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Stock Market Risk in the Financial Crisis

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Abstract

In this paper, we look at the effect of the financial crisis from an angle overlooked to date in the finance literature by investigating composition effects arising from the financial crisis. A composition effect is a change in the market risk of a sector that is caused not by a direct change in that sector but by a change in another sector that affects the composition of the stock market. In the paper we investigate the pre and during crisis market risk of the industrial, banking and utilities sectors. Amongst other results, we find, across the G12 countries, a positive relationship between the increase in the market risk of industrials during the crisis and both the pre-crisis market risk of the banking sector and the scale of the systemic crisis in a country. The six G12 countries that experienced a major systematic banking crisis are amongst the seven countries with the largest increases in the market risk for industrials. Results drawn from our detailed analysis using US data are consistent with these findings. Finally, we show how the results add to our understanding of the linkages between the financial and real sector and conclude that composition effects of the financial crisis could have a significant chilling effect on investment industrials, which is in addition to the effect of other linkages already documented.

JEL classification: G1, G01, G15

Keywords: financial crisis, systemic risk, market risk, utilities, banking sector, industrials

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1. Introduction

The financial crisis of 2007 began in the US, rapidly took the form of a full blown systemic crisis in the US and almost immediately became a global phenomenon (Covitz et al., 2013; Lane, 2012; Mishkin, 2011; Shiller, 2012). By 2008 there were major systemic banking crises in a large number of economies, e.g., Austria, Belgium, Denmark, Germany, Iceland, the Netherlands, Nigeria, Spain and the UK, and 'borderline' systemic crises in many others such as France, Italy, Portugal, Russia, Sweden and Switzerland. The financial crisis has had enormous impact on the financial sector of many developed countries, decimating values of financial companies and leading some of the biggest world names in banking to be dependent on state financial support to avoid collapse or, in some cases, to be nationalised. Although the financial sector has been hardest hit by the crisis, its effect has been felt across the economies around the world as the financial crisis has spread, through transmission channels, to the real economy. In the US, for example, average annual real GDP growth between 2007 and 2014 was only 1.22%. This situation is common, e.g., French, German, Dutch and the UK GDP real annual growth rate figures for the equivalent period are 0.31%, 1.07%, 0.53%, and 0.82%.[2] The financial crisis and the associated decline of stock market capitalisation has also affected the stock market composition in many countries. The aim of this paper is to look at the effect of the financial crisis from an angle overlooked to date in the finance literature by investigating whether and how this change in the composition of stock markets has impacted on the market based risk measures of selected sectors, given that such changes can have economically significant implications for the transmission mechanism from the financial to real economy and for investment strategies.

It is common to discuss the financial crisis from the perspective of changes in stock price volatility and correlations of individual stocks or whole sectors (e.g., Bartram and Bodnar, 2009; Bartram et al., 2012; Bates, 2012; Campello et al, 2010), or in the context of financial constraints (e.g., Campbell et al., 2011; Duygan-Bump et al., 2015; Dell'Ariccia et al., 2015). In this paper, we approach the impact of the financial crisis through an approach that has not been investigated so far in the finance literature. That is, we address the question of whether there is evidence that the collapse of the banking sector as a proportion of the stock market may have impacted on the CAPM factor betas of specific sectors simply because the composition of the stock market has changed. It is important to investigate this effect as its existence could

[2] The statistics are calculated using OECD data from http://data.oecd.org/gdp/real-gdp-forecast.htm

potentially dampen investment in lower risk sectors and contribute to other transmission mechanisms from the financial sector to the real sector. In the paper we focus on the risk of industrials, utilities and banking sectors before and during the crisis as there are good arguments why these sectors should experience different effects during the crisis. Whilst utilities are traditionally seen as defensive stocks, the sector appears to have been thought of as particularly low risk and safe havens for investment during the financial crisis. Berkshire-Hathaway's utility focused strategy and its expansion in the financial crisis is one of the better known examples of this. Unlike utilities, however, industrials have not had a favoured 'halo effect' during the crisis. We look at the differences in the changes in risk of industrials and utilities in the G12 countries and relate this to the impact of the financial crisis on banking.

The theoretical idea underlying our investigation in this paper is straightforward and is outlined in the next section. Here we summarise the basic intuition in a simple example where there are only two sectors in the stock market. Consider a special simple case where the composition of the market changes in such a way that the proportion of the comparatively risky sector falls, whilst at the same time the variance-covariance matrix of the expected returns of the two sectors remain unchanged. Given that the market weighted sum of the CAPM factor betas must sum to one, the CAPM factor beta of the comparatively low risk sector must increase if the overall constraint is to be achieved (indeed, the CAPM factor beta can actually increase to such an extent that the lower risk sector becomes the higher risk sector). We refer to a change in the CAPM factor beta in one sector that arises not from fundamental changes in that sector but as a result of the other sector growing or declining as a composition effect. That is, over and above any other changes that may be going on, there will be a simple spill-over from the change in the higher risk sector on the CAPM factor beta of the low risk sector. If one also makes the specific assumption that the returns on the two sectors are the same both before and after the composition change, then absent other changes, unless an investor also makes the consequent change in their view of the required risk premium, the expected return of the comparatively lower market risk sector will appear to be a worse risk adjusted return than before. This may lead to difficulties in raising finance in the comparatively low market risk sector or underperformance of portfolios based on this sector. However, any such changes arising from composition effects would be an 'erroneous' transmission mechanism since they do not arise from fundamental changes in the lower risk sector.

It is worth noting that there is some empirical evidence suggesting that such ‘composition effects’ are not unusual. For example, Grout and Zalewska (2006) document that during the dotcom bubble the Kalman filter daily betas of old economy stocks fell, both in the UK and in the US, for a short period during the dotcom bubble. The dot-com bubble is minor in scale when compared to the financial crisis, which suggests that, given the duration, scale of impact and global reach of the financial crisis, it may be possible to find significant market risk changes induced by the composition changes associated with the financial crisis. It is also interesting to note that the driver behind the composition change in the dot-com bubble was the ‘opposite’ of the driver behind the composition change arising in the financial crisis. In the financial crisis the composition change is driven by a reduction of the proportion of the market taken by banking whereas during the dot-com bubble the composition changes arose because comparatively higher risk stocks grew as a percentage of the stock market (both through price increase and new entry). Therefore, if the new thesis that we investigate in this paper is correct, namely that the composition effect of the financial crisis is material and leads to increases in risk measures for industrials that may make it harder for them to attract funding, then the opposite should have been the case during the dot-com bubble, namely old economy companies should have found funding easier despite the competition from high tech stocks. There is evidence that the latter is exactly the case (e.g., Campello and Graham, 2013).

The analysis is initially performed on US daily data on sector indexes provided by Professor Kenneth French using the three and five Fama-French specification, and using S&P1500 daily observations sourced from DataStream using a single factor CAPM. We then undertake a comparative investigation of G12 countries (this sample also includes the US) using DataStream calculated sector indexes. The sample covers 1 January 1996 – 31 July 2014. An interesting feature of the crisis for the purposes of the paper is that the scale of the crisis was not uniform even across G12 countries. For example, according to Laeven and Valencia’s Systemic Crisis Data Bank (Laeven and Valencia, 2013a), amongst the G12 countries the financial crisis developed into a major systemic banking crisis in Belgium, Germany, the Netherlands, Spain, the UK, and the US, whilst France, Italy, Sweden, and Switzerland faced a marginal systemic crisis, and Australia, Canada, Japan, had no systemic crisis at all. Utilising these differences we are able to compare the risk changes across countries that have well developed banking systems but suffered different severity of the crisis, with the expectation that composition effects would be greatest in countries that experienced major systemic crisis.

We find that the CAPM factor beta (further referred to as the beta) of industrials is higher during the crisis than before the crisis in the US and for most of the G12 countries. To the extent that this increase is caused by composition effects arising from the financial crisis one would expect the increase in the beta for industrials to be larger the higher the pre-crisis beta of the banking sector and also larger the more severe the systemic banking crisis in a country. Across the G12 countries we find such a positive relationship between the increase in the beta of industrials relative to pre-crisis levels and the pre-crisis beta of the banking sector. Indeed, with the exception of Sweden, we find that all countries with pre-crisis beta of the banking sector above one experienced increases in the beta of industrials during the crisis and that all countries with pre-crisis beta of the banking sector below one experienced declines in the beta of industrials. Furthermore, the six G12 countries that experienced a severe systematic banking crisis are amongst the seven countries with the largest increases in the beta for industrials (again Sweden is the exception). Although the beta of the banking sectors changed during the crisis, there is no systematic relationship between the scale of the systemic crisis in a country and the change in beta of the banking sector in that country. This may result from the policies adopted by individual governments and regulators to rescue the sector and limit the consequences of the financial crisis.

The position of utilities is more nuanced. If, as we argue, utilities were seen as particularly low risk during the crisis then in the absence of any composition effect we would expect the beta to fall. However, the evidence of changes in the beta of industrials suggests that if a composition effect is present we would expect a less clear picture with the possibility of beta increases. This is exactly the case, i.e., we find that the beta of the utility sector falls in some countries and rises in others with increases in the beta outnumbering the declines.

The format of the paper is as follows. The following section, Section 2, outlines our analytical approach and related literature. Section 3 provides justification for the sample selection and Section 4 presents the data and methodology. Sections 5 and 6 present the results for the US and the G12 countries respectively. Section 7 concludes and discusses the implications. Appendix 1 shows a mathematical proof of the fact that a change in weights of one sector affects the aggregate beta of the other sectors. Appendix 2 provides tables with the GARCH effects estimated for the regression specifications used in the paper as well as tables with an alternative definition of the financial crisis dummy.

2. Analytical Approach

We begin by giving a more formal discussion of the underlying premise outlined in the introduction. Appendix 1 provides more details and the proof of Proposition 1 (see below).

Following from the assumption of the existence of a linear relationship between risk and expected returns, the CAPM determined market risk of individual assets used to construct the market portfolio sum to one when weighted by their market capitalisation. That is, if there are N assets traded on the market, $w^T\beta = 1$, where $w^T = [w_1,\dots, w_N]$ is a vector of capitalisation-based weights and $\beta^T = [\beta_1, \dots, \beta_N]$ is a vector of systematic risks (i.e., the betas) corresponding to these N assets. Hence, if the proportion of any asset included in the market portfolio changes other conditions held constant (e.g., volatility of the individual assets, their cross-correlations, expected returns), then changes in the weights of the other assets can be expected. This, however, changes the composition of the market portfolio and, consequently, the interdependencies of each asset with the market portfolio and the volatility of the market portfolio. Hence, changes in the beta of the assets can be expected even if there were no changes in the variance-covariance matrix of these assets and their expected returns. Obviously, in the real world, additional changes can occur at the same time as the change in the weights. However, to keep the model mathematically tractable, it is necessary to make same simplifying assumptions that will enable us to focus on the impact of the variables of interest.

In this case, as we wish to investigate the impact of the decline of the banking sector on the betas of the other sectors, we assume that in our model: (i) there are just to sectors: banking (B) and non-banking (A), (ii) the sectors are positively correlated, (iii) the banking beta before the change in the weights is greater than one, (iv) the variance-covariance matrix of the banking and non-banking sectors does not change.

It is important to note that limiting attention to a two sector market is not unreasonable. Let us use N to denote the number of sectors (not individual assets). Let us use subscript B for one of these sectors (namely, the banking sector), and denote the sum of weights of the other N-1 sectors as w_A, i.e., $\sum_{i=1}^{N-1} w_i = w_A$. Then, $w_A + w_B = 1$, and if R_A is defined as $R_A = w_A \sum_{i=1}^{N-1} \frac{w_i}{w_A} R_i$ it satisfies $\sum_{i=1}^{N-1} w_i R_i = w_A R_A$. This however means that $w_A\beta_A + w_B\beta_B = 1$ where

$$\beta_A = \frac{w_A\sigma_A^2 + (1-w_A)\operatorname{cov}_{A,B}}{w_A^2\sigma_A^2 + (1-w_A)^2\sigma_B^2 + 2w_A(1-w_A)\operatorname{cov}_{A,B}} \quad (1)$$

where σ_A^2 denotes the variance of sector A and $\mathrm{cov}_{\mathrm{A,B}}$ denotes the covariance between sectors A and B.

It is clear that w_{A} enters (1) in a non-linear way, and also that the sign of the first derivative of β_{A} with respect to w_{A} depends on the sign of the numerator (the denominator will always be positive) which has a polynomial form. Moreover, whether β_{A} increases or decreases will be determined by the quadratic polynomial and, in particular, it is important whether σ_A^2 is greater or smaller than $\sigma_{\mathrm{A,B}}$ (details of the calculations are in Appendix 1). Figure 1 illustrates these two possibilities. In Panel A the position of the sectoral betas are plotted for $\sigma_{\mathrm{A}}^2 = 0.09$, $\sigma_{\mathrm{B}}^2 = 0.36$, $\mathrm{cov}_{\mathrm{A.B}} = 0.11$, which correspond to the values observed on the US market for the utilities sector (A) and the banking sector (B) over the period of the sample. The covariance of 0.11 corresponds to a correlation of 60% between the two sectors, which is also calculated from the data. Panel B shows a more hypothetical situation, when the two sectors have zero correlation while the variances are the same as those used in Panel A.

These examples given in Figure 1 suggest a particular relationship. Namely, hold the variance-covariance matrix constant and take any proportion of the stock market for A, say $\mathrm{w}_{\mathrm{A}}^{'}$, such that $\beta_{\mathrm{A}}^{'}$ <1, then β_{A} is greater than $\beta_{\mathrm{A}}^{'}$ for all $\mathrm{w}_{\mathrm{A}} > \mathrm{w}_{\mathrm{A}}^{'}$. This is a general feature, as is given in Proposition 1.

Proposition 1

If $\sigma_A^2 < \sigma_B^2$, $\operatorname{cov}_{A,B} \geq 0$ *and* σ_A^2, σ_B^2, $\operatorname{cov}_{A,B}$ *remain constant as* w_A *changes, then, for any* $w_A^{'}$ *such that* $\beta_{\mathrm{A}}(\mathrm{w}_{\mathrm{A}}^{'}) < 1$, $\beta_{\mathrm{A}}(\mathrm{w}_{\mathrm{A}}^{'}) < \beta_{\mathrm{A}}(\mathrm{w}_{\mathrm{A}})$ *for every* $\mathrm{w}_{\mathrm{A}} > \mathrm{w}_{\mathrm{A}}^{'}$.

The formal proof of Proposition 1 is provided in Appendix 1. Note Proposition 1 does not imply that A's beta is always increasing as A's proportion of the market increases (Panel B of

Figure 1 shows this is not the case). However, it does imply that if for a given w'_A, $\beta'_A < 1$, then β_A must be higher whenever A's proportion of the market is higher.

Of course, when there is a decline in the proportion of a particular asset in the market it is unlikely that the other things will remain constant but it is worth noting, however, that this does not have to be the case. For example, the increase in the proportion of A in the market may arise because a proportion of asset B is simply taken off the market and in such a case it may be possible for the variance-covariance matrix to be unaffected. However, particularly in the case of a major financial crisis, we can expect that the effect we document formally in Proposition 1 will only be part of a more general crisis impact. Even so, it may still be possible to identify such an effect in the data.

