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# **Essays on Financial Markets**

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Doctor of Philosophy  
The University of Edinburgh  
2018



## Declaration

I hereby declare that the thesis has been composed by myself and that the work has not be submitted for any other degree or professional qualification. Chapter 2 is jointly co-authored with Dr Angelica Gonzalez and Dr Ufuk Gucbilmez. Chapter 3 is jointly co-authored with Dr Candie Chang and Prof Ben Jacobsen.

Signed: Lizhen Zhu

A handwritten signature in black ink, appearing to be the Chinese characters '朱丽珍' (Zhu Lizhen).

Date: 20<sup>th</sup> May 2019



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## Dedication

*This dissertation is dedicated to my dear grandmother.*



## Abstract

This thesis comprises three empirical studies, which investigate the influential factors of financial markets and their participants' behaviour. These studies can be read independently.

Using a sample of European banks, the first study, "Corruption culture and bank short-termism", provides evidence that country-level corruption is strongly associated with short-termism (a behaviour that focuses on short-term benefits at the expense of long-term shareholders' wealth growth). To measure short-termism, I construct a multi-dimensional index which combines earnings management, tail risk, and short-term debt ratio. I show that banks headquartered in countries that are more corrupt behave more short-sightedly than banks headquartered in countries that are less corrupt. I further demonstrate that foreign shareholders act as a channel through which corruption is imported. For banks located in countries with a lower than average corruption level, having more shareholdings by investors domiciled in countries that are more corrupt leads to more short-termism. This study highlights the link between bank short-termism and corruption of both headquartered countries and foreign shareholders.

The second study, "Macroeconomic and political uncertainty and cross sectional return dispersion around the world", examines whether return dispersion (the cross sectional variation in stock returns) could be used to measure the macroeconomic and political uncertainty of international financial markets. I show that return dispersion is able to capture

uncertainties including local and global business cycles, international political instability, market general uncertainties, international country risk, and economic policy uncertainty. Stocks that are more sensitive to return dispersion have higher returns. Moreover, I compare return dispersion with another commonly used uncertainty measure: implied volatility. I find that they capture different aspects of uncertainty. This study aims to provide a simple and easy-to-use measure of uncertainty for both academic purposes and professional practice.

The third study, “The performance of asset allocation strategies across datasets and over time”, evaluates the ex-ante performance of various commonly used asset allocation strategies including equal weighting, mean variance weighting, risk parity weighting, minimum variance weighting, equal risk contribution weighting, and maximum diversification weighting. The results show that there are no statistically significant differences between asset allocation strategies if the portfolios are based on country or industry indices. If the portfolios are formed of stocks or multi-asset classes, then the differences between strategies are large; however, none of the strategies can consistently outperform the others over time. I also identify that the implementation of the mean variance rule leads to wide fluctuation in risk shifting, which is undesirable for investors. Last but not least, I illustrate how all of the strategies are far from ex-ante optimal.

## Lay Summary

This thesis comprises three empirical studies, which investigate the influential factors of financial markets and their participants' behaviour. These studies can be read independently.

The first study, "corruption culture and bank short-termism", provides evidence that country-level corruption is strongly associated with short-termism (a behaviour that focus on short-term benefit at the expenses of long-term shareholders' wealth growth). To measure short-termism, I construct a multi-dimensional index which combines earnings management, tail risk, and short-term debt ratio. I show that banks headquartered in countries that are measured to be more corrupt behave more short-sightedly than banks headquartered in countries that are less corrupt. I further demonstrate that foreign shareholders act as a channel to import corruption. For banks located in countries with lower than average corruption level, having more shareholdings by investors domiciled in countries that are more corrupt leads to more short-termism. This study highlights the link between bank short-termism and corruption of both headquartered countries and foreign shareholders.

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# Chapter 1 Introduction

Financial markets are essential for a country's economic development, because mature and properly-functioning financial markets raise and allocate capital for the economy. They connect participants through activities that include the forming of healthy banking systems, operating corporations, institutional trading, personal wealth management etc. This thesis aims to enhance the understanding of international financial markets from different perspectives. The first chapter considers the perspective of financial intermediaries, namely banks. The other two chapters consider the perspective of investors. These three studies can be read independently, however, all three studies revolve round the influential factors that can affect financial markets and their participants' behaviour.

In the first study, I analyse an influential factor that affects financial market intermediaries' myopic behaviour: corruption culture. The myopic behaviour of financial institutions has been cited as a major cause of the 2008 financial crisis (Dallas, 2011), yet it has been difficult to measure this behaviour in the banking sector. Previous studies have different interpretations of short-termism such as short-term oriented investment horizons (e.g. Bushee, 1998; Laux, 2012), earnings management under market pressure (e.g. Bird, Ertan, Karolyi, and Ruchti, 2017; Graham, Harvey, and Rajgopal, 2005; Houston, Lev, and Tucker, 2010), and executive compensation designed to focus on short-term performance (Fahlenbrach and Stulz, 2011; Gopalan et al., 2014; Kolasinski and Yang, 2018). Those studies show that short-termism has many facets. In

order to capture as many actions that may be interpreted as short-termism, this study creates a multidimensional index that combines earnings management, tail risk, and short-term debt ratio.

