nov-10	2	PORTUGAL PSI GENERAL	POPSIGN(PI)~U$
Romania	19-Sep-97	30-Nov-10	3	ROMANIA BET (L)	RMBETRL(PI)~U$
Russia	1-Sep-95	30-Nov-10	3	RUSSIA RTS INDEX	RSRTSIN(PI)~U$

Saudi Arabia	31-Dec-97	30-Nov-10	3	S&P/IFCG D SAUDI ARABIA	IFGDSB$(RI)
Singapore	1-Jan-73	30-Nov-10	1	SINGAPORE-DS MARKET EX TMT	TOTXTSG(RI)~U$
Slovakia	14-Sep-93	30-Nov-10	2	SLOVAKIA SAX 16	SXSAX16(PI)~U$
Slovenia	31-Dec-93	30-Nov-10	2	SLOVENIAN EXCH. STOCK (SBI)	SLOESBI(PI)~U$
South Africa	31-Dec-79	30-Nov-10	1	SOUTH AFRICA-DS MARKET	TOTMSA$(RI)
South Korea	31-Dec-79	30-Nov-10	1	KOREA SE COMPOSITE (KOSPI)	KORCOMP(PI)~U$
Spain	31-Dec-79	30-Nov-10	1	MADRID SE GENERAL	MADRIDI(PI)~U$
Sri Lanka	2-Jan-85	30-Nov-10	2	COLOMBO SE ALLSHARE	SRALLSH(PI)~U$
Sweden	28-Dec-79	30-Nov-10	1	OMX STOCKHOLM (OMXS)	SWSEALI(PI)~U$
Switzerland	31-Dec-79	30-Nov-10	1	SWITZ-DS Market	TOTMKSW(RI)~U$
Taiwan	31-Dec-84	30-Nov-10	2	TAIWAN SE WEIGHTED	TAIWGHT(PI)~U$
Thailand	2-Jan-87	30-Nov-10	2	THAILAND-DS MARKET	TOTMTH$(RI)
Trinidad	29-Dec-95	30-Nov-10	3	S&P/IFCF M TRINIDAD & TOBAGO	IFFMTTL(PI)~U$
Tunisia	31-Dec-97	30-Nov-10	3	TUNISIA TUNINDEX	TUTUNIN(PI)~U$
Turkey	4-Jan-88	30-Nov-10	2	ISE TIOL 100	TRKISTB(PI)~U$
Ukraine	30-Jan-98	30-Nov-10	3	S&P/IFCF M UKRAINE	IFFMURL(PI)~U$
Utd. Arab Emirates	1-Jun-05	30-Nov-10	3	MSCI UAE	MSUAEI$
United Kingdom	31-Dec-79	30-Nov-10	1	UK-DS MARKET	TOTMUK$(RI)
United States	31-Dec-79	30-Nov-10	1	S&P 500 COMPOSITE	S&PCOMP(RI)~U$
Venezuela	2-Jan-90	30-Nov-10	2	VENEZUELA-DS MARKET	TOTMVE$(RI)
Zimbabwe	6-Apr-88	6-Oct-06	2	ZIMBABWE INDUSTRIALS	ZIMINDS(PI)