Given the simplicity of the CAPM assumptions (e.g., normality of returns) and numerous issues with the empirical testing of its validity, additional factors that attempt to better isolate idiosyncratic effects from those that can be attributed to various market forces have been long debated in the literature (e.g., Campbell and Vuolteenaho, 2004; Carhart, 1997; Chung et al., 2006; Fama and French, 1992, 1993). The Fama-French factors (Fama and French, 1992,1993) are among most popular ones, however, these factors are not without criticism either (e.g., Asness and Frazzini, 2013; Bartholdy and Peare, 2005, Connor et al., 2015). These factors do not carry similar properties of the CAPM betas and most importantly for our purposes, the coefficients associated with the Fama-French factors do not sum to one or any other constant, so the impact we identify will be restricted to the market risk factor.

Section 3 discusses the relevant literature in relation to the relevant countries and sectors during the crisis but here we discuss the transmission mechanism and effect of the crisis on risk more generally. There are many paper addressing the contagion across markets, both across global stock markets and from the financial sector to the real sector. Looking at stock markets, Bartram and Bodnar (2009) address the timing and scale of value destruction and document on average a 40% decline across a broad array of stock markets, identifying the period mid-September to end October 2008 as the core period of contagion. Mishkin (2011) also documents the speed of the development of the financial crisis based around Lehman's bankruptcy, the AIG collapse and the struggle to get the Troubled Asset Relief Program approved by Congress. Covitz et al. (2013) document that runs in asset-backed commercial paper market spread rapidly from August 2007. Karanasos et al. (2014) find increased contagion across markets during the financial crisis. Addressing banking stocks particularly, Dias and Ramos (2014) undertake a clustering analysis of the world banking sector (across 40 countries) in the crisis and find periods of intense contagion. They also find almost all European countries are placed together in a group that also includes those countries whose banking sectors that experienced the most severe crisis. Gandhi and Lustic (2015) find large banks have lower risk adjusted returns than smaller banks, notably in the period 2002 to 2007 (probably indicating a 'too big to fail' overvaluation of large banks during this period). Horta et al. (2014) show a significant increase in the correlation of local Hurst exponents across eight G12 countries in the crisis which indicates financial contagion across these markets.

Turning to broader impact, Bekaert et al. (2014) use a factor model to predict crisis returns on 415 country-industry portfolios and use factor loadings and residual correlations to indicate contagion and determine the process of transmission. They argue that contagion effects from the US and global financial sector are small compared to contagion effects from domestic markets to the individual portfolios. Duchin et al. (2010) find that corporate investment declines significantly following the onset of the financial crisis, the effects being greatest for firms that have low cash reserves or high short term debt. Similarly, Campello et al. (2010) using survey evidence from Chef Financial Officers in the US, Europe and Asia found significant declines in corporate spending plans following the crisis and found the planned cuts were deeper for credit constrained firms.

In terms of transmission mechanisms, Graham and Harvey (2010) show, using evidence derived from surveys of chief financial officers, that the level of disagreement over what respondents believed the appropriate equity risk premium to be increased significantly during the crisis and that the average view of the equity risk premium level also grew markedly. Derrien and Kecskés (2013) address the real impact of a particular financial shock, the reduction in analyst coverage arising from broker closures and mergers, and find investment and financing of firms falls by approximately 2% for each unit drop in the number of analysts covering the firm. Keraney and Poti (2008) find that market and idiosyncratic volatility in European stocks is pro-cyclical, rising during times of low market risk. Campbell et al. (2011) find distressed stocks have variable returns and market betas and tend to underperform safe stocks by more in times of high market volatility. Dell'Ariccia et al. (2008) find sectors that depend more on external finance are hit hardest during crises. Duygan-Bump et al. (2015) find that financing constraints of small firms was one of the big drivers of unemployment during the 2007-2009 crisis. Laeven and Valencia (2013b) find that financially dependent firms benefit most from bank recapitalisation, indicating that bank weakness hits financially dependent firms hardest. Ivashina and Scharfstein (2010) show that new lending to large borrowers fell by 47% during the 4th quarter of 2008 compared to second quarter of 2007 and that lending for real investment fell by 14%. Claessens et al. (2012) using company data from 42 countries found that firms with greater sensitivity to trade developments were most affected by the financial crisis. See also Allen et al. (2009), Cerra and Saxena (2008), Laeven and Valencia (2010), Reinhart and Rogoff (2008), Reinhart and Rogoff (2009), and Antony and Broer (2010) for a survey.

A particular feature of the literature is that the transmission of the financial shock to output and stock values of the real sector appears to arise through the reduction in loans and this is particularly an issue for firms that are constrained. This does not directly explain why funding is harder to come by. One explanation is that banks are themselves constrained but this paper offers an alternative explanation, namely that the change in the composition of the stock market suggests that low risk sectors require a higher return during the crisis.

3. Countries and sectors

In this section we discuss in more detail the justification for the choice of the countries used in the analysis, and the focus on the industrials and utilities sectors.

3.1. The countries

The global financial crisis of 2007 initially developed in the US, although it has had enormous impact on the financial sector of almost all developed countries (Baur, 2012). Given the central role of the US in the financial crisis and wide range of available data, we begin our analysis by focusing on potential composition effects in the US, using daily returns of the utility, industrials and banking sector indexes constructed using data from AMEX, NASDAY and NYSE. However, given that the impact of the financial crisis was not uniform across countries, we seek to utilize this fact by comparing the effects across a series of countries with different severities of the crisis. A good measure of the extent of the differences can be gauged by looking at the group of 12 countries, G12 (actually 13 as a result of Switzerland’s membership), since this is a group of industrially advanced countries whose central banks co-operate to regulate international finance. As indicated in the introduction, the scale of the impact of the financial crisis in these countries is classified in the Systemic Crisis Data Bank as a major systemic banking crisis in Belgium, Germany, the Netherlands, Spain, the UK, and the US, as 'marginal' in France, Italy, Sweden and Switzerland, and absent, in Australia, Canada, Japan, (Laeven and Valencia, 2013a). We use this exogenous metric (i.e., classification of the countries into these with (i) major systemic crisis, (ii) marginal and (iii) no systemic crisis) as an indicator of the scale of impact of the financial crisis in a country. The basic conjecture is that the greater the scale of the crisis, then the greater should be the composition effects. Within the G12 group, there were also significant differences in government responses. For example, the US, the UK and the Netherlands engaged in significant nationalisation whereas this was often comparatively or sometimes totally absent in other countries, and by 2012 within the G12, the average cost of asset purchases and guarantees was 12% of GDP in the countries with major systemic crisis (Belgium 7.7%, Germany 17.2%, Netherlands 3.3%, Spain 1.8%, UK 30.8%, and US 13%) and 1.75% of GDP for the countries categorised as marginal (France 0.3%, Italy 0%, Sweden 0%, and Switzerland 6.7%).[3]

3.2. The sectors

The banking sector was at the heart of the financial crisis and is at the centre of our analysis. We have argued that the dramatic changes in the banking, and broader financial sectors, could lead to spill-over effects onto other sectors, and given that we utilise differences in the scale of systemic crisis across the countries, we begin with a brief discussion of the banking sector in our sample. The notion of, what we call, a composition effect is that changes in market share of one part of the market are very likely to spill-over to the betas of other sectors, as a result of the overall constraint, and thus we may observe a relationship between the severity of the systemic crisis and the betas of other sectors. Figure 2 provides data on how the banking sector's shares of the stock markets have differed during the crisis relative to the pre-crisis period. For each country we calculate the average market share of the banking sector during the crisis to the equivalent average share over the period of the same length before the crisis (monthly observations are used). We adopt two alternative dates as the relevant markers for the start of the crisis. These are August 2007 and September 2008 (see below, Section 3.3, for discussion). Thus, for each country, the left hand bar shows the ratios using August 2007 as

[3] Laeven and Valencia (2013a).

the start of the financial crisis and the right hand bar relates to September 2008 as the start of the financial crisis.

*********************** insert Figure 2 here ***********************

There is significant disparity across countries. The Netherlands provides the most dramatic change with the banking sector's share of the stock market during the crisis averaging about only 3.9% of the pre-crisis figure. This dramatic effect was heavily due to the nationalisation programme that made the government owner of ABN AMRO, ASR, and SNS REALL, although the government has a stated commitment to return the companies to the market. At the other extreme, Australia and Canada, both having avoided a systemic crisis, have seen noticeable increases in the share of the banking sector rather than falls. The countries in Figure 2 are grouped according to the three categories of systemic crisis, the first three countries having no systemic crisis, the next having marginal systemic crisis and the final six are those countries which had a major systemic crisis. There is a clear relationship between the categories and the changes in market share. Australia, Canada and Japan have an average ratio of 1.03, those countries with marginal systemic crisis have an average of 0.82 and those with major systemic crisis the average market share of the banking sector during the crisis is half of the pre-crisis share, 50.8 (for these numbers August 2007 is used as the start of the financial crisis).

Spain and Sweden are outliers from their groups (both having ratios of almost 1 relative to averages of 0.76 and 0.43 for the other countries in the marginal systemic crisis and major systemic crisis groups). The fact that the mean market share of Spain's banking sector during the crisis is almost as high as its pre-crisis level may be a reflection of several factors (the systemic crisis in Spain arose in 2011 (compared to 2008 in Belgium, Netherlands, UK and US and 2009 in Germany (see also Royo, 2013)), the fact that the pre-crisis Spanish debt to income ratio was low, there has been no nationalisation of the Spanish banks, Spain received enormous EU support, and the non-banking sector in Spain has been hit comparatively harder than in the other countries that have experienced a major systemic crisis). As noted, Sweden has a higher ratio than the other countries in the marginal systemic crisis group. The reason probably lies in the fact that Sweden went through a banking crisis in 1991-1992 that was similar in many respects to the subprime crisis that precipitated the global financial crisis (Drees and

Pazarbasioglu, 1998; Sandal, 2004). Hence there was significant intervention and restructuring in Sweden before the current crisis. Indeed Sweden's response to the 1991-1992 crisis has been held as a model for the current crisis (See Krugman, 2008; Jonung, 2009). Following on from that crisis Swedish banks were profitable and had substantial buffers following a number of good years. As a result of the previous crisis they did granted loans as hastily as the banks in the United States and they have not been exposed to any great extent to the type of financial products that have been part of the problem.[4] Thus in many regards Sweden is an outlier with regard to the position of its banking sector both pre- and during the crisis.

In the paper we analyse the change in risk of the industrial sector and the utility sector. We address the utility sector because there is strong anecdotal evidence that this sector have been particularly attractive in the crisis. Utility infrastructure companies are typically considered defensive stocks but there is evidence that utilities have been perceived as even safer homes for investment during the period of heightened uncertainty arising from the recent financial crisis. There are obvious reasons why this may be the case. For example, the prices and/or the returns for a large proportion of the companies are regulated and hence revenues are somewhat protected during periods of high business risk. Furthermore, the outputs are more essential to consumers and the economy than other sectors so demand is far less volatile even for those companies that are not directly regulated.

Utility industries around the world have been for several years the focus of major investment programmes. The most obvious example is probably the energy sector where in most western economies traditional, carbon heavy generation capacity is being replaced with renewable generation (wind, solar, nuclear, biomass) on a large scale. This new generation is typically sited away from traditional generation hence, in addition to cost of the new generation, the transmission systems require billions of dollars of additional investment to upgrade and extend national transmission systems. IT developments in modern smart networks also call for large-scale upgrades to network systems. Other sectors, such as transport, similarly require massive infrastructure inputs. Despite the financial crisis, these sectors have found it relatively easy to find funding. For instance, across different sectors Afonja (2012), Cambridge Economic Policy Associates (2014), Hansen (2010), Ofgem (2013) and PWC (2013) emphasise that funding has been robust at attractive rates. Moreover, Maung and Mehrota (2010) show that utilities credit ratings have been more robust than other sectors during the crisis.

[4] Speech by Svante Öberg, Deputy Governor of Riksbank (Swedish Central Bank), in 2009.

The attraction of utilities during the financial crisis also appears to hold when one looks at private equity. The strategy of Berkshire Hathaway through the crisis is a classic example of this point. Berkshire Hathaway (2008) emphasised the importance of utility businesses to the company's strategy looking forward. Between 2009 and 2013, Berkshire Hathaway's revenue from railroad, utilities and energy business increased from $11,434bn to $73,757bn (Berkshire Hathaway, 2013), mostly funded by acquisitions. Recently, Charles Munger, Berkshire Hathaway's Vice Chairman, suggested that Berkshire Hathaway will soon be the biggest utilities business in the US (Wall Street Journal, 2014). The perception of utilities as being particularly low risk in the financial crisis should indicate that a fall in market risk relative to the pre-crisis level should be observed, unless some other factor acts to offset this. Hence failure to observe a relatively uniform decline in market risk for utilities could be taken as providing some evidence of an offsetting composition effect.

As indicated in the introduction, industrials have not had a favoured 'halo effect', and we therefore assume that general industrial stocks are far more likely to experience a stock market composition effect rather than be seen as a safe haven in the crisis. So when the financial market declines as a share of the stock market we conjecture that industrials will face a composition effect leading to upward pressure on its stock market risk measure. Furthermore, we conjecture that those countries that suffered the greater systemic crisis are more likely to observe an increase in the risk measures of industrials compared to their pre-crisis levels.

4. Data

As discussed above, testing for our hypotheses is conducted at two levels. First, the case of the US market is studied, and then the analysis of international markets is performed. Below we describe the samples created for the US and the G12 countries.

4.1 The US sample

To analyse the US market we use time series collected from the webpages of Professor Kenneth French[5] and DataStream, to which we refer to as KF-Data and DS-Data respectively.

The KF-Data provide time series of daily returns on a wide range of industry indexes, excess return on the market, risk free rate of return and returns on the SML, HML, RMW and CMA factors. The industry indexes based on 49 Compustat SIC classifications are selected for the study because this is the most detailed classification that is available. It provides returns for the utilities and the banking sectors which we refer to as R_{U49} and R_{B49} respectively. However, the industrials index needs to be calculated.[6] Following the specification of the DS Industrials Index (ICB Code 2000) we calculate the returns on the KF industrials index using returns on the following indexes: Construction materials, Machinery, Electrical Equipment, Automobile and trucks, Aircraft, Shipbuilding and railroad equipment, Defense, Business services, Measuring and control equipment, Business supplies, Shipping containers, and Transportation. We equally weight these returns and refer to the returns of this newly created industrials index as R_{I49}.

However, given that the industrials sector index we created may be biased towards particular sectors (e.g., it may overweigh components with small weights) we also construct an alternative control sample. Grout and Zalewska (2006), when analysing the effect of proposed changes in regulation of utilities on the market risk of UK utilities, constructed a sample of 'old-economy' stocks that could be expected to respond in a similar way to changes in general market conditions save for the proposed changes in regulation. Following this approach, a comparator index is calculated as the equally weighted index of the Agriculture, Food products, Candy and soda, Beer and liquor, Tobacco products, Apparel, Textiles, Wholesale, Retail, Restaurants, hotels and motels indexes and the indexes included in the construction of the industrials index. The returns on this control index are referred to as R_{C49}.