After computing this novel measure of bank short-termism, I test whether national level corruption culture is related to it. Although corruption is found to significantly influence corporate cash holding and leverage (Smith, 2016), misconduct (Liu, 2016), and tax avoidance (DeBacker, Heim, and Tran, 2015), there is no documented evidence to link it with bank myopic behaviour. Thus, I test the impact of corruption on the overall measure of short-termism on a sample of public banks in Europe. I use the Corruption Perception Index (CPI) to measure the corruption level of bank-headquartered country. I find that banks are more myopic if they are headquartered in countries with a relatively high degree of corruption. To mitigate potential endogeneity concerns, I use an instrumental variable approach where the instrument is the distance between a bank's headquartered country and the least corrupt country in Europe, which is Denmark. The results are robust to the two-stage least square regressions using this instrument. In addition, I test whether corruption as an inherent human cognition would influence bank short-termism under uncertainty. I find that the effect of corruption on short-termism is stronger during periods of higher economic policy uncertainty.

I further test if corruption could influence a bank's short-termism through its foreign shareholders. I find that, for banks headquartered in relatively clean countries (with a corruption value lower than average), having a higher percentage of shareholdings held by foreign shareholders, who are domiciled

in countries with higher corruption level, is associated with more short-termism. In contrast, having more shares held by foreign shareholders who are domiciled in countries that are less corrupt than a bank's headquartered country does not curb short-termism. Overall, these results indicate that corruption culture could influence banks' myopic behaviour through their headquartered countries and foreign shareholders.

In the second study, I link the financial markets with macroeconomic and political uncertainties. I show that the cross-sectional return dispersion is a good measure for uncertainty, and it can be easily obtained at any time. In contrast, the commonly used National Bureau of Economic Research (NBER) business cycle data and International Crisis Behaviour (ICB) crisis data are not updated monthly not to mention daily. Previous literature has shown that return dispersion is associated with unemployment (Loungani, Rush, and Tave, 1990), business cycle (Loungani, Rush, and Tave, 1991), and the state of the aggregate economy (Gomes, Kogan, and Zhang, 2003). Therefore, it is natural to link it with uncertainties that could influence returns of securities traded in financial markets. I compute return dispersion in 18 countries using the standard deviation of the fifty largest market capitalisation stocks' returns in each country. I find that return dispersion is significantly higher during local recessions and global recessions raise return dispersion even more. Return dispersion is also to capture political crises in all but one of the countries I test. When I count articles containing words related to uncertainty in Bloomberg and employ it as a proxy for general uncertainty, return dispersion is higher in 11 out of 18 countries. Also, return dispersion is linked to the economic policy

uncertainty proxy developed by Baker, Bloom, and Davis (2016). Overall, return dispersion is a model free measure and it can systematically capture all sorts of political and macroeconomic uncertainties. It is particularly useful for practitioners as it can be obtained daily or even hourly by practitioners. Therefore, investors can use it as a tracer to closely track the financial market and regulators can use it to monitor the economy at any point of time.

Moreover, I test whether return dispersion is linked with stock returns. I find that firms that are more sensitive to return dispersion offer higher returns. Additionally, I compare return dispersion with implied volatility. The evidence shows that return dispersion does a better job in measuring global business cycles and political crises, while, implied volatility significantly captures economic policy uncertainty.

In the third study, I evaluate the performance of asset allocation strategies of financial market participants. I compare various asset allocation strategies that are commonly used including equally weighting, mean-variance weighting based on Markowitz model, risk parity based on variance, risk parity based on volatility, minimum variance weighting, equal risk contribution weighting developed by Qian (2006), and maximum diversification strategy created by Choueifaty and Coignard (2008). I construct portfolios using four different datasets including five country indices, ten US industries, individual US stocks and multi-assets with bonds and stocks. I employ the rolling-sample approach and estimate the out-of-sample performance for each strategy.

I use the Sharpe ratio and alphas from asset pricing models to measure performance. I find that none of the strategies is statistically different from the equally weighted portfolio for country- and industry-based portfolios. For stock- and multi-assets-based portfolios, there are differences between strategies; however, none of the strategies can consistently outperform the others in the long-term. Furthermore, I compare the risk factor loadings of those strategies in order to estimate the time varying risk exposures associated with the strategies. I find that the mean variance weighting strategy has the largest fluctuation in risk loadings, which implies high risk shifting towards market, size, value, and momentum factors. Last but not least, I find that no strategy can outperform the others consistently and across all datasets. This study provides guidance in portfolio construction for both academic research and professional practice.

In summary, the structure of this thesis is as follows. Chapter 2 looks into the impact of corruption culture on bank short-termism. In Chapter 3, I illustrate the link between the cross-sectional return dispersion and multiple uncertainties. Chapter 4 runs comprehensive tests on asset allocation strategies. Each of those chapters contain separate motivations, research questions, methodologies, empirical results, and robustness tests. Chapter 5 summarises the thesis and includes overall contributions, limitations and directions for future studies.



## **Chapter 2 Corruption culture and bank short-termism**

### **2.1 Introduction**

A major cause of the Financial Crisis of 2007-2008 is believed to be the financial sector's focus on short-term results rather than long-term value creation (Dallas, 2011). The importance of understanding the determinants of short-termism has been recognized in the literature. According to Edmans (2009, p. 2), "many academics and practitioners believe that myopia is a first-order problem faced by the modern firms". Given the importance of this issue, previous literature has suggested several factors that influence short termism, such as CEO equity vesting (Edmans, Fang, and Lewellen, 2013), board effectiveness (Gonzalez and André, 2014), institutional investors (Bushee, 1998), stock liquidity (Chen, Rhee, Veeraraghavan, and Zolotoy, 2015), and corporate governance (Cornett, McNutt, and Tehranian, 2009). Yet the impact of corruption culture as a driver of short termism has not received much academic attention.