Using the KF-Data has two advantages. First, it provides indexes representative for the whole US economy, as the stocks used to construct indexes are traded on NYSE, AMEX, or NASDAQ. Second, the SML, HML, RMW and CMA factors are constructed using the same methodology as the other indexes. There are, however, three issues that need to be addressed when dealing with this data. First, as discussed above, the KF-Data do not provide an industrial index for the economy and construction of the equally weighted index may create a bias

[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research
[6] There are 5, 10, 12, 17, 30, 38, 48, and 49 industry classifications available.

towards components with small weights. Second, there are no indexes for other counties constructed using the same methodology. Third, using several indexes defined on overlapping subsets of the same set of stocks causes there are potential issues with multicollinearity.

To deal with the first two issues we also use US industry indexes provided by DataStream. To check the robustness of our findings we collected S&P1500 indexes and DS-calculated indexes. The S&P1500 indexes are collected because, (i) there is a 'ready-calculated' industrials index, and (ii) in addition to the returns on the utilities index, returns on four sub-indexes are also available. In particular, there are indexes for electricity utilities, gas utilities, water utilities and multi-utilities. The DS calculated indexes, on the other hand, do not have detailed sub-indexes for the utilities sector but they are calculated for many countries providing a comparable sample for the G12 analysis. Both sources provide indexes for the banking sector which we also collected and use in the analysis. For all these indexes we calculate log-returns and denote as R_{SP} with an additional superscript to indicate a sector (B for banking, I for industrials, etc.). The issue with potential multicollinearity requires a more detailed discussion and will be addressed in Section 4 when we discuss the US sample results.

The sample starts on 1 January 1996 and ends on 31 July 2014. The beginning of the sample is dictated by the data availability. The KF-Data series go back to July 1926 and end on 31 July 2014 (at the time of the sample collection), but the other time series are much shorter. The S&P1500 time series start on 3 February 2004, and some DS-calculated time series start at various points through 1995.

To keep the sample as long and as representative as possible we start the KF-Data and DS-calculated time series on 1 January 1996 and end on 31 July 2014. The S&P1500 time series start on 3 February 2004 and end on 31 July 2014. We do not truncate all the time series to 2004 to maintain the sample long enough to have a good overview of the changes that occurred after 2007.

Basic summary statistics of the returns on the KF and S&P1500 indexes are presented in Table 1. The statistics for the log-returns on the DS-calculated indexes are presented in the next section, i.e., together with the statistics for the other G12 countries.

******************* insert Table 1 here ***********************

4.2. The G12 sample

To further understand the analysed phenomena we provide an international comparison of the changes in the market risk of the utilities, the industrials and the banking sectors over the period 1 January 1996 – 31 July 2014. The choice of countries was partly dictated by data availability, i.e., information about stock market returns of the industrials and the utilities sector was available for long enough, but also a range of countries' experiences since 2007. Ideally, we targeted to construct a sample of countries that experienced severe economic and stock market repercussions during the financial crisis, and countries that did not seem to be affected by the collapse of the sub-prime mortgage market in the US.

The attention has been focused on the G12, a group of 13 highly industrial countries whose central banks co-operate to regulate international finance. As mentioned in Section 2.2, according to Laeven and Valencia (2013a) the G12 countries can be divided into three groups depending on the severity of the systemic problems in their banking sectors, those which experienced a major systemic banking crisis (Belgium, Germany, the Netherlands, Spain, the UK, and the US), those with a 'marginal' systemic banking crisis (France, Italy, Sweden and Switzerland), and those without it (Australia, Canada, Japan).

We collected the DS-calculated stock market and the banking sector indexes for all the 13 countries. However, the utilities index was not available for Sweden and the Dutch one stopped being calculated on 24 February 2004. Therefore, changes in the market risk of the utilities sectors are analysed for 11 countries only. Moreover, there are also some issues with the DS General Industrials indexes. The French index is available from 29 January 1999 and there are no General Industrials indexes for Spain and Sweden. In the case of these three countries the DS-calculated Industrials indexes use used. These indexes are much broader, and may not be directly comparable with the General Industrials index, but they are available for the whole period of interest and are the best proxy that we have. All the time series (except those for France) are collected for the 1 January 1996 – 31 July 2014 period. The summary statistics of the log-returns on market, banking, industrials and utilities indexes are presented in Table 2.

******************** insert Table 2 here ********************

4.3 Methodology

To test for the existence of the composition effect time dummies are needed to observe the potential impact of the financial crisis on market risk across sectors and across countries. Although it is common to treat 2007 as the starting year of the financial crisis, it is not altogether clear which exact date is to be singled out. Moreover, the financial crisis did not start in all countries at the same time. While in the US and the UK the financial crisis started in 2007, other countries started to experience it in 2008 (Laeven and Valencia, 2013a). We tie the start of the financial crisis dummies to specific market events. In particular, we pick two specific dates to define two time dummies. The first date is 9 August 2007, i.e., the day when BNP Paribas announced that it was ceasing activities in three large hedge funds specialising in US mortgage market. This was probably the first point in time that it was stated openly that many trillions of dollars of derivatives were likely to be worth far less than was assumed at the time. The second date is 15 September 2008, i.e., the day Lehman Brothers went bankrupt.

We use two dummies to capture the time change in risk measures. Dummy D_{07} is defined as 1 from 9 August 2007 till 31 July 2014 (the end of the sample) and zero otherwise, and Dummy D_{08} is defined as 1 from 15 September 2008 till 31 July 2014, and zero otherwise.

When testing for the composition effect on US data (Section 4) we only use D_{07}. This is because the financial crisis started in the US in 2007 (Laeven and Valencia, 2013a). In the regressions for the G12 countries both dummies are used. This is because in all these countries, but the US and the UK, the financial crisis started in 2008. As the month of the beginning of the financial crisis for the individual countries are hard to be determined we use both D_{07} and D_{08} to test the robustness of our findings. The regressions with the D_{08} dummy are presented in Appendix 2.

The Fama-French 3-Factor and 5-Factor CAPM specifications, i.e.,

$$\begin{aligned} R_t = \alpha + \alpha_D D_{07} + \beta(R_{M,t} - R_{free,t}) + \beta_D D_{07}(R_{M,t} - R_{free,t}) \\ + \gamma SMB_t + \gamma_D D_{07} SMB + \delta HML_t + \delta_D D_{07} HML_t + \varepsilon_t \end{aligned} \tag{2}$$

and

$$\begin{aligned} R_t = \alpha + \alpha_D D_{07} + \beta(R_{M,t} - R_{free,t}) + \beta_D D_{07}(R_{M,t} - R_{free,t}) + \gamma SMB_t + \gamma_D D_{07} SMB \\ + \delta HML_t + \delta_D D_{07} HML_t + \chi RMW_t + \chi_D D_{07} RMW_t + \varphi CMA_t + \varphi_D D_{07} CMA_t + \varepsilon_t \end{aligned} \tag{3}$$

respectively, as well as a simple market CAPM specification

$$R_t = \alpha + \alpha_D D_{07} + \beta R_{M,t} + \beta_D D_{07} R_{M,t} + \varepsilon_t \tag{4}$$

are used with R_t denoting daily excess returns (Eqs. (2) and (3)) or returns (Eq. (4)) on individual indexes (utilities, industrials, banking and control index) or differences between returns on indexes of utilities sector and returns on indexes of industrials or of the control sample. For the G12 countries we used Eq. (4) specification only.[7]

Tables 1 and 2 clearly show that time series of returns are far from normally distributed. To deal with the potential bias in the estimated coefficients and standard errors a GARCH (p,q) specification of the variance is applied. The magnitude of p and q was determined for each individual regression based on the correlation tests of squared standardised residuals, Durbin-Watson statistics and Schwartz criterion. As the GARCH effects are not of main interest they are presented in Appendix 2.

At this point a few words are necessary to explain our choice of using a univariate GARCH model specification. Since Engle and Sheppard (2001) showed that an estimation of a multivariate DCC model can be significantly simplified DCC models gained significantly on popularity. The estimations we provide in the paper are in fact the first step for the DCC models calculations. The next step would be to utilise the residuals of the univariate GARCH to estimate conditional correlations. This would however require strong assumptions about the joint distribution of the standardised residuals (Bollerslev et al., 1988; Bauwens et al., 2006).

Each country in our sample experiences of the financial crisis were different. It is not only that market turbulences happened at slightly different times, but also their local markets, including effects on the banking sector, utilities, and industrials were different as the result of differences in fundamental organisation, structures, regulatory regimes and approaches of the local authorities to weakening economies and confidence. Therefore, the fundamental assumption of the DCC models that conditional correlations must obey the same dynamics is most likely unrealistic.[8]

One of the fundamental assumptions of the multivariate GARCH model is that all investors have the same expectations about mean, variances and covariances of returns. This may not be true across countries, and especially during the financial crisis. Numerous anecdotal evidence

[7] We also controlled for potential changes in market risk during the dotcom bubble but this had no impact on the results and is not reported.

[8] It is commonly accepted that it is sufficient to specify conditional variances of financial time series as GARCH(1,1). However, as it is shown in Appendix 2, more lags in the GARCH specifications were needed for nearly all time series we consider. They vary between the commonly used GARCH(1,1) and GARCH(3,2).

suggests that confidence in the success of the local policymakers in dealing with the weakening situation was very different (e.g., while the Greek electorate seemed to put lots of trust in solutions proposed by Syriza, other countries remained sceptical about them). Finally, to maintain comparability of regressions across the samples (i.e., the KF-Data, DS-Data and G12 sample), it seems reasonable to use the same method of estimation across the samples.

5. US results

Before we discuss the results a few words about the sample are needed. Any multivariate model is potentially exposed to multicollinearity. The Fama-French factors have been constructed by regrouping a set of stocks and it can be expected that there are some potential interdependencies among the factors and the market index. These interdependencies may be time varying and more importantly, may intensify during particular market conditions. Table 3 shows three sets of correlations between the excess returns on the market and the four Fama-French factors for the whole period (panel A), for the 1 January 1996 – 8 August 2007 period (panel B), and for the 9 August 2007 – 31 July 2014 period (panel C).

****************** insert Table 3 here ************

The Panel A correlations are not particularly high except for the one estimated for the HML and CMA that exceeds 50%. However, the pre-financial crisis correlations show much higher levels: HML correlates with CMA at 70.6%, HML is also highly correlated with the market excess returns (-63.9%) and RMW (44.8%). Moreover, RMW correlates at -45% with SML and the market excess returns correlate with CMA at -47.7%. The post 9 August 2007 correlations are lower, which probably reflects significant changes in the compositions of the factors (e.g., banks may have become smaller, and reduced their B/M ratios) but still three correlation coefficients are around 50% (HML v. RMW, R_M-R_{free} v. HML and R_M –R_{free} v. RMV).

One can expect therefore that putting all these variables and their interactions with the time dummy in one regression specification may create issues with multicollinearity. Table 4 presents tolerance (1-R^2 or 1/VIF) for the independent variables of Eqs. (2) and (3). The tolerance statistics are much higher when the three rather than five factors are used. In particular, the HML's tolerance is low for the five-factor specification. It shows that only 20% of the variable variance is independent of the other variables. This suggests that the 3-Factor model is potentially more reliable than the five-factor model for the problem at hand. Given that we are interested in the effects of the financial crisis on the CAPM beta only, we do not further investigate the best way to estimate the 5-factor model coefficients, especially that the rest of the paper will use the classic-CAPM one-factor specification.

*********************** insert Table 4 here *****************

Table 5 shows regression results for the Fama-French 3-Factor model and Table 6 shows the regression results for the Fama-French 5-Factor model as discussed in Section 4.3. The R^2 are high, but this is not surprising given the discussion above.

The first column of Tables 5 and 6 show that the beta coefficients estimated for the industrials index increased during the financial crisis. The increase is statistically significant at 1%. Moreover the statistically significant increase is observed for the SMB, RWM and CMA factor and statistically significant decrease is obtained for the HML factor. The increase of the beta coefficient is consistent with our hypothesis. In addition, the same effects (in the size of statistical significance and direction of change except for SMB in the five-factor specification) are observed for the control index constructed to mimic old-economy stocks. This supports the expectation that the control index has similar properties to the industrials index although consists of a much broader asset class. The next two columns show the coefficients estimated for the banking sector ($R_{B49} – R_{free}$) and the utilities sector ($R_{U49} – R_{free}$). They show that the beta of the banking sector increased (however, not significant for the five-factor specification) and the beta of utilities declined during the financial crisis.

The last two columns of Tables 5 and 6 confirm our expectations that the utilities sector, in general, is less risky than the industrials and the old-economy stocks, and that the difference in the market risk of the industrials index and of the control index increased statistically significantly during the financial crisis.

********************** insert Table 5 here *********************

********************** insert Table 6 here *********************

The results obtained for S&P1500 indexes confirm these findings. Tables 7 and 8 show the regression results obtained for the level and differences specifications, respectively, obtained for S&P1500 indexes. Table 7 confirms that the market risk of the banking and of the industrials sectors increased statistically significantly during the financial crisis. It is also clear that the risk of utilities decreased. A statistically significant decline is obtained for the S&P1500 utilities index and all its sub-indexes except for the gas utilities which does not show a statistically significant change in the beta coefficient.

********************** insert Table 7 here *********************

Table 8 documents the relative changes in the market risk of the utility companies. It shows the estimates of the coefficients when the returns on the utilities index, or its sub-indexes, minus returns on the industrials index are used as the dependent variable. All the interactive effects of the slope coefficient are statistically significantly negative at 1% and 5%. The decline in the coefficient is also substantial. Except for the gas utilities, the gap between the market risk of the utilities and of the industrials, at least, doubled during the financial crisis.

********************** insert Table 8 here *********************

All in all the above results show that during the financial crisis the market risk of the industrials sector increased, while it decreased for the utilities sector. This resulted in a statistically significantly wider gap between the market risks of these two sectors.

5. G12 sample

The primary objective of this section is to undertake an international comparison of the change in the pattern of the industrials and utilities beta coefficients across the G12 countries.

Table 9 shows the results of regressions across the 13 countries for industrials (Panel A) and banks (Panel B) using D_{07} to capture the change in beta during the crisis period. Looking at industrials first, the change in the beta within the crisis period from the pre-crisis level, the coefficient estimates for $R_m x D_{07}$ are statistically significant at 1% for all of the countries with the exception of Switzerland, significant at 5%, and Canada, where the coefficient is not significant. For most countries there is an increase in the beta of industrials during the crisis but Australia, Canada and Italy show a decline in the beta of industrials during the crisis.

********************** insert Table 9 here *********************

Before discussing the differences in the betas of industrials across the countries, it is helpful first to look at the beta of the banking sector in these countries. Panel B shows the beta of the banking sector before 2007, the column marked R_M, and the change in the beta during the crisis, the column marked $R_M x D_{07}$. This shows that before the crisis the betas of the banking sector were greater than one in most countries, with Australia, Canada and Italy, again being the exception. The betas of the banking sector increased during the crisis compared to the pre-crisis levels for all countries except Canada (the coefficient is positive although not statistically significant) and the Netherlands for which the beta halved during the financial crisis (the estimates are statistically significant at 1%).

If the change in the beta of industrials can in part be explained by the composition effects arising from the decline of the banking sector during the financial crisis then on average we would expect that the effect would be more pronounced the more severe the country's banking crisis and the higher the beta of the country's banking index. Figure 3 helps to see whether the regressions shown in Table 9 suggest that there is any evidence of such a relationship. The vertical axis in Figure 3 measures the increase in risk of industrials compared to the pre-crisis levels. The horizontal axis measures the beta of the banking sector before the crisis, and the vertical axis is drawn through one. All 13 countries are plotted in this space.

********************* insert Figure 3 here ******************

The first point to note is that there are no countries except Sweden in either the upper left or lower right quadrant. Put another way, save for Sweden there are no countries with pre-crisis beta of the banking sector above one that did not have an increase in the beta of industrials during the crisis and no country that had a fall in the beta of industrials which did not have the pre-crisis level of risk of the banking index less than one. Furthermore, there is a clear positive correlation in the graph. In Figure 3 the countries with major systemic banking crisis are marked by triangles, those with marginal systemic banking crisis are marked by diamonds and those with no systemic banking crisis are marked by circles. The figure shows clearly that the six countries that experienced a major systemic banking crisis are amongst the seven countries with the biggest increase in betas of industrials (Sweden again be the exception). Two of the four countries that had a marginal systemic banking crisis have small but positive increases in the beta of industrials and two of the three where there was no systemic banking crisis experienced small falls in the beta of industrials.[9]

[9] It is interesting to note that in recent years it is being claimed that both Australia and Canada engaged in secretive bailouts, well hidden from the public eye. McDonald (2012) argues that secretive bailouts took place in Canada and similar stories have been leaked in Australia (http://www.moneymorning.com.au/20101203/nab-and-westpacs-secret-bailout-revealed.html)

.

The presence of a composition effect will be somewhat mitigated by a large increase in risk of the banking sector. However, as Table 9 shows, although in general there is an increase in risk in the banking sector there is no systematic relationship between increases in risk and the severity of the banking crisis. For example, the two largest increases in risk of the banking sector occur in countries with only marginal systemic banking crisis (France and Italy). Furthermore, the biggest fall in the risk of the banking sector occurred in a country classified as having a major systemic crisis (Netherlands). The large decline in risk in the Netherlands banking sector may in part be caused by the large-scale nationalization that took place. Note that the Netherlands also experienced the biggest increase in risk of industrials and one might conjecture that part of the impact arose because of the fall in the risk of the banking sector.

Overall, not only do we observe the increase in the beta of industrials as anticipated but in general the scale of change seems to fit the underlying notion that the composition effect will be greatest where the crisis has been most severe and where pre-crisis banking index betas were highest.

The economic impact of these changes in the industrial sector will depend whether investors adjust their view of the equity risk premium as a result of composition changes. This would require a downward revision of the equity risk premium whereas all the evidence points to an uplift (e.g., Graham and Harvey (2010)) in the perceived equity risk premium. We can obtain some view of the potential impact on funding for industrials by taking the increases in industrial betas in Table 9 and, for given equity risk premia, identifying how much greater is the required return to compensate for the increase in risk. Here we consider three equity risk premia: the best estimates of Campbell and Thompson (2008) and Goyal and Welch (2008), 3.1% and 14.5% respectively, and the average (5.7%) drawn across 20 reputable published studies (including Campbell and Thompson (2008) and Goyal and Welch (2008)) reported by Duarte and Rosa (2015). For the six countries that suffered major systemic crisis the increase in required return for the industrial sector would be (in the order Campbell and Thompson (2008) followed by Goyal and Welch (2008)) then Duarte and Rosa (2015)): Belgium 0.78%, 3.6%, and 1.4%; Germany 1.3%, 6.1% and 2.4%; the Netherlands 1.95%, 9.1%, and 3.6%; Spain 0.6%, 2.7%, and 1%; UK 0.7%, 3.2%, and 1.3%; and the US 0.6%, 2.7%, and 1.1%.

********************** insert Table 10 here *********************

Table 10 shows the results of regressions across the eleven countries for utilities (Panel A) and utilities minus industrials (Panel B), using D_{07} to capture the change in beta during the crisis period. Looking at utilities first, the change in the beta within the crisis period from the pre-crisis level, $R_M xD_{07}$, is mixed across the countries. There are four countries where this fell, two of which had coefficients that are not significant. Furthermore, the fact that utilities have proved popular during the crisis and yet many display increases in betas during the crisis period lends weight to the presence of a composition effect. A far clearer picture emerges when one looks at the change in beta for utilities minus industrials. Here the coefficient on $R_M xD_{07}$ is significant at 1% in every country. This is strong evidence that utilities were comparatively favoured. These results suggest that there has been a flight to quality but one of the outcomes of the composition effect is that this is masked by changes in the composition of the market. However, recognition of the composition effect could potentially reduce the transmission of shocks from the financial sector to the real sector in the future.

Figure 4 gives a histogram of the coefficients on $R_M xD_{07}$ in Panel B of Table 10 with the countries allocated into groups: major systemic banking crisis, which is placed first, marginal systemic banking crisis, placed next, or no systemic banking crisis, placed last (countries are placed alphabetically within group). The five countries with a major systemic banking crisis appear fairly consistent with every country having a negative coefficient. In contrast, the marginal systemic banking crisis and no systemic banking crisis appear far more randomly allocated, with both groups having positive and negative coefficients.

********************* insert Figure 4 here *****************

6. Conclusions

The aim of this paper is to look at the effect of the financial crisis from an angle overlooked to date in the finance literature by investigating what we call composition effects, in particular, the impact of composition effects arising from the financial crisis. A composition effect is a change in the market risk of a sector that is caused not by a direct change in that sector but by a change in another sector that affects the composition of the stock market. For example, assume that the proportion of a high market risk sector falls (rises). Other things being equal, since the market weighted sum of betas of the market portfolio has to be one, other sectors must have higher (lower) market risk measures if the overall constraint is to be achieved. The exact relationship is summarised in Proposition 1, which is proved in Appendix 1 of the paper.

In the paper we investigate, in the US in detail and across G12 countries, the pre and during crisis market risk of banking, industrials and utilities. We find that the market risk of industrials is higher during the crisis than pre-crisis in the US and for most of the G12 countries. Furthermore, to the extent that this increase is caused by composition effects arising from the financial crisis, one would expect the increase in market risk for industrials larger the more severe the systemic banking crisis in a country. Across the G12 countries we find such a positive relationship between the increase in the market risk of industrials relative to pre-crisis levels and the pre-crisis market risk of the banking sector. The six G12 countries that experienced a severe systematic banking crisis are amongst the seven countries with the largest increases in the market risk for industrials (the exception is Sweden). We also find that, with the exception of Sweden, all countries with pre-crisis market risk of the banking sector above one experienced increases in market risk of industrials during the crisis and all countries with pre-crisis market risk of the banking sector below one experienced declines in market risk of industrials. Note that, although the market risk of banks changed during the crisis, there is no such systematic relationship between the scale of the systemic crisis and the change in market risk of the banking sector.

Turning to utilities, if, as we argue, utilities were seen as having particularly low market risk during the crisis, then in the absence of any composition effect we would expect their market risk to fall. However, we find that the market risk of the utility sector falls in some countries and rises in others with increases in market risk outnumbering the declines, which we interpret as additional support for a composition effect.

One of the reasons that composition effects are important is that in the context of the financial crisis they have economically significant implications for the transmission mechanism from the financial to real economy and for investment strategies. In the paper we suggest that the collapse of the banking sector contributed to an increase in the market risk of industrials purely because of the composition effect, which would be in addition to any direct real impacts on the sector. Absent other changes, unless an investor also makes the consequent change in their view of the required risk premium, the expected return of the comparatively lower market risk sector will appear to have a worse risk adjusted return than before, which may lead to difficulties in raising finance in the comparatively low market risk sector or underperformance of portfolios. We show, using the evidence from the regressions for the countries that faced a major systemic banking crisis, that these effects can be large, ranging from 0.6% increase in expected return from equity for the US using the best estimates for the equity risk premium of Campbell and Thompson (2008) and to 9.1% for the Netherlands using the best estimates of the equity risk premium of Goyal and Welch (2008). Such an impact could have a significant chilling effect on industrials, in addition to the effect of other linkages arising through economic channels, which is not a reflection of true long term weakness in the sector. These results add to our understanding of the transmission of the financial shock to output and stock values of the real sector. The existing literature suggests the transmission arises through the reduction in loans and this is particularly an issue for firms that are constrained. This does not directly explain why funding is harder to come by for these particular sectors but our results indicate that such a change can arise naturally from the change in the composition of the stock market that occurred in the financial crisis.

Finally, Grout and Zalewska (2006) document declines in the Kalman filter daily betas of old economy stocks during the dotcom bubble. However, the driver behind composition changes in the dot-com bubble was the 'opposite' of the driver behind the composition change arising in the financial crisis since during the dot-com bubble the composition changes arose because comparatively higher market risk stocks grew as a percentage of the stock market. Applying the arguments we have given in the paper, one should therefore expect that old economy companies should have found funding easier despite the competition from high tech stocks. Analysis by Campello and Graham (2013) shows that this is exactly the case. They document significant increases in investment by, and stock price increases of, non-tech firms during this period. They also find significant stock issuance by non-tech firms. They do not investigate the mechanism behind what they refer to as 'cross-sectoral spill-over price effects' but they do attribute it to aggregate stock price changes and overvaluation of the market. In contrast, our results in this paper provide a formal justification for the effects identified in Campello and Graham (2013), which do not depend on overvaluation per se but lie purely in the composition change that took place in the market. In addition to adding useful insight into the effects of the dot-com boom on old economy sectors, this evidence also serves as further strengthening of the arguments for the real impact of composition effects.

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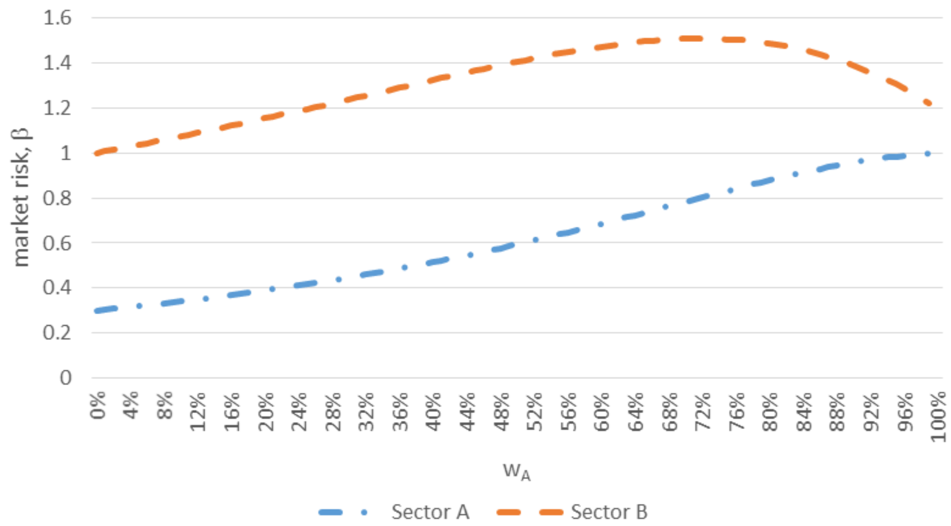
Figure 1. Market risk as a function of weight for a two sector (A and B) market. That is $w_A\beta_A + w_B\beta_B = 1$ where sector A (B) is a lower (higher) risk sector.

Panel A: $\sigma_A^2 = 0.09, \quad \sigma_B^2 = 0.36, \quad \text{cov}_{A.B} = 0.11$



Panel B: $\sigma_A^2 = 0.09, \quad \sigma_B^2 = 0.36, \quad \text{cov}_{A.B} = 0.$

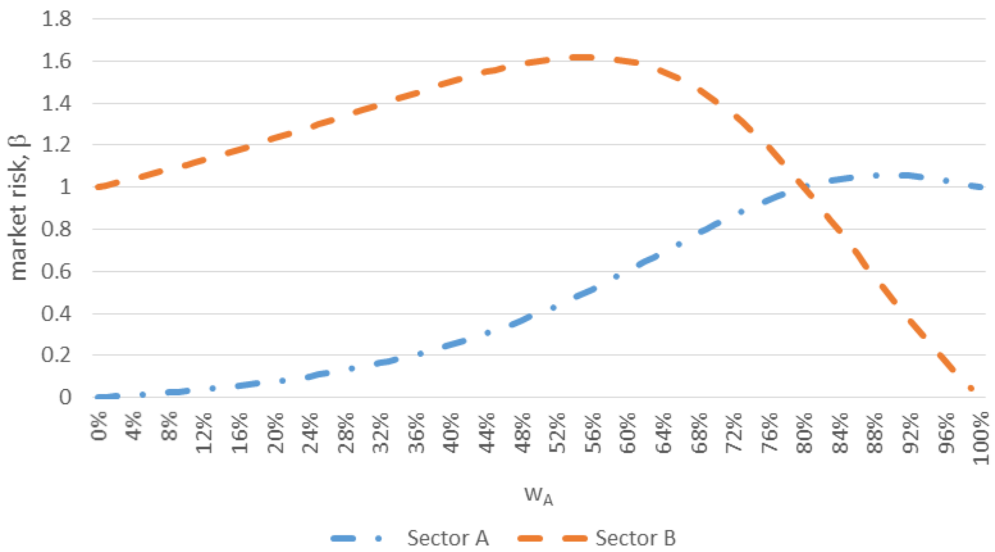


Figure 2. Ratios of the average of market capitalisation of the banking sector as a fraction of the market capitalisation of the corresponding stock market during the financial crisis to the equivalent average over the same length period before the crisis. The start of the financial crisis is defined as August 2007 (darker bars) or September 2008 (lighter bars). The G20 countries are grouped into those without systemic banking crisis (green bars), marginal banking crisis (blue bars) and with the systemic banking crisis (red bars).

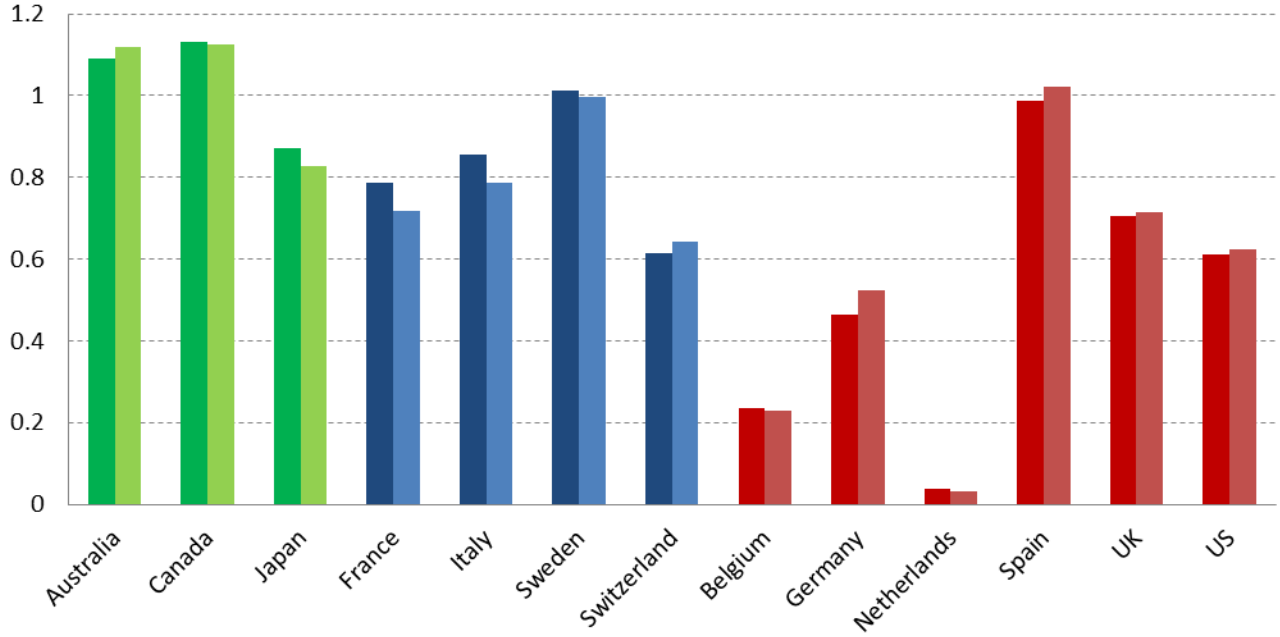


Figure 3. The pre-crisis market risk of the banking sector versus the change in the market risk of the industrials sector for 13 G12 countries. The triangles denote countries classified by Laeven and Valencia (2013a) as those which major systemic banking crisis, the diamonds denote 'marginal' cases of the systemic banking crisis and the circles denote countries that did not experienced the systemic banking crisis in the period 2008-2013.