In this chapter, I provide two sets of evidence that suggest corruption is strongly associated with short-termism in the banking sector. In the first part, I show a significant positive relationship between short-termism and domestic corruption which is the level of corruption in the country where the bank is headquartered. In the second part, I show an asymmetrical impact of foreign

corruption on short-termism where foreign corruption is the level of corruption in banks' foreign institutional shareholders' domiciled countries. Banks headquartered in less corrupt countries behave more myopically if they have larger numbers of shareholders from more corrupt countries. However, having larger numbers of shareholders from less corrupt countries does not reduce the level of myopia for banks with higher than average domestic corruption.

Myopic behaviour can be defined as types of firm behaviour that inflate current profits at the expense of long-term benefits (Stein 1988, 1989). It is difficult to come up with direct empirical measures of myopia as it is hard to observe the time horizon firms have in mind when making corporate decisions. Moreover, previous literature interprets various corporate actions as evidence of myopia. These corporate actions mainly fall into three categories. First, cutting investments that would provide long-term growth or setting high hurdle rates for accepting investment projects can be interpreted as myopic behaviour (Bushee, 1998; Laux, 2012). Second, attempts to maximize short-term profits due to pressure from capital markets can be considered as myopic behaviour as well (Houston, Lev, and Tucker, 2010; Bird, Ertan, Karolyi, and Ruchti, 2017). In particular, due to the pressure exerted by transient investors, including institutional shareholders, firms might be tempted to manipulate earnings to meet or beat current period market expectations even if that comes at the expense of long-term stability. Third, executive compensation designed to focus on short-term performance is taken as evidence of short-termism (Fahlenbrach and Stulz, 2011; Gopalan et al., 2014; Kolasinski and Yang, 2018). This is because short-term oriented compensation structures can give

perverse incentives to executives, leading them to make myopic decisions. Overall, previous studies tend to focus on a single facet of myopia and their sample selection procedures are often affected by their choice of the proxy for short-termism (for instance, firms with detailed compensation information only, firms with analyst coverage only, or firms with long-term investment figures only).

In order to capture different facets of myopia simultaneously, I build a multidimensional index of myopia. However, the above mentioned three categories of corporate actions are not completely applicable for banks. Banks do not report R&D costs as their long-term investment. Also, executive compensation data for European banks is limited. Therefore, my multidimensional myopia index is designed particularly for banks which includes earnings management, tail risk, and short-term debt ratio. This approach is similar in nature to the one adopted by Bernile, Bhagwat, and Yonker (2018) who incorporate six dimensions of board characteristics to establish a multidimensional index of diversity as they want to combine the effects of different sources of board diversity. I use the same method as them, such that I first standardize each dimension and, then, add them up.

The first dimension of the index is earnings management. Myopic managers would have an incentive to manage earnings in order to meet short-term targets, worrying the stock price might drop sharply if they fail to meet a target. Earnings management is widely accepted as a symptom of myopia in the literature (for instance, Cheng and Warfield, 2005; Bird et al., 2017; Bergstresser and Philippon, 2006). I classify banks as being short-termist if

they either meet or beat analyst forecast consensus by less than two cents. Second, I choose tail risk as another dimension of myopia. One of the causes of the Financial Crisis of 2007-2008 was the excessive tail risk undertaken at the expense of long-term outcomes in the banking industry (Ellul and Yerramilli, 2013). Managers may be willing to take on tail risks to boost performance in the short run but this can cause significant damage to the institutions when such risks materialise. Tail risk is calculated as the negative of the average return on the bank's stock over the 5% worst return days of each year. Third, I use bank short-term debt ratio as another dimension of short-termism. Banks are considered to be myopic if they depend disproportionately on short-term wholesale funding and are not concerned about whether they could meet long-term demands. Diamond and Rajan (2009) point out that one of the reasons for the recent financial crisis is the heavy focus upon short-term debt. Short-term funds incur short-term management through a natural chain of incentives which is very harmful for the long-term stability of financial system (Barton, 2011). The aim for this multidimensional index is to combine all major aspects of bank characteristics that constitute short-termism as none of these aspects would fully capture short termism when examined separately.

Using the multidimensional myopic index, I analyse myopic behaviour in the banking industry using a sample of listed European banks over the period running from 1998 to 2016. I show that there are significant cross-country differences in bank myopic behaviour. The myopia index comprises various of signs that might reveal short-termism. Moreover, I find that there is no significant correlation among the three components of the myopia index,

supporting the view that short termism is multidimensional and that focusing on each dimension individually would not capture the full extent of myopic behaviour<sup>1</sup>. For example, we would fail to detect a large number of short-term oriented banks if we only focused on meeting or beating analyst forecasts.

Short-termism may be influenced by corruption in two ways. First, societies with high levels of corruption are glutted with high levels of uncertainty, which makes short-term profit maximizing a better choice over speculating on an unanticipated future (The World Bank, 2014). Firms can find it difficult to focus on long-term strategies in such societies. Previous studies have shown that corruption impedes firm innovation (Huang and Yuan, 2016) and long-term growth (Fisman and Svensson, 2007). Second, corruption affects myopic behaviour through culture as behaviour is cultivated by the biological predisposition and shared metrics of value in the surrounding environment. In a corrupted environment, firms would have strong incentives to knowingly ignore the long-term consequences of their actions since the cost of violating social norms is low. For instance, a more corrupt environment is associated with a higher likelihood of corporate misconduct (Liu, 2016), greater agency problems and more self-dealing actions (Dass, Nanda, and Xiao, 2018).