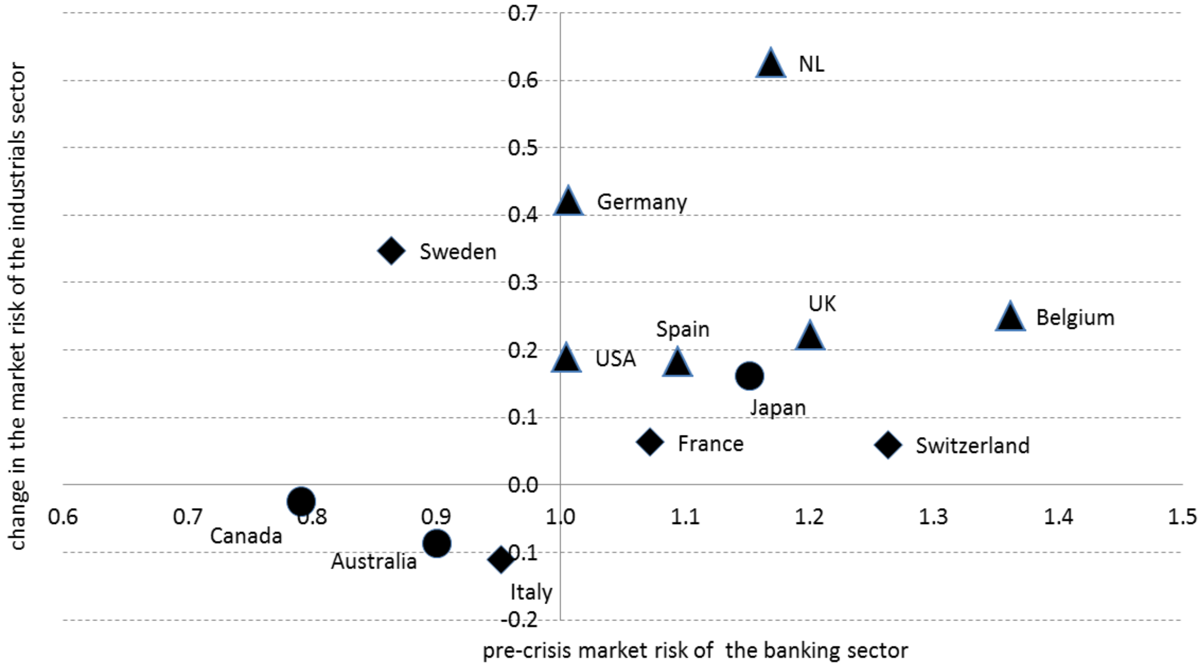


Figure 4. Change in the difference of the market risk of the utilities and the industrials for 11 G12 countries. The blue bars denote countries classified by Laeven and Valencia (2013a) as those which major systemic banking crisis, the red bars denote 'marginal' cases of the systemic banking crisis and the green bars denote countries that did not experienced the systemic banking crisis in the period 2008-2013.

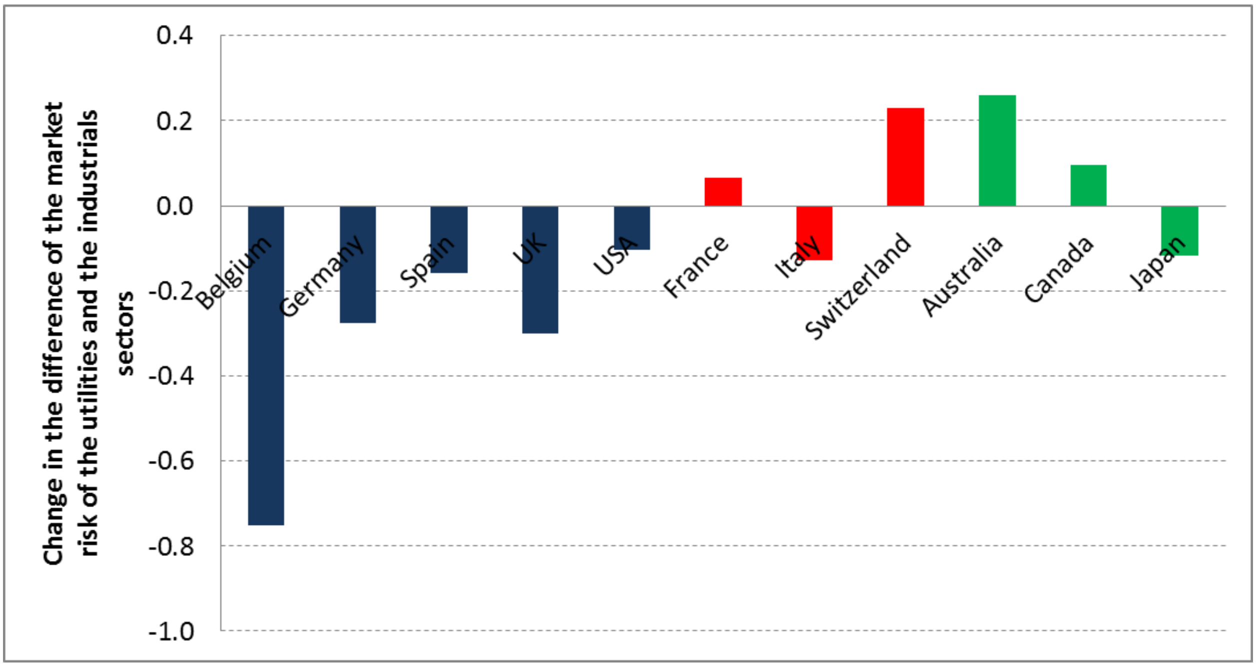


Table 1. Summary statistics of daily stock market -returns for indexes based on Kevin French data (panel A) and for daily log-returns (x100) of S&P1500 indexes provided by DataStream (Panel B). Panel A is based on 4677 observations (1 January 1996 – 31 July 2014) and Panel B is based on 2641 observations (3 February 2004 – 31 July 2014).

	Mean	Median	Min	Max	St. dev	Skewness	Kurtosis
Panel A							
R_{U49}	0.041	0.080	-8.920	14.430	1.136	0.235	16.821
R_{I49}	0.049	0.090	-9.480	10.020	1.301	-0.222	8.463
R_{C49}	0.051	0.090	-7.820	9.960	1.173	-0.144	9.047
R_{B49}	0.044	0.050	-16.98	16.960	1.946	0.426	16.805
$R_M – R_{free}$	0.030	0.080	-8.950	11.350	1.253	-0.105	9.999
SMB	0.006	0.020	-4.620	4.290	0.606	-0.274	6.963
HML	0.014	0.010	-4.860	3.950	0.634	0.083	8.712
RMW	0.019	0.000	-2.860	4.060	0.485	0.329	5.622
CMA	0.015	0.000	-5.900	2.510	0.458	-0.570	10.960
R_{free}	0.010	0.010	0.000	0.030	0.009	0.047	1.500
Panel B							
R_{SPU}	0.032	0.080	-8.500	12.469	1.137	0.047	1.500
$R_{SPUelectricity}$	0.038	0.079	-8.623	12.865	1.140	0.384	16.582
R_{SPUgas}	0.048	0.079	-10.942	14.973	1.365	-0.062	18.750
$R_{SPUwater}$	0.038	0.001	-8.876	11.664	1.474	0.222	10.222
$R_{SPUmulti}$	0.043	0.098	-7.761	11.046	1.111	0.283	15.010
R_{SPI}	0.035	0.067	-9.458	9.190	1.361	-0.356	8.368
R_{SPB}	0.013	0.009	-24.101	25.385	2.702	0.500	19.917
R_{SPM}	0.032	0.072	-9.459	10.958	1.249	-0.233	10.679

Table 2. Summary statistics of daily stock market log-returns (x100) for the DS calculated stock market indexes (R_M), banking indexes(R_B), industrials indexes (R_I) and utilities indexes (R_U) for G12 countries (except for the Netherlands and Sweden for which R_U are not available) over 1 January 1996 - 31 July 2014 (4848 observations).

	Mean	Median	Min	Max	St. dev	Skewness	Kurtosis
Australia							
R_M	0.036	0.032	-8.658	5.778	0.970	-0.486	6.541
R_B	0.054	0.034	-8.494	9.686	1.240	0.035	5.591
R_I	0.035	0.019	-10.298	5.053	1.108	-0.553	5.283
R_U	0.050	0.019	-10.436	8.140	1.230	-0.180	4.538
Belgium							
R_M	0.034	0.051	-8.125	8.240	1.127	-0.158	5.874
R_B	0.005	0.030	-25.407	18.604	2.335	-0.331	11.120
R_I	0.040	0.020	-10.719	11.427	1.649	-0.052	5.032
R_U	0.046	0.015	-9.928	16.656	1.096	0.813	16.332
Canada							
R_M	0.038	0.068	-9.563	8.979	1.060	-0.687	9.530
R_B	0.056	0.024	-14.050	12.168	1.345	0.135	9.762
R_I	0.052	0.006	-12.055	12.403	1.708	0.088	5.578
R_U	0.054	0.032	-6.782	7.975	0.871	-0.196	7.398
France							
R_M	0.035	0.049	-8.411	9.938	1.294	-0.089	4.666
R_B	0.032	0.026	-13.418	18.326	2.157	0.208	6.892
R_I	0.031	0.007	-21.767	25.072	1.825	0.350	20.946
R_U	0.023	0.013	-12.325	21.352	1.853	0.293	8.386
Germany							
R_M	0.029	0.067	-7.787	16.062	1.265	0.084	9.149
R_B	0.000	0.014	-16.458	15.869	1.904	-0.073	9.552
R_I	0.041	0.024	-11.733	14.697	1.686	-0.113	5.731
R_U	0.022	0.023	-10.738	14.748	1.511	0.028	7.605
Italy							
R_M	0.025	0.034	-8.611	10.509	1.370	-0.136	4.432
R_B	0.018	0.022	-11.940	15.802	1.886	-0.114	5.334
R_I	0.013	0.005	-10.038	11.975	1.666	0.106	2.857
R_U	0.038	0.019	-10.258	12.211	1.422	0.234	7.595
Japan							
R_M	0.003	0.005	-9.838	12.304	1.313	-0.333	6.030
R_B	-0.022	0.002	-12.822	14.119	1.859	0.201	4.592
R_I	0.010	0.004	-19.469	13.071	1.815	-0.349	5.613
R_U	0.014	0.007	-12.344	9.079	1.312	-0.098	5.229
Netherlands							
R_M	0.025	0.057	-9.199	9.323	1.301	-0.286	5.597
R_B	-0.017	0.008	-127.00	15.176	2.324	-6.919	210.265
R_I	0.040	0.023	-13.143	13.355	1.742	-0.175	6.055
Spain							
R_M	0.038	0.075	-8.469	11.772	1.330	-0.059	4.717
R_B	0.038	0.033	-14.251	19.080	1.853	0.283	8.517
R_I	0.041	0.020	-10.913	10.126	1.607	-0.025	3.044
R_U	0.047	0.080	-8.032	8.054	1.293	-0.464	4.063
Sweden							
R_M	0.043	0.041	-8.488	10.872	1.500	0.012	3.929
R_B	0.050	0.015	-10.746	14.673	1.858	0.354	6.007
R_I	0.048	0.029	-8.793	10.904	1.613	0.079	3.922
Switzerland							
R_M	0.028	0.034	-7.248	9.826	1.090	-0.218	5.850
R_B	0.013	0.009	-11.432	17.782	1.870	0.142	7.565
R_I	0.042	0.025	-17.015	17.350	1.431	-0.162	13.179
R_U	0.019	0.008	-7.252	10.470	1.025	0.044	7.678
UK							
R_M	0.028	0.041	-8.692	8.885	1.127	-0.216	6.133
R_B	0.017	0.015	-19.428	18.829	1.858	-0.069	11.522

R_I	0.022	0.026	-10.347	9.664	1.459	-0.192	4.026
R_U	0.045	0.039	-9.223	11.858	1.104	-0.028	7.850
US							
R_M	0.032	0.049	-9.396	10.913	1.232	-0.258	7.749
R_B	0.021	0.011	-21.641	19.351	2.120	0.115	17.106
R_I	0.016	0.016	-9.673	12.079	1.547	-0.293	6.453
R_U	0.030	0.046	-9.267	14.188	1.284	-0.282	10.356

Table 3. Correlation coefficients of daily returns on the five risk factors provided on http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research.
Panel A: 1 January 1996 – 31 July 2014; Panel B: 1 January 1996 – 8 August 2007; Panel C: 9 August 2007 – 31 July 2014

	$R_M - R_{free}$	SMB	HML	RMW	CMA
Panel A					
$R_M - R_{free}$	1.000				
SMB	0.029	1.000			
HML	-0.137	-0.133	1.000		
RMW	-0.376	-0.381	0.160	1.000	
CMA	-0.344	-0.048	0.540	0.216	1.000
Panel B					
$R_M - R_{free}$	1.000				
SMB	-0.074	1.000			
HML	-0.639	-0.209	1.000		
RMW	-0.374	-0.450	0.448	1.000	
CMA	-0.477	-0.085	0.706	0.272	1.000
Panel C					
$R_M - R_{free}$	1.000				
SMB	0.158	1.000			
HML	0.456	-0.015	1.000		
RMW	-0.437	-0.235	-0.501	1.000	
CMA	-0.141	0.053	0.161	-0.021	1.000

Table 4. Tolerance indicators for the daily returns on the five risk factors provided on http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research.

	3 Factors	5 Factors
R_M-R_{free}	0.264	0.244
(R_M-R_{free})xD_{07}	0.306	0.279
SMB	0.549	0.430
SMBxD_{07}	0.579	0.500
HML	0.315	0.202
HMLxD_{07}	0.393	0.277
RWM		0.483
RWMxD_{07}		0.507
CMA		0.411
CMAxD_{07}		0.659

Table 5. Regression results for Eq.(2) specification using KF-data for the 1 January 1996 – 31 July 2014 period (4677 daily observations). D_{07} is equal to 1 from 9 August 2007 till 31 July 2014 and zero otherwise. Standard errors are in parentheses. ***: 1% significance; **: 5% significance and *: 10% significance.