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<sup>1</sup> The myopia index is constructed follow the method of Bernile, Bhagwat, and Yonker (2018) who create a multidimensional measure of board diversity and explore the impact of diversity on corporate risk taking. They sum up the normalized values of six board characteristics including gender, breadth of board experience, age, ethnicity, education, and expertise. Those components are weakly correlated and some of them even negatively correlated. They argue that diversity can come from different aspects that are not correlated with each other.

This study explores the impact of corruption on short termism using a sample of European banks, since the European economy is heavily bank-oriented (García-Kuhnert, Marchica, and Mura, 2015). It is useful to understand the function of informal institution, such as corruption culture, behind the European banking system. Most importantly, empirical research on the myopic behaviour of banking sector has been limited mainly due to difficulties in capturing this type of behaviour. I aim to provide new insights on factors that contribute to myopic behaviour in the banking industry.

I use the Corruption Perceptions Index (CPI) to measure corruption and assign corruption levels to banks based on their headquartered locations. My baseline test shows that the level of corruption in a country is positively associated with the extent of short-termism exhibited by that country's banks. For instance, A bank headquartered in Italy (a country with a relatively high level of CPI) is, on average, 0.75 higher in myopic behaviour (which is 44% of a standard deviation), compared to a similar bank headquartered in the UK (a country with a relatively low level of CPI). Bank headquartered corruption values also raise up all three dimensions of the myopic index.

In the analysis, I acknowledge the possibility of an endogenous relationship between short termism and corruption. I rule out reverse causality since a bank's behaviour is unlikely to induce a change in the culture of corruption at the country level. However, self-selection bias is a concern as banks themselves can select the country they wish to locate their headquarters in. Also, I investigate whether my results are driven by unobserved country time-invariant factors that are correlated with corruption culture. I adopt an

instrumental variable approach to tackle potentially omitted variables bias. I use the geographic distance between Denmark (the cleanest country in Europe in terms of corruption) and a bank's headquartered country as my instrumental variable. As Hofstede (2001) suggests that geography is one of the key determinants of cultural differences across countries, the instrument is relevant to the corruption culture. To visualize this instrument, I have drawn a heatmap in Figure 2-1 where corruption level increases from green to red. It is clear that the countries nearer to Denmark are greener (cleaner) than the countries located further away. This instrument satisfies the exclusion restriction as the geographic distance between a bank's domiciled country and Denmark is unlikely to have any direct impact on the behaviour of the bank. Additionally, the distance between two countries is not likely to be influenced by other omitted variables such as regulations or economic status. Using this instrument in a two-stage least squares (2SLS) regressions, I find significant and consistent support for the view that a higher domestic corruption norm leads to bank short-termism.

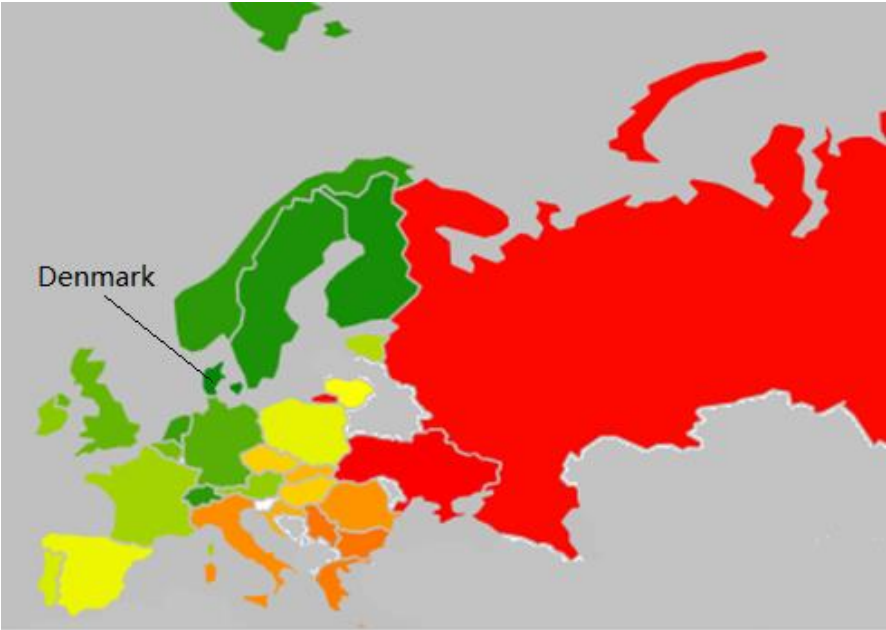
I further investigate whether the effect of domestic corruption on myopic behaviour is stronger during periods of high economic policy uncertainty (EPU). Clark (2011) shows that uncertainty amplifies myopia since myopia is considered to be a good tactic in response to unexpected events, but there is a large difference in the levels of myopia under uncertainty owing to agents' skills and judgement. It is therefore, interesting to test whether corruption, as an inherent human cognition would influence the myopic behaviour under uncertainty. I employ the monthly European EPU index developed by Baker,

Bloom, and Davis (2016) as a measure of uncertainty. I then compute the average annual EPU and take the natural logarithm. I find that in line with my intuition, the effect of domestic corruption on bank short-termism is stronger during periods of high-uncertainty compared with the effect during periods of low-uncertainty.