Panel A

	R_{I49} - R_{free}	R_{C49} - R_{free}	R_{B49} - R_{free}	R_{U49} - R_{free}	R_{U49} - R_{I49}	R_{U49} - R_{C49}
Constant	-0.001	-0.001	0.000***	-0.014	-0.014	-0.015
	(0.006)	(0.005)	(0.009)	(0.010)	(0.012)	(0.011)
D_{07}	0.012	0.015**	-0.019***	0.032**	0.015	0.014
	(0.009)	(0.007)	(0.015)	(0.016)	(0.019)	(0.017)
R_M-R_{free}	1.012***	0.933***	1.063***	0.777***	-0.228***	-0.154***
	(0.007)	(0.005)	(0.011)	(0.012)	(0.014)	(0.013)
(R_M-R_{free})xD_{07}	0.066***	0.066***	0.124***	-0.100***	-0.167***	-0.179***
	(0.009)	(0.007)	(0.017)	(0.017)	(0.020)	(0.019)
SMB	0.212***	0.186***	-0.289***	0.045***	-0.223***	-0.188***
	(0.011)	(0.009)	(0.016)	(0.017)	(0.020)	(0.019)
SMBxD_{07}	0.088***	0.044***	0.355***	-0.149***	-0.278***	-0.237***
	(0.017)	(0.013)	(0.030)	(0.030)	(0.037)	(0.033)
HML	0.314***	0.284***	0.276***	0.906***	0.566***	0.564***
	(0.012)	(0.010)	(0.022)	(0.023)	(0.024)	(0.024)
HMLxD_{07}	-0.274***	-0.310***	0.784***	-0.782***	-0.497***	-0.394***
	(0.019)	(0.015)	(0.039)	(0.034)	(0.036)	(0.036)
R^2 adj.	0.904	0.920	0.800	0.585	0.321	0.253

Table 6. Regression results for Eq. (3) specification using KF-data for the 1 January 1996 – 31 July 2014 period (4677 daily observations). D_{07} is equal to 1 from 9 August 2007 till 31 July 2014 and zero otherwise. Standard errors are in parentheses. ***: 1% significance; **: 5% significance and *: 10% significance.

Panel A

	R_{I49} - R_{free}	R_{C49} - R_{free}	R_{B49} - R_{free}	R_{U49} - R_{free}	R_{U49} - R_{I49}	R_{U49} - R_{C49}
Constant	0.013**	-0.005	-0.010	-0.015	-0.014	-0.010
	0.006	0.004	0.008	0.010	0.012	0.011
D_{07}	-0.004	0.014**	-0.003	0.025*	0.014	0.010
	0.009	0.007	0.015	0.016	0.019	0.017
R_M-R_{free}	1.018***	0.953***	1.113***	0.781***	-0.230***	-0.169***
	0.007	0.005	0.010	0.012	0.015	0.014
$(R_M$-$R_{free})$xD_{07}	0.075***	0.069***	0.010	-0.068***	-0.141***	-0.149***
	0.010	0.007	0.017	0.018	0.021	0.020
SMB	0.241***	0.248***	-0.164***	-0.004	-0.226***	-0.229***
	0.010	0.008	0.017	0.019	0.022	0.020
SMBxD_{07}	0.065***	-0.004	0.174***	-0.192***	-0.273***	-0.200***
	0.017	0.012	0.029	0.031	0.038	0.033
HML	0.201***	0.162***	0.242***	0.876***	0.681***	0.700***
	0.014	0.011	0.024	0.027	0.030	0.028
HMLxD_{07}	-0.210***	-0.230***	0.754***	-0.771***	-0.565***	-0.500***
	0.021	0.015	0.043	0.037	0.043	0.040
RWM	0.082***	0.222***	0.372***	0.042*	-0.071**	-0.201***
	0.014	0.011	0.023	0.025	0.032	0.029
RWMxD_{07}	0.080***	-0.009	-0.906***	0.134**	0.118*	0.182***
	0.029	0.022	0.054	0.051	0.062	0.056
CMA	0.133***	0.191***	0.094***	0.012	-0.159***	-0.194***
	0.016	0.012	0.026	0.027	0.032	0.029
CMAxD_{07}	0.082***	0.060***	-0.344***	0.242***	0.178***	0.189***
	0.029	0.022	0.060	0.054	0.064	0.058
R^2 adj.	0.908	0.935	0.811	0.592	0.312	0.266

Table 7. Regression results for Eq. (4) specification using S&P1500 data collected from DataStream for the 3 February 2004 – 31 July 2014 period (2641 daily observations). D_{07} is equal to 1 from 9 August 2007 till 31 July 2014 and zero otherwise. Standard errors are in parentheses. ***: 1% significance; **: 5% significance and *: 10% significance.

	R_{SPI}	R_{SPB}	R_{SPU}	$R_{SPUelectricity}$	R_{SPUgas}	$R_{SPUwater}$	$R_{SPUmulti}$
Constant	0.000	0.000	0.000	0.001***	0.000	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
D_{07}	0.000	0.000	0.000	0.000*	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R_M	1.038***	0.864***	0.779***	0.749***	0.848***	1.043***	0.788***
	(0.016)	(0.024)	(0.028)	(0.030)	(0.025)	(0.045)	(0.028)
R_M xD_{07}	0.090***	0.428***	-0.144***	-0.180***	0.012	-0.355***	-0.168***
	(0.017)	(0.030)	(0.030)	(0.033)	(0.028)	(0.048)	(0.030)
R^2 adj.	0.899	0.527	0.617	0.542	0.692	0.392	0.594

Table 8. Regression results for Eq. (4) specification using S&P1500 data collected from DataStream for the 3 February 2004 – 31 July 2014 period (2641 daily observations). D_{07} is equal to 1 from 9 August 2007 till 31 July 2014 and zero otherwise. Standard errors are in parentheses. ***: 1% significance; **: 5% significance and *: 10% significance.

	$R_{SPU} - R_{SPi}$	$R_{SPUelectricity} - R_{SPI}$	$R_{SPUgas} - R_{SPI}$	$R_{SPUwater} - R_{SPI}$	$R_{SPUmulti} - R_{SPI}$
Constant	0.000	0.000*	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
D_{07}	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R_M	-0.264***	-0.298***	-0.200***	-0.008	-0.240***
	(0.033)	(0.036)	(0.030)	(0.048)	(0.034)
$R_M x D_{07}$	-0.229***	-0.260***	-0.073**	-0.425***	-0.262***
	(0.036)	(0.039)	(0.034)	(0.052)	(0.036)
R^2 adj.	0.186	0.191	0.022	0.113	0.217

Table 9. Regression results for Eq. (4) specification using DS-data for the G12 countries for the 1 January 1996 – 31 July 2014 period (4848 daily observations). D_{07} is equal to 1 from 9 August 2007 till 31 July 2014 and zero otherwise. Standard errors are in parentheses. ***: 1% significance; **: 5% significance and *: 10% significance.

	Panel A: R_I					Panel B: R_B				
	Const.	D_{07}	R_M	R_M xD_{07}	R^2 adj.	Const.	D_{07}	R_M	R_M xD_{07}	R^2 adj
Australia	0.000	0.000	0.795***	-0.086***	0.384	0.000	0.000	0.901***	0.166***	0.652
	(0.000)	(0.000)	(0.013)	(0.021)		(0.000)	(0.000)	(0.009)	(0.015)	
Belgium	0.000**	0.000	0.622***	0.251***	0.290	0.000***	0.000	1.362***	0.230***	0.627
	(0.000)	(0.000)	(0.017)	(0.024)		(0.000)	(0.000)	(0.009)	(0.019)	
Canada	0.000	0.000	0.687***	-0.025	0.533	0.000*	0.000	0.791***	0.022	0.485
	(0.000)	(0.000)	(0.024)	(0.033)		(0.000)	(0.000)	(0.013)	(0.020)	
France	0.000**	0.000	0.969***	0.064***	0.810	0.000	-0.001*	1.072***	0.582***	0.648
	(0.000)	(0.000)	(0.009)	(0.012)		(0.000)	(0.000)	(0.012)	(0.015)	
Germany	0.000**	-0.001**	0.723***	0.421***	0.459	0.000	-0.001***	1.007***	0.272***	0.579
	(0.000)	(0.000)	(0.014)	(0.021)		(0.000)	(0.000)	(0.011)	(0.021)	
Italy	0.000	0.000	0.871***	-0.111***	0.434	0.000	0.000**	0.952***	0.468***	0.796
	(0.000)	(0.000)	(0.015)	(0.022)		(0.000)	(0.000)	(0.008)	(0.014)	
Japan	0.000**	-0.001**	1.020***	0.162***	0.606	0.000*	0.000	1.152***	-0.014	0.674
	(0.000)	(0.000)	(0.014)	(0.019)		(0.000)	(0.000)	(0.012)	(0.016)	
Netherlands	0.001***	0.000	0.455***	0.626***	0.344	0.000	-0.001***	1.169***	-0.687***	0.340
	(0.000)	(0.000)	(0.015)	(0.025)		(0.000)	(0.000)	(0.012)	(0.022)	
Spain	0.000***	0.000*	0.673***	0.183***	0.626	0.000	0.000	1.094***	0.295***	0.865
	(0.000)	(0.000)	(0.010)	(0.013)		(0.000)	(0.000)	(0.007)	(0.010)	
Sweden	0.000**	0.000*	0.845***	0.347***	0.751	0.000	0.000	0.864***	0.308***	0.639
	(0.000)	(0.000)	(0.009)	(0.013)		(0.000)	(0.000)	(0.011)	(0.017)	
Switzerland	0.001***	0.000	0.577***	0.059**	0.235	0.000***	-0.001	1.263***	0.151***	0.696
	(0.000)	(0.000)	(0.014)	(0.027)		(0.000)	(0.000)	(0.012)	(0.023)	
UK	0.000	0.000	0.794***	0.221***	0.450	0.000	0.000	1.201***	0.144***	0.676
	(0.000)	(0.000)	(0.017)	(0.023)		(0.000)**	(0.000)	(0.012)	(0.019)	
US	0.000	0.000	0.924***	0.189***	0.674	0.000**	0.000	1.005***	0.368***	0.635
	(0.000)	(0.000)	(0.012)	(0.015)		(0.000)	(0.000)	(0.010)	(0.020)	

Table 10. Regression results for Eq.(4) specification using DS-data for 11 of the G12 countries for the 1 January 1996 – 31 July 2014 period (4848 daily observations). D_{07} is equal to 1 from 9 August 2007 till 31 July 2014 and zero otherwise.***: 1% significance; **: 5% significance and *: 10% significance.

	Panel A: R_U					Panel B: $R_U - R_I$				
	Const.	D_{07}	R_M	R_M xD_{07}	R^2 adj.	Const.	D_{07}	R_M	R_M xD_{07}	R^2 adj.
Australia	0.000**	0.000*	0.501***	0.247***	0.238	0.001**	-0.001**	-0.227***	0.260***	0.008
	(0.000)	(0.000)	(0.021)	(0.026)		(0.000)	(0.000)	(0.026)	(0.034)	
Belgium	0.000	0.000*	0.622***	-0.459***	0.229	0.000	0.000	0.016	-0.752***	0.116
	(0.000)	(0.000)	(0.013)	(0.015)		(0.000)	(0.000)	(0.024)	(0.032)	
Canada	0.000***	0.000	0.414***	0.049***	0.256	0.000	0.000	-0.259***	0.094***	0.043
	(0.000)	(0.000)	(0.011)	(0.016)		(0.000)	(0.000)	(0.027)	(0.037)	
France	0.000	0.000	0.909***	0.102***	0.485	0.000	0.000	0.723***	-0.116***	0.158
	(0.000)	(0.000)	(0.014)	(0.022)		(0.000)	(0.001	(0.024)	(0.034)	
Germany	0.000**	-0.001**	0.724***	0.104***	0.384	0.000	-0.001	-0.083***	-0.276***	0.029
	(0.000)	(0.000)	(0.014)	(0.019)		(0.000)	(0.000)	(0.004)	(0.018)	
Italy	0.000	0.000	0.627***	-0.148***	0.375	0.000	0.000	-0.126***	-0.129***	0.022
	(0.000)	(0.000)	(0.012)	(0.015)		(0.000)	(0.000)	(0.020)	(0.029)	
Japan	0.000	0.000	0.399***	0.129***	0.195	0.000	0.001	-0.597***	-0.116***	0.216
	(0.000)	(0.000)	(0.014)	(0.016)		(0.000)	(0.000)	(0.021)	(0.027)	
Spain	0.000	0.000	0.795***	-0.024	0.431	0.000	0.000	0.355***	0.085***	0.066
	(0.000)	(0.000)	(0.014)	(0.018)		(0.000)	(0.000)	(0.024)	(0.031)	
Switzerland	0.001***	-0.001***	0.123***	0.235***	0.110	0.000	-0.001***	-0.445***	0.229***	0.078
	(0.000)	(0.000)	(0.013)	(0.021)		(0.000)	(0.000)	(0.021)	(0.035)	
UK	0.000**	0.000	0.541***	-0.028	0.325	0.000**	0.000	-0.201***	-0.301***	0.058
	(0.000)	(0.000)	(0.013)	(0.020)		(0.000)	(0.000)	(0.021)	(0.031)	
US	0.000**	0.000	0.601***	0.114***	0.433	0.000**	0.000	-0.305***	-0.105***	0.091
	(0.000)	(0.000)	(0.013)	(0.016)		(0.000)	(0.000)	(0.018)	(0.022)	

Appendix 1

Assume that there are N assets in a market each of which has a return R_i, and standard deviation σ_i. The return on the CAPM market portfolio based on these N assets is therefore equal $R_M = \sum_{i=1}^{N} w_i R_i$, where w_i denotes a capitalisation-based weight of asset i (i=1,2,…, N).

Obviously, $\sum_{i=1}^{N} w_i = 1$ and $w_i > 0$ for every i =1,…,N. To investigate the impact of changes in asset weights on market risk let us assume that it is asset N that experiences a change in its share in the market portfolio, and look at the effect of its change on the rest of the market.

To simplify the notation let us denote $\sum_{i=1}^{N-1} w_i = w_Z$. Then, $\sum_{i=1}^{N-1} w_i + w_N = w_Z + w_N = 1$,

Moreover, we can write that $\sum_{i=1}^{N-1} w_i R_i = w_Z R_Z$, where $R_Z = w_Z \sum_{i=1}^{N-1} \frac{w_i}{w_Z} R_i$. In other words, $w_Z \beta_Z + w_N \beta_N = 1$. Market risk of each asset n is therefore given as

$$\beta_n = \frac{w_Z \operatorname{cov}_{n,Z} + (1 - w_Z)\operatorname{cov}_{n,N}}{w_Z^2 \sigma_Z^2 + (1 - w_Z)^2 \sigma_N^2 + 2 w_Z (1 - w_Z)\operatorname{cov}_{Z,N}}$$

and the market risk of portfolio Z can be written as

$$\beta_Z = \frac{w_Z \sigma_Z^2 + (1 - w_Z)\operatorname{cov}_{Z,N}}{w_Z^2 \sigma_Z^2 + (1 - w_Z)^2 \sigma_N^2 + 2 w_Z (1 - w_Z)\operatorname{cov}_{Z,N}} \tag{A1}$$

where σ_Z denotes the standard deviation of Z and $\operatorname{cov}_{i,j}$ denotes the covariance between assets i and j.