Additionally, I conduct robustness checks to see whether the effect of domestic corruption on the myopic behaviour of the bank holds. My results are robust when using alternative measures of corruption, when removing of large banks from the sample, when utilising different ways of constructing the myopia index, and when using alternative measures of both earnings management and risk-taking.

Figure 2-1 Corruption Levels in European Countries

This figure illustrates the level of corruption of European countries. Countries in red have the highest corruption scores, countries in yellow have medium level of corruption, and countries in green are the least corrupt countries.



In the next part of this study, I explore whether the degree of corruption in the countries where foreign shareholders of a bank are located would also be a determinant of the bank's short-termism. Previous literature shows that shareholders play a prominent role in influencing corporate behaviour either directly by engaging in bank decision-making or indirectly by trading their shares. However, there are two opposing views regarding the effect of foreign shareholders on myopic behaviour. One school of thought says that foreign shareholders only care about short-term profits rather than the long-term prospects of the firm; reference is made to foreign investors being like locusts that strip companies bare (e.g. Brennan and Cao, 1997; Borensztein and Gelos, 2003). The other view suggests that foreign institutional investors are more effective monitors than domestic investors, and this is because foreign investors have fewer social ties with the firms they monitor (e.g. Aggarwal, Erel, Ferreira, and Matos, 2011; Ferreira and Matos, 2008; Gillan and Starks, 2003).

To test the influence of foreign corruption on short-termism, I divide banks into two groups, banks with higher than average domestic corruption values and banks with lower than average domestic corruption values. The reason is that the incentive for an individual to engage in unethical behaviour is influenced by the perceived activities of the environment. Dong, Dulleck, and Torgler (2012) refer to this behaviour as "conditional corruption" and provide evidence on how the contagious nature of corruption depends on the corruption levels of other individuals in a society. In my case, the willingness for foreign shareholders to engage in corrupt practices depends largely on the level of corruption of the country where the investees are domiciled. I find that,

in terms of corruption, foreign shareholders only have effect on banks with lower than average domestic corruption values and the effect is positive. I further test if this positive effect is due to shareholders, who come from countries with higher corruption values (than the banks' headquartered countries), importing their corruption norms to banks, because prior studies have shown that culture can be imported by shareholders. For instance, Schein (1992) argues that foreign investors often use their home countries' culture as a tool to integrate and control the overseas firms in which they invest. Adding to that, DeBacker, Heim, and Tran (2015) suggest that shareholder culture can be transmitted to the company as a whole through socialization, education, selection of employees, and the provision of incentives. So, for each bank, I sum up the percentage of shareholdings of investors from countries with a higher degree of corruption than the country where the bank is headquartered. The results are asymmetric; for banks with lower than average domestic corruption values, more shareholdings from institutions domiciled in countries with higher corruption values is associated with more myopic behaviour. In contrast, for banks with higher than average domestic corruption values, more shareholdings from institutions domiciled in countries with lower corruption values does not remit short-termism. These asymmetrical results might be explained by the contagious nature of corruption as documented in the literature (see for instance, Goel and Nelson, 2007; Dong, Dulleck and Torgler, 2012).

This research contributes to the literature in a number of ways. First, I contribute to the banking literature by studying the myopic behaviour of the

banking sector where the main challenge is measurement. I capture all perspectives that may reveal myopic behaviour and combine them. By doing this, I add to our understanding of myopia in a systematic way. Previous studies mainly focus on a single dimension of short-termism and, thus, do not capture the full extent of myopic behaviour. For instance, myopic banks may not be meeting-and-beating analyst forecasts, but they may be taking high levels of tail risk or having high ratios of short-term debt.

Second, I contribute to the literature that examines the impact of corruption on various corporate activities. It is important to study the roles informal institutions, namely corruption culture, play in bank behaviour as regulators and academics have become more aware of the importance of having a healthy culture. To that end, in a recent speech, the president of Federal Reserve Bank of New York, John Williams, even emphasized the role of enhancing a healthy banking culture (Federal Reserve Bank of New York, 2018). While a growing body of literature shows that national culture has an impact on economic growth (King and Levine, 1993; Kwok and Tadesse, 2006), individuals' perceptions (Tabellini, 2010) and corporate governance (Licht, Goldschmidt, and Schwartz, 2005; Stulz and Williamson, 2003), the natural link between corruption and corporate behaviour has been understudied. Complementing these earlier studies, I identify both 'domestic culture' and the 'foreign culture' as having a significant impact on myopic behaviour.

Third, I add to the literature on the role of foreign shareholders by providing evidence that foreign shareholders import their own countries' corruption culture to the banks they invest in. I provide supporting evidence that foreign

shareholders act as channels to import their own countries' corruption culture. Even though banks are considered to be highly regulated, their shareholders' corruption norms could still influence bank decision-making. This research has wide implications for banks' supervisors and regulators. It is vital to take into account the corruption culture when making incentive scheme in order to curb short-termism.

The remainder of the chapter is organized as follows. Section 2.2 summarizes earlier studies in the literature. In section 2.3, I provide the details of short-termism measurement, corruption measurement and data description. Section 2.4 presents the effect of domestic corruption on short-termism. I show the results during the European Economic Policy Uncertainty period in section 2.5. I conduct several robustness tests in section 2.6. Section 2.7 provides evidence on bank foreign shareholders' corruption. Section 2.8 concludes.

## **2.2 Literature review and hypothesis development**

The focus of this chapter is at the intersection of three strands of literature: myopic behaviour, corruption culture, and corporate ownership. Bank myopic behaviour can be influenced by corruption culture at three levels: country level (regulations, laws, and economic development), firm level (ownership and compensation practices), and individual level (managers and employees) (Li, Griffin, Yue, and Zhao, 2013). In this study, I examine the first two levels. Specifically, I examine the influence of country corruption culture and shareholders corruption culture.

### **2.2.1 Measures and determinants of short-termism**

Short-termism is a situation where firms focus on short-term results rather than long-term value creation. This problem exists prevalently. Short-termism is shown to exist around the world and has been documented in the literature for a long time. Jacobs (1991) and Porter (1991) show that US companies are obsessed on high short-term profits rather than long-term interests of shareholders. Graham, Harvey, and Rajgopal (2005) find that 78% of executives would sacrifice long-term value to meet earnings targets. Dichev, Graham, Harvey, and Rajgopal (2013) report that 20% of firms manage earnings in an attempt to influence stock prices and to avoid adverse compensation and career concerns. The excessive focus on short-term earnings results in detriment of long-term shareholder value (Krehmeyer, Orsagh, and Schacht, 2006) and causes a misallocation of resources. It is also thought to be one of the reasons behind the recent financial crisis (Bair, 2011). Therefore, it is essential to measure short-termism and understand the drivers behind it.

It is hard to quantify short-termism as it cannot be observed directly. Thus, previous studies have different interpretations of short-termism which can be categorized into three sorts. First, previous studies consider a firm's decision to cut long-term investments or forgo long-term projects as a symptom of myopia as they think such an action is used to boost current period earnings. For instance, Bushee (1998) measures myopia using an indicator variable that is equal to one if a firm reduces R&D expenditure relative to the prior year, and zero otherwise. However, this proxy would not work for financial firms, as

banks do not record R&D expenses. Sampson and Shi (2016) use the market discount rate as a measure of short-termism as firms may adopt higher hurdle rates to forgo profitable long-term investments.

The second interpretation of short-termism is the capital market pressure from transient institutional shareholders under which, firms would manage earnings in order to meet current period benchmarks. In other words, earnings management, is used to measure managers' tendencies of misleading the focus of shareholders towards a short-term performance measure. Houston et al. (2010) consider quarterly earnings guidance as an action that would induce managerial myopia and they examine the causes as well as consequences of such guidance cessation. Bird et al. (2017) investigate how myopia spillovers from banks to corporate sectors using meet-or-beat analyst forecasts as the measure for bank short-termism. However, earnings management is not considered to be a clean measure of myopia. Managers could manipulate earnings because of other factors such as seasoned equity offerings (Cohen and Zarowin, 2010), audit quality (Becker, DeFond, Jiambalvo, and Subramanyam, 1998), and audit committee governance practices (Bédard, Chtourou, and Courteau, 2004) instead of being short-termist. Earnings management is one of the symptoms of short-termism but not a comprehensive measure of it.

Third, the structure of executive compensation is also a commonly used proxy for myopia. The executive compensation that is not properly designed to align the long-term benefit of shareholders is considered to be an incentive of corporate short-termism. In particular, Fahlenbrach and Stulz (2011) use the

ratio of cash bonus to base salary as a measure of managerial myopia but they find no evidence that myopia leads to worse performance during the financial crisis. In contrast, Kolasinski and Yang (2018) use equity duration as the measure of managerial myopia and they suggest that myopia leads to worse performance during the crisis. Although myopia is convinced to be the cause of the crisis by prominent policy makers, using executive compensation as a measure of myopia in the empirical tests would come out contradictory results. Besides, Mauboussin and Callahan (2015) criticize the use of executive compensation as the measure of short-termism. They argue that nowadays firms are equipped with more long-term focused compensation, more independent board of directors, and higher diversified governance committees, short-termism is still a big issue. Unfortunately, in this study, the access to data on CEO remuneration information varies across countries. I fail to incorporate executive compensation into the multidimensional myopia index due to the barrier of finding compensation data for European banks.

Besides the mainstream measures above, there are also several alternative measures. Brochet, Loumiotis, and Serafeim (2012) take a different approach and measure short termism based on the usage of words that are likely to reflect short-termist thinking in firm conference call transcripts. Furthermore, firm risk-taking has also been used as a proxy for managerial myopia (Gonzalez and André, 2014), however, myopia is not risk per se. Overall, there need a comprehensive measure of myopia tailored for the banking sector.

There are many papers which examine the causes of managerial myopia. Narayanan (1985) finds that managers have incentives to boost short-term earnings that sacrifice long-term earnings. The incentive for suboptimal decisions is inversely related to managers' experience, the duration of their contract and the risk-taking of the firm. Stein (1988) shows that managers may choose to reduce the likelihood of a takeover at an unfavourable price by inflating current earnings. Von Thadden (1995) suggests that myopia is a behaviour caused by the fear of early project termination by outside investors. Bolton, Scheinkman, and Xiong (2006) show that executive compensation may focus on short-term performance in order to urge managers pursue stock price growth. Gumbel (2005) shows that investors may want managers to trade on short-term information in part because performance observations under long-term informed trading are contaminated by noise in stock prices.