Let us assume that asset N is more volatile than portfolio Z (i.e., $\sigma_N > \sigma_Z$) and has a higher market risk than portfolio Z (i.e., $\beta_N > \beta_Z$). To keep the case close to real market conditions, let us assume that portfolio Z and asset N are non-negatively correlated, i.e., $\operatorname{cov}_{Z,N} \geq 0$. Assume that the weight of asset N, i.e., w_N changes.

Given that we are interested in changes in β_Z that result from changes in w_N ($w_Z = 1 - w_N$), the beta that corresponds to a given weight w_Z will be denoted $\beta_Z(w_Z)$.

Proposition 1

If $\sigma_Z < \sigma_N$, $\operatorname{cov}_{Z,N} \geq 0$ and σ_Z, σ_N, $\operatorname{cov}_{Z,N}$ remain constant as w_Z changes then, for any w_Z' such that $\beta_Z(w_Z') < 1$, $\beta_Z(w_Z') < \beta_Z(w_Z)$ for every $w_Z > w_Z'$.

Before we prove Proposition 1 it is useful to prove the following Lemma 1:

Lemma 1

For any two, positively correlated assets, A and B,

$$\frac{\sigma_A^2 + \sigma_B^2}{2} > \mathrm{cov}_{A,B}$$

where σ_A^2, σ_B^2 *and* $\mathrm{cov}_{A,B}$ *denote the variance of A, variance of B and covariance of A and B respectively, and* $\sigma_A^2 \neq \sigma_B^2$.

<u>*Proof of Lemma 1*</u>

We begin by assuming that the opposite is true, i.e., $\mathrm{cov}_{A,B} > \frac{\sigma_A^2 + \sigma_B^2}{2}$. Then, given that $\frac{\mathrm{cov}_{A,B}}{\sigma_A \sigma_B} < 1$ (A and B are less than perfectly correlated) it would be true that

$$\frac{\sigma_A^2 + \sigma_B^2}{2\sigma_A \sigma_B} < \frac{\mathrm{cov}_{A,B}}{\sigma_A \sigma_B} \leq 1.$$

which would imply $(\sigma_A - \sigma_B)^2 \leq 0$, which is impossible.

□

<u>*Proof of Proposition 1*</u>

First, note that $\beta_Z(0) = \frac{\mathrm{cov}_{Z,N}}{\sigma_N^2} < 1$ and $\beta_Z(1) = 1$. Moreover, there is some $w_1 \neq 1$ such that $\beta_Z(w_1) = 1$, although this need not be in the unit interval. To find w_1 we need to solve the equation

$$w_1 \sigma_Z^2 + (1 - w_1)\mathrm{cov}_{Z,N} = w_1^2 \sigma_Z^2 + (1 - w_1)^2 \sigma_N^2 + 2w_1(1 - w_1)\mathrm{cov}_{Z,N}$$

which can be rewritten as:

$$(\sigma_Z^2 + \sigma_N^2 - 2\mathrm{cov}_{Z,N})w_1^2 - (\sigma_Z^2 + 2\sigma_N^2 - 3\mathrm{cov}_{Z,N})w_1 + \sigma_N^2 - \mathrm{cov}_{Z,N} = 0.$$

There always are two solutions to the above equation:

$$w_1^{'} = \frac{\sigma_Z^2 + 2\sigma_N^2 - 3\mathrm{cov}_{Z,N} - \left|\sigma_Z^2 - \mathrm{cov}_{Z,N}\right|}{2\left(\sigma_Z^2 + \sigma_N^2 - 2\mathrm{cov}_{Z,N}\right)} \quad \text{and} \quad w_1^{''} = \frac{\sigma_Z^2 + 2\sigma_N^2 - 3\mathrm{cov}_{Z,N} + \left|\sigma_Z^2 - \mathrm{cov}_{Z,N}\right|}{2\left(\sigma_Z^2 + \sigma_N^2 - 2\mathrm{cov}_{Z,N}\right)}.$$

If $\sigma_Z^2 - \mathrm{cov}_{Z,N} < 0$, then $w_1^{'} = 1$ and, $w_1^{''} = \dfrac{\sigma_N^2 - \mathrm{cov}_{Z,N}}{2\left(\sigma_Z^2 + \sigma_N^2 - 2\mathrm{cov}_{Z,N}\right)} > 1$, given Lemma 1 and the fact that $\mathrm{cov}_{Z,N} \le \sqrt{\sigma_Z^2\sigma_N^2} < \sqrt{\sigma_N^4} = \sigma_N^2$. This, however, means that $w_1^{''}$ is outside of the allowed range of w_Z, as $w_Z \in [0,1]$.

If $\sigma_Z^2 - \mathrm{cov}_{Z,N} \ge 0$, then $w_1^{''} = 1$ and $w_1^{'} = \dfrac{\sigma_N^2 - \mathrm{cov}_{Z,N}}{2\left(\sigma_Z^2 + \sigma_N^2 - 2\mathrm{cov}_{Z,N}\right)} \le 1$.

To determine the values of w for which the beta (i.e., $\beta_Z(w)$) increases and decreases, let us focus on the properties of beta's first derivative.

The sign of the first derivative of β_Z in regard to w_Z depends on the sign of the numerator as the denominator of the derivative (being the squared value of the market variance) is always positive. Simple algebraic operations allows the numerator of the first derivative of β_Z to be expressed as:

$$\mathrm{Numerator}\left(\frac{d\beta_Z}{dw_Z}\right) = \left(\sigma_Z^2 + \sigma_N^2 - 2\mathrm{cov}_{Z,N}\right)\left(-\left(\sigma_Z^2 - \mathrm{cov}_{Z,N}\right)w_Z^2 - 2\mathrm{cov}_{Z,N}w_Z + \mathrm{cov}_{Z,N} + \frac{\sigma_Z^2\left(\sigma_N^2 - \mathrm{cov}_{Z,N}\right)}{\sigma_Z^2 + \sigma_N^2 - 2\mathrm{cov}_{Z.,N}}\right)$$

If $w_Z = 0$, then

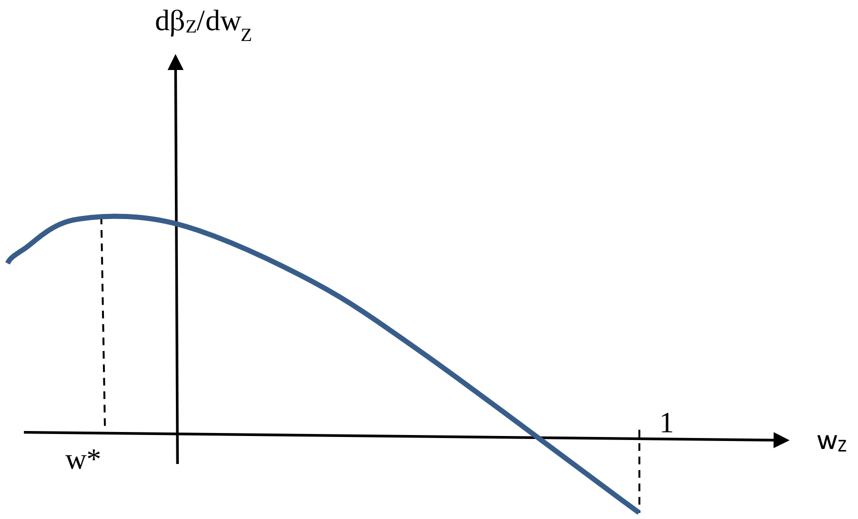
$\mathrm{Numerator}\left(\dfrac{d\beta_Z}{dw_Z}\right)\Bigg|_{w_Z=0} = \dfrac{\sigma_Z^2\sigma_N^2}{\sigma_Z^2 + \sigma_N^2 - 2\mathrm{cov}_{Z,N}} > 0$ because, from Lemma 1, we know that $\sigma_Z^2 + \sigma_N^2 - 2\mathrm{cov}_{Z,N} > 0$.

If $w_Z = 1$, then $\mathrm{Numerator}\left(\dfrac{d\beta_Z}{dw_Z}\right)\Bigg|_{w_Z=1} = \sigma_Z^2\left(-\sigma_Z^2 + \mathrm{cov}_{Z,N}\right)$, which is positive when $\sigma_Z^2 - \mathrm{cov}_{Z,N} < 0$ and non-positive when $\sigma_Z^2 - \mathrm{cov}_{Z,N} \ge 0$. Notice that the quadratic form $-\left(\sigma_Z^2 - \mathrm{cov}_{Z,N}\right)w_Z^2 - 2\mathrm{cov}_{Z,N}w_Z + \mathrm{cov}_{Z,N} + \dfrac{\sigma_Z^2\left(\sigma_N^2 - \mathrm{cov}_{Z,N}\right)}{\sigma_Z^2 + \sigma_N^2 - 2\mathrm{cov}_{Z.,N}}$ has the extreme point at

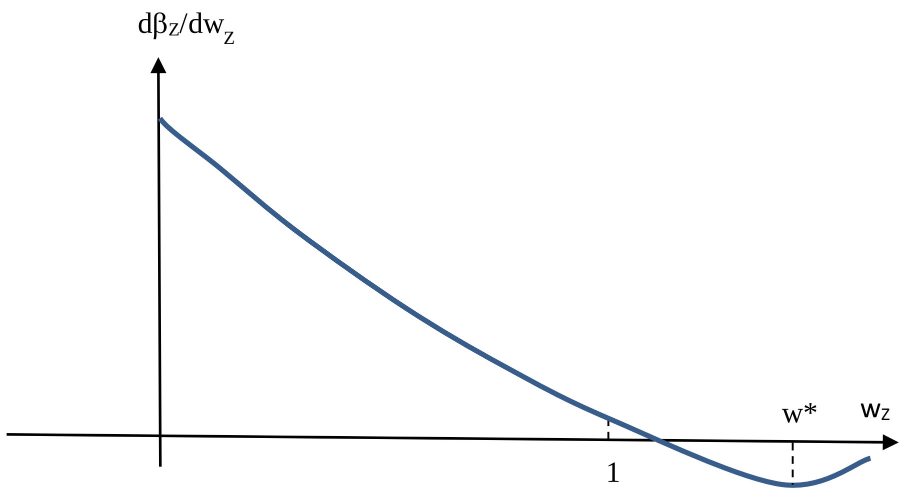
$w^* = \dfrac{\mathrm{cov}_{Z,N}}{\mathrm{cov}_{Z,N} - \sigma_Z^2}$ which is positive and greater than one for $\sigma_Z^2 - \mathrm{cov}_{Z,N} < 0$, and negative for $\sigma_Z^2 - \mathrm{cov}_{Z,N} > 0$. Therefore, in both cases w* is outside of the allowed range of w_Z.

Pulling all this information together distinguishes two cases: (i) $\sigma_Z^2 - \text{cov}_{Z,N} > 0$, and (ii) $\sigma_Z^2 - \text{cov}_{Z,N} < 0$.

In case (i) the derivative of β_Z switches sign from positive to negative in the unit interval as shown below.



In case (ii) the derivative of β_Z is positive for all values of w_Z in the unit interval, as shown below



In case (i) β_Z as a function of w_Z initially increases monotonically until it reaches a maximum on the unit interval, and then declines to unity (as is shown in the example in Figure 1 Panel A). Given that β_Z is equal to one when $w_1^{''} = 1$ and $w_1^{'} < 1$, β_Z is an increasing function of w_Z for $w_Z \leq w_1^{'}$.

In case (ii) the derivative is positive on [0,1], so β_Z increases in w_Z.

This proves Proposition 1.

□

Appendix 2

Table A1. Variance equations for Table 5. The variance equation of the error term is specified as GARCH(p,q):

$\sigma_t^2 = \varpi + \sum_{i=1}^{p} \xi_i \varepsilon_{t-1}^2 + \sum_{i=1}^{q} \zeta_{2i} \sigma_{t-1}^2$. Standard errors are in parentheses. ***: 1% significance; **: 5% significance and *: 10% significance.

	R_{I49}- R_{free}	R_{C49}- R_{free}	R_{B49}- R_{free}	R_{U49}- R_{free}	R_{U49} – R_{I49}	R_{U49} – R_{C49}
ω	0.002***	0.001***	0.002***	0.007***	0.005***	0.005***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
ξ_1	0.116***	0.089***	0.141***	0.192**	0.160***	0.155***
	(0.017)	(0.016)	(0.017)	(0.017)	(0.015)	(0.015)
ξ_2	0.062***	-0.055***	-0.085***	0.048**	-0.099***	-0.077***
	(0.009)	(0.020)	(0.017)	(0.019)	(0.015)	(0.016)
ξ_3	-0.072***	0.037**		-0.105***		
	(0.017)	(0.015)		(0.022)		
ζ_1	0.173***	0.921***	0.941***	-0.002	0.934***	0.916***
	(0.125)	(0.008)	(0.004)	(0.073)	(0.005)	(0.007)
ζ_2	0.707***			0.855***		
	(0.115)			(0.069)		

Table A2. Variance equations for Table 6. The variance equation of the error term is specified as GARCH(p,q): $\sigma_t^2 = \varpi + \sum_{i=1}^{p} \xi_i \varepsilon_{t-1}^2 + \sum_{i=1}^{q} \zeta_{2i} \sigma_{t-1}^2$. Standard errors are in parentheses. ***: 1% significance; **: 5% significance and *: 10% significance.

	R_{I49}- R_{free}	R_{C49}- R_{free}	R_{B49}- R_{free}	R_{U49}- R_{free}	R_{U49} –R_{I49}	R_{U49} – R_{C49}
ω	0.001***	0.001***	0.002***	0.004***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
ξ_1	0.107***	0.105***	0.137***	0.191***	0.164***	0.158**
	(0.017)	(0.016)	(0.016)	(0.017)	(0.015)	(0.014)
ξ_2	-0.044***	-0.050***	-0.080***	-0.119***	-0.104***	-0.083***
	(0.017)	(0.016)	(0.017)	(0.017)	(0.015)	(0.015)
ζ_1	0.929***	0.938***	0.941***	0.921***	0.934***	0.920***
	(0.006)	(0.006)	(0.004)	(0.007)	(0.005)	(0.007)

Table A3. Variance equation coefficients for Table 7. The variance equation of the error term is specified as GARCH(p,q): $\sigma_t^2 = \varpi + \sum_{i=1}^{p} \xi_i \varepsilon_{t-1}^2 + \sum_{i=1}^{q} \zeta_{2i} \sigma_{t-1}^2$. Standard errors are in parentheses. ***: 1% significance; **: 5% significance and *: 10% significance.