Besides firm-level factors, myopic behaviour is likely to be affected by country-level culture. Previous studies show that national culture has a large impact on managerial behaviour and decision making through its effects on individual perceptions (Tabellini, 2010), economic choices and individuals' behaviour (Chui, Titman, and Wei, 2010; Guiso, Sapienza, and Zingales, 2006). To be specific, national culture is shown to have a significant impact on various activities that is linked to myopia, such as, innovation and R&D development (Taylor and Wilson, 2012), earnings smoothing and earnings management (Kanagaretnam, Lim, and Lobo, 2011), earnings discretion (Han, Kang, Salter, and Yoo, 2010), risk-taking (Mihet, 2013), and corporate behaviour standards (Griffin, Guedhami, Kwok, Li, and Shao, 2015).

### **2.2.2 How corruption influences bank myopic behaviour**

Corruption is the fraudulent conduct by powerful parties for personal gains. There are two competing hypotheses regarding the effect of political corruption on the real economy. The 'sanding wheel hypothesis' argues that corruption distorts investment and causes a misallocation of resources as it imposes an extortionary tax (Shleifer and Vishny, 1993; Murphy et al., 1991, 1993). Most previous empirical evidence supports the sanding wheel hypothesis. For instance, on the macroeconomic level, corruption is shown to have a negative effect on economic growth (Mauro, 1995), governmental expenditures (Mauro, 1998), efficiency of credit allocation (Beck, Demirgüç-Kunt, and Levine, 2006), and credit risk (Butler, Fauver, and Mortal, 2009). On the corporate level, corruption is shown to have negative effect on multinational firm investment (Wei, 2000), firms' foreign investment (Zhao, Kim, and Du, 2003; Cuervo-Cazurra, 2006), firm growth (Fisman and Svensson, 2007), and firm innovation (Huang and Yuan, 2016; Ellis, Smith, and White, 2015). Alternatively, the 'greasing wheel hypothesis' suggests that corruption increases efficiency by cutting through bureaucratic ties since firms may benefit from smoothing the regulatory process (Leff, 1964; Leys, 1965). Heo, Hou and Park (2017) find that corruption is positively linked with firm innovation in developed countries. In summary, previous literature observes relationships between corruption and corporate behaviour but there are disagreements concerning the signs of these relationships.

In this study, I hypothesize that corruption exacerbates myopia. There might be two channels where corruption exert its effect, uncertainty and culture.

First, corruption leads to uncertainty (Shleifer and Vishiny, 1993; Mauro, 1995) and uncertainty makes firms less likely to be long-term oriented since it is harder to speculate an uncertain future. Consequently, firms tend to focus on short-term gains and care less about the unpredictable future. As a result, firms' long-term activities such as innovation and investment are impeded (Huang and Yuan, 2016; Ellis, Smith, and White, 2015). As the distortion of long-term investment is interpreted as one of the evidences of short-termism, corrupt environment is likely to affect firms' choice of time horizon.

Second, corruption culture creates an environment that amplifies myopia. Myopia is a human trait and can be amplified by the characteristics of the environment (Clark, 2011). In a corrupted environment, people are more tolerant about corporate misconduct. In fact, myopia is considered as the “fast route to unethical business behaviour” (Ethical Leadership, 2016). Thus, once corruption is widely accepted in a society, concerns about the long-term consequences of unethical behaviour grow smaller. For instance, Parsons, Sulaeman, and Titman (2014) show that a firm's likelihood of engaging in misconduct is related to the misconduct rates of firms in the same locale and that the relation is likely driven by social interactions among neighbouring firms. Lourenço, Rathke, Santana, and Branco (2018), who utilise data from 33 countries worldwide, find that the perceived level of corruption in an emerging country is related to stronger incentives for firms to manipulate earnings. Liu (2016) demonstrates that corruption is associated with several types of corporate misconduct including earnings management, accounting fraud,

option backdating, and opportunistic insider trading. Based on the above arguments, I hypothesize the following:

H1. *Banks headquartered in countries with higher corruption levels are more likely to be short-termist.*

I further link the effect of corruption on bank short-termism to the degree of economic policy uncertainty. With the increase in uncertainty, firms seeking favours from government could not ensure that they would actually obtain those favours eventually. Thus, firms are more likely to “wait-and-see” during high uncertainty periods as long-term results are less foreseeable at such times (Arif, Marshall, and Yohn, 2016). Previous literature has shown how uncertainty affects corporate behaviour that are considered to be myopic such as earnings management (Stein and Wang, 2016) and cutting investments (Gulen and Ion 2015). In particular, Campos, Lien, and Pradhan (1999) argue that corruption has a less negative impact on investment when corruption induced uncertainty is lower. Thus, the second hypothesis is:

H2. *Banks headquartered in countries with higher corruption levels are more likely to be short-termist during periods of greater Economic Policy Uncertain.*

### **2.2.3 The impact of shareholders on firm short-termism**

Besides country social norms, firm-level governance also plays an essential role in curbing myopic behaviour. Shareholders are considered to act as a channel for promoting better governance directly through voting rights and indirectly through trading on shares (Aggarwal, Erel, Ferreira, and Matos, 2011). I expect shareholders to have impact on short-termism since they play

an important role in curbing the agency problem. For instance, Florackis (2008) shows that managerial ownership and ownership concentration mitigate agency costs for UK listed firms. Shareholders have the incentives to monitor and discipline managers to ensure that the firms' strategies are in line with long-term value maximization (Shleifer and Vishny, 1986). Shareholders are also shown to influence firm long-term investment (Bushee, 1998) and innovation output (Aghion, Van Reenen, and Zingales, 2013).