	R_{SPI}	R_{SPB}	R_{SPU}	$R_{SPUelectricity}$	R_{SPUgas}	$R_{SPUwater}$	$R_{SPUmulti}$
ω	0.000***	0.000***	0.000***	0.000**	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ξ_1	0.100***	0.192***	0.135***	0.125***	0.120***	0.174***	0.129***
	(0.022)	(0.023)	(0.022)	(0.020)	(0.015)	(0.020)	(0.024)
ξ_2	-0.044**	-0.129***	-0.088***	-0.069***	-0.070***	-0.122***	-0.073***
	(0.023)	(0.024)	(0.031)	(0.027)	(0.015)	(0.021	(0.025)
ξ_3			0.012				
			(0.020)				
ζ_1	0.931***	0.935***	0.928***	0.977***	0.938***	0.930***	0.926***
	(0.007)	(0.004)	(0.011)	(0.300)	(0.008)	(0.008)	(0.012)
ζ_2				-0.046			
				(0.275)			

Table A4. Variance equation coefficients for Table 8. The variance equation of the error term is specified as GARCH(p,q): $\sigma_t^2 = \varpi + \sum_{i=1}^{p} \xi_i \varepsilon_{t-1}^2 + \sum_{i=1}^{q} \zeta_{2i} \sigma_{t-1}^2$. Standard errors are in parentheses. ***: 1% significance; **: 5% significance and *: 10% significance.

	$R_{SPU} - R_{SPi}$	$R_{SPUelectricity} - R_{SPI}$	$R_{SPUgas} - R_{SPI}$	$R_{SPUwater} - R_{SPI}$	$R_{SPUmulti} - R_{SPI}$
ω	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ξ_1	0.133***	0.141***	0.114***	0.178***	0.111***
	(0.019)	(0.019)	(0.021)	(0.020)	(0.020)
ξ_2	-0.076***	-0.083***	-0.065***	-0.129***	-0.049**
	(0.020)	(0.021)	(0.023)	(0.021)	(0.021)
ζ_1	0.925***	0.925***	0.941***	0.939***	0.915***
	(0.009)	(0.010)	(0.008)	(0.007)	(0.011)

Table A5. Variance equation coefficients for Table 9. The variance equation of the error term is specified as GARCH(p,q): $\sigma_t^2 = \varpi + \sum_{i=1}^{p} \xi_i \varepsilon_{t-1}^2 + \sum_{i=1}^{q} \zeta_{2i} \sigma_{t-1}^2$. Standard errors are in parentheses.

	Panel A				Panel B					
	ω	ξ_1	ξ_2	ζ_1	ω	ξ_1	ξ_2	ξ_3	ζ_1	ζ_2
Australia	0.000***	0.110***	-0.084***	0.971***	0.000***	0.148***	-0.084***	-0.032***	0.965***	
	(0.000)	(0.012)	(0.012)	(0.002)	(0.000)	(0.014)	(0.020)	(0.012)	(0.002)	
Belgium	0.000***	0.113***	-0.091***	0.976***	0.000***	0.168***	-0.195***	0.035	1.688***	-0.695***
	(0.000)	(0.016)	(0.016)	(0.002)	(0.000)	(0.018)	(0.037)	(0.022)	(0.057)	(0.054
Canada	0.000***	0.091***	-0.064***	0.971***	0.000***	0.159***	-0.089***	-0.025**	0.953***	
	(0.000)	(0.014)	(0.014)	(0.003)	(0.000)	(0.013)	(0.017)	(0.012)	(0.003)	
France	0.000***	0.057***	0.937***		0.000***	0.174***	-0.133***		0.959***	
	(0.000)	(0.004)	(0.004)		(0.000)	(0.015)	(0.015)		(0.002)	
Germany	0.000***	0.121***	-0.080***	0.955***	0.000***	0.187***	-0.133***		0.947***	
	(0.000)	(0.011)	(0.011)	(0.003)	(0.000)	(0.015)	(0.014)		(0.003)	
Italy	0.000***	0.106***	-0.069***	0.945***	0.000***	0.159***	-0.097***		0.934***	
	(0.000)	(0.014)	(0.014)	(0.005)	(0.000)	(0.015)	(0.016)		(0.005)	
Japan	0.000***	0.124***	-0.077***	0.948***	0.000***	0.200***	-0.140***		0.941***	
	(0.000)	(0.012)	(0.013)	(0.005)	(0.000)	(0.014)	(0.014)		(0.004)	
Netherlands	0.000***	0.128***	-0.103***	0.968***	0.000***	0.209***	-0.128***		0.926***	
	(0.000)	(0.013)	(0.013)	(0.003)	0.000	0.016	0.016		(0.003)	
Spain	0.000***	0.082***		0.893***	0.000***	0.156***	-0.059***		0.900***	
	(0.000)	(0.006)		(0.007)	(0.000)	(0.014)	(0.013)		(0.006)	
Sweden	0.000***	0.118***	-0.094***	0.973***	0.000***	0.114***	-0.078***		0.962***	
	(0.000)	(0.014)	(0.014)	(0.002)	(0.000)	(0.012)	(0.012)		(0.003)	
Switzerland	0.000***	0.114***	-0.100***	0.984***	0.000***	0.208***	-0.165***		0.951***	
	(0.000)	(0.010)	(0.010)	(0.001)	(0.000)	(0.016)	(0.015)		(0.004)	
UK	0.000***	0.086***	-0.055***	0.966***	0.000***	0.156***	-0.032	-0.088***	0.962***	
	(0.000)	(0.012)	(0.013)	(0.003)	(0.000)	(0.015)	(0.022)	(0.014)	(0.003)	
US	0.000***	0.115***	-0.089***	0.972***	0.000***	0.162***	-0.111***		0.948***	
	(0.000)	(0.012)	(0.012)	(0.002)	(0.000))	(0.015)	(0.016)		(0.003)	

Table A6. Variance equation coefficients for Table 10. The variance equation of the error term is specified as GARCH(p,q): $\sigma_t^2 = \varpi + \sum_{i=1}^{p} \xi_i \varepsilon_{t-1}^2 + \sum_{i=1}^{q} \zeta_{2i} \sigma_{t-1}^2$. Standard errors are in parentheses. ***: 1% significance; **: 5% significance and *: 10% significance.

	Panel A				Panel B			
	ω	ξ_1	ξ_2	ζ_1	ω	ξ_1	ξ_2	ζ_1
	0.000***	0.196***	-0.177***	0.979***	0.000***	0.086***	-0.066***	0.976***
Australia	(0.000)	(0.010)	(0.010)	(0.002)	(0.000)	(0.012)	(0.012)	(0.002)
	0.000***	0.207***	-0.094***	0.863***	0.000***	0.130***	-0.108***	0.975***
Belgium	(0.000)	(0.008)	(0.009)	(0.008)	(0.000)	(0.009)	(0.010)	(0.002)
	0.000***	0.079***	-0.022***	0.930***	0.000***	0.127***	-0.096***	0.966***
Canada	(0.000)	(0.013)	(0.014)	(0.006)	(0.000)	(0.015)	(0.016)	(0.003)
	0.000***	0.220***	-0.177***	0.951***	0.000***	0.183***	-0.139***	0.946***
France	(0.000)	(0.013)	(0.013)	(0.003)	(0.000)	(0.010)	(0.010)	(0.004)
	0.000***	0.140***	-0.085***	0.934***	0.000**	0.138***	-0.096***	0.961***
Germany	(0.000)	(0.014)	(0.014)	(0.005)	(0.000)	(0.012)	(0.012)	(0.002)
	0.000***	0.109***	-0.066***	0.954***	0.000***	0.112***	-0.083***	0.966***
Italy	(0.000)	(0.012)	(0.012)	(0.003)	(0.000)	(0.015)	(0.015)	(0.003)
	0.000***	0.143***	-0.102***	0.956***	0.000***	0.086***	-0.043***	0.950***
Japan	(0.000)	(0.014)	(0.014)	(0.003)	(0.000)	(0.014)	(0.015)	(0.005)
	0.000***	0.103***	-0.065***	0.961***	0.000***	0.119***	-0.079***	0.953***
Spain	(0.000)	(0.014)	(0.014)	(0.002)	(0.000)	(0.015)	(0.015)	(0.004)
	0.000***	0.168***	-0.126***	0.951***	0.000***	0.070***	-0.016***	0.934***
Switzerland	(0.000)	(0.014)	(0.014)	(0.003)	(0.000)	(0.009)	(0.009)	(0.005)
	0.000***	0.129***	-0.072***	0.921***	0.000***	0.106***	-0.064***	0.950***
UK	(0.000)	(0.014)	(0.014)	(0.007)	(0.000)	(0.013)	(0.013)	(0.004)
	0.000***	0.108***	-0.061***	0.951***	0.000***	0.136***	-0.101***	0.962***
US	(0.000)	(0.014)	(0.014)	(0.003)	(0.000)	(0.013)	(0.014)	(0.003)

Table A7. Regression results for Eq. (3) specification using DS-data for the G12 countries for the 1 January 1996 – 31 July 2014 period (4848 daily observations). D_{08} is equal 1 from 15 September 2008 till 31 July 2014 and zero otherwise. Standard errors are in parentheses. ***: 1% significance; **: 5% significance and *: 10% significance.

	Panel A: R_I					Panel B: R_B				
	Const.	D_{08}	R_M	R_M xD_{08}	R^2 adj.	Const.	D_{08}	R_M	R_M xD_{08}	R^2 adj
Australia	0.000	0.000	0.760***	0.003	0.381	0.000	0.000	0.901***	0.178***	0.649
	(0.000)	(0.000)	(0.012)	(0.023)		(0.000)	(0.000)	(0.009)	(0.016)	
Belgium	0.000**	0.000	0.637***	0.336***	0.295	0.000***	-0.001	1.372***	0.464***	0.637
	(0.000)	(0.000)	(0.016)	(0.030)		(0.000)	(0.000)	(0.008)	(0.020)	
Canada	0.000	0.001**	0.686***	-0.026	0.235	0.000*	0.000	0.792***	0.022	0.485
	(0.000)	(0.000)	(0.023)	(0.033)		(0.000)	(0.000)	(0.013)	(0.020)	
France	0.000	0.000	0.984***	0.042***	0.809	0.000	0.000	1.092***	0.593***	0.644
	(0.000	(0.000)	(0.008)	(0.012)		(0.000)	(0.000)	(0.011)	(0.015)	
Germany	0.000**	-0.001*	0.761***	0.372***	0.451	0.000	-0.001***	1.021***	0.253***	0.577
	(0.000)	(0.000)	(0.013)	(0.021)		(0.000)	(0.000)	(0.010)	(0.024)	
Italy	0.000	0.000	0.876***	-0.133***	0.436	0.000	-0.001**	0.970***	0.506***	0.797
	(0.000)	(0.000)	(0.015)	(0.022)		(0.000)	(0.000)	(0.008)	(0.015)	
Japan	0.000	-0.001**	1.027***	0.176***	0.606	0.000*	0.000	1.176***	-0.060***	0.674
	(0.000)	(0.000)	(0.013)	(0.018)		(0.000)	(0.000)	(0.011)	(0.016)	
Netherlands	0.001***	0.000	0.501***	0.556***	0.324	0.000	-0.001***	1.173***	-0.832***	0.352
	(0.000)	(0.000)	(0.015)	(0.028)		(0.000)	(0.000)	(0.011)	(0.024)	
Spain	0.000**	0.000	0.726***	0.098***	0.617	0.000	0.000	1.105***	0.321***	0.867
	(0.000)	(0.000)	(0.009)	(0.013)		(0.000)	(0.000)	(0.007)	(0.010)	
Sweden	0.000*	0.000	0.886***	0.309***	0.740	0.000***	0.000***	0.887***	0.301***	0.636
	(0.000)	(0.000)	(0.008)	(0.014)		(0.000)	(0.000)	(0.010)	(0.017)	
Switzerland	0.001***	0.000	0.569***	0.107***	0.237	0.000	-0.001**	1.271***	0.139***	0.694
	(0.000)	(0.000)	(0.013)	(0.028)		(0.000)	(0.000)	(0.011)	(0.026)	
UK	0.000	0.000	0.848***	0.162***	0.44	0.000	0.000*	1.210***	0.158***	0.675
	(0.000)	(0.000)	(0.015)	(0.023)		(0.000)	(0.000)	(0.011)	(0.021)	
US	0.000*	0.000	0.945***	0.170***	0.674	0.000	0.000*	1.020***	0.336***	0.625
	(0.000)	(0.000)	(0.011)	(0.016)		(0.000)	(0.000)	(0.010)	(0.021)	

Table A8. Regression results for Eq. (3) specification using DS-data for 11 of the G12 countries for the 1 January 1996 – 31 July 2014 period (4848 daily observations). D_{08} is equal 1 from 15 September 2008 till 31 July 2014 and zero otherwise. Standard errors are in parentheses. ***: 1% significance; **: 5% significance and *: 10% significance.

	Panel A: R_U					Panel B: R_U - R_I				
G12(11)	Const.	D_{08}	R_M	R_M xD_{08}	R^2 adj.	Const.	D_{08}	R_M	R_M xD_{08}	R^2 adj.
Australia	0.000***	-0.001**	0.515***	0.265***	0.241	0.001**	-0.001**	-0.190***	0.230***	0.007
	(0.000)	(0.000)	(0.016)	(0.024)		(0.000)	(0.000)	(0.021)	(0.034)	
Belgium	0.000	0.000	0.521***	-0.333***	0.215	0.000	0.000	-0.097***	-0.700***	0.111
	(0.000)	(0.000)	(0.012)	(0.015)		(0.000)	(0.001	(0.020)	(0.034)	
Canada	0.000***	0.000	0.429***	0.016	0.253	0.000	-0.001	-0.238***	0.065	0.041
	(0.000)	(0.000)	(0.011)	(0.016)		(0.000)	(0.000)	(0.026)	(0.037)	
France	0.000	-0.001**	0.899***	0.141***	0.485	0.000	0.000	-0.100***	0.119***	-0.005
	(0.000)	(0.000)	(0.013)	(0.022)		(0.000)	(0.000)	(0.013)	(0.026)	
Germany	0.000***	-0.001***	0.715***	0.153***	0.386	0.000	-0.001*	-0.084***	-0.239***	0.023
	(0.000)	(0.000)	(0.013)	(0.019)		(0.000)	(0.000)	(0.004)	(0.019)	
Italy	0.000*	0.000	0.623***	-0.152***	0.375	0.000	0.000	-0.141***	-0.109***	0.021
	(0.000)	(0.000)	(0.012)	(0.014)		(0.000)	(0.000)	(0.019)	(0.029)	
Japan	0.000	0.000	0.400***	0.139***	0.196	0.000	0.000	-0.597***	-0.146***	0.216
	(0.000)	(0.000)	(0.013)	(0.016)		(0.000)	(0.000)	(0.019)	(0.027)	
Spain	0.000	0.000	0.793***	-0.024	0.430	0.000	0.000	0.028	-0.062***	0.000
	(0.000)	(0.000)	(0.013)	(0.017)		(0.000)	(0.000)	(0.018)	(0.025)	
Switzerland	0.001***	-0.001***	0.148***	0.191***	0.103	0.000	-0.001***	-0.413***	0.137***	0.072
	(0.000)	(0.000)	(0.012)	(0.023)		(0.000)	(0.000)	(0.020)	(0.037)	
UK	0.000***	0.000	0.546***	-0.049**	0.324	0.000**	0.000	-0.249***	-0.261***	0.053
	(0.000)	(0.000)	(0.013)	(0.020)		(0.000)	(0.000)	(0.019)	(0.032)	
US	0.000***	0.000	0.609***	0.114***	0.343	0.000***	0.000	-0.316***	-0.095***	0.091
	(0.000)	(0.000)	(0.012)	(0.016)		(0.000)	(0.000)	(0.017)	(0.022)	