Moreover, there are reasons to expect that cultural values of foreign shareholders are imported to the corporations they invest in. Peters and Austin (1985) suggest that owners are able to influence the ethical standards of their employees. Schneider (1988) suggests that culture can be used as a tool for owners to exert control over overseas firms in which they invest. Bushee (1998) shows that firms dominated with myopic shareholders are more likely to cut long-term investment to meet short-term earnings targets. Bolton, Scheinkman, and Wei (2005) find that more long-term-oriented shareholders are less likely to encourage short-termist strategies taken by top managers. In a recent paper, DeBacker et al. (2015) find that shareholders import their corruption culture to US firms. Shareholders from more corrupted countries invade more tax in the US. Based on the above studies, I infer that shareholders' corruption culture is associated with bank short-termism.

Then it is natural to raise up two questions. Would corrupted foreign shareholders corrupt the banks they invested in? Would clean shareholders restrain the banks they invested in if the bank is already located in a corrupted environment? The conjecture for those questions is that corruption corrupts.

For the first question, corrupted foreign shareholders would contaminate the bank they invested in as corruption is highly contagious. Dong, Dulleck and Torgler (2012) show the contagious nature of corruption using both micro and macro level international data. Goel and Neilson (2007) provide evidence of the contaminating effect of corruption using state-level US data. For the second question, as the surrounding environment is tolerant towards unethical activities, it would be hard to stand out and survive being the only honest player in the system. Thus, I hypothesize the following:

*H3a. Banks that have a lower than average domestic corruption level, and that have more shareholdings by foreign institutions that are domiciled in countries with higher corruption levels, are more likely to be short-termist.*

*H3b. For banks that have a higher than average domestic corruption level, and that have more shareholdings by foreign institutions domiciled in countries with lower corruption levels, their level of short-termism is not likely to be affected.*

## **2.3 Data and summary statistics**

### **2.3.1 Sample construction**

The sample comprises all financial firms in the European countries between the fiscal years of 1998 and 2016. I select all firms that are classified in the financial sector according to Global Industry Classification Standard (GICS). Accounting data and stock prices are collected from Datastream. Furthermore, I utilize the Thomson Reuters ownership database to get shareholders' information for each bank. Finally, I use the unadjusted detail file

in the Institutional Brokers' Estimate System (I/B/E/S) to get analyst forecast figures.

### **2.3.2 Measures of bank short-termism**

To measure the level of bank short-termism, I construct an index based on different aspects of bank characteristics. I choose those aspects based on previous literature and data availability. For each bank-year, I combine three characteristics: the meet-or-beat analyst forecast, tail risk, and short-term funding.

First, I use meet-or-beat analyst forecast (*beat\_analyst*) as a proxy for earnings management. *Beat\_analyst* is an indicator variable that equals one if a bank's actual earnings-per-share either meets or beats the I/B/E/S analyst consensus forecast by less than two cents (Bird et al., 2017). I use the unadjusted detail file in I/B/E/S as previous studies concerns on rounding errors in adjusted estimates (Cheong and Thomas, 2011; Diether, Malloy, and Scherbina, 2002). I follow Fang, Huang, and Karpoff (2016) and drop observations if the firm has less than three analysts in a given year. I calculate the mean analyst forecast estimated earnings per share (EPS) that are issued within 90 days of the fiscal year-end and before the earnings announcement. If the difference between the mean value of analyst forecast EPS and actual EPS is less than 2 cents, I classify that bank-year as myopic. In the sample, only 8.84% banks meet-or-beat analyst forecast (109 out of 1233 observations).

Second, I use tail risk (*Tail\_risk*) as an indicator that captures another aspect of short-termism. I calculate tail risk as the negative value of the mean return on the bank's stock over the 5% worst return days of each year. As tail risk implies events with a low probability to happen, myopic managers that only focus on short-term conditions might neglect it. Ellul and Yerramilli (2013) point out that managers and traders in the financial industry are willing to take tail risk in order to boost their short-term performance although it might induce devastating damage if such risk materializes. Thus, tail risk captures bank myopia from a risk standpoint of view. A higher tail risk indicates that banks are more likely to be behaving myopically.

Third, I use bank short-term debt (*Stfund*) to capture another dimension of short-termism. The structure of debt maturity has a large impact on a firm's behaviour (Custódio, Ferreira, and Laureano, 2013). Short-term debt is an important component in bank financing policy and it implies the institutional environment in which the investors are expected to enforce repayment (Diamond and Rajan, 2000). If banks rely more on short-term funding such as money market funding, they are more likely to have short-term strategies. Those banks assume that they can keep borrowing at the short-term rates, failing to take long term perspectives or consider any long-term demands. These types of activities may hurt long-term stability. I calculate *Stfund* as the ratio of short-term loans to total liabilities. A higher value indicates the banks are more myopic.

I normalise each component by its mean and standard deviation. I construct my myopia index by summing up all three components:

$$Myopia = STD(Beat\ analyst) + STD(Tail\ risk) + STD(Stfund) \quad (2.1)$$

where  $STD(Beat\ analyst)$ ,  $STD(Tail\ risk)$ , and  $STD(Stfund)$  are the normalised values of *beat\_analyst*, *Tail\_risk*, and *Stfund* respectively.

Panel A of Table 2-1 presents the correlations between the components of the myopia index. The average correlation between a component and the myopia index is around 0.6. However, the correlations between the component are quite low. This suggests that these components indeed capture different aspects of myopic behaviour in banks.

To further illustrate the importance of having a composite measure of short-termism instead of solely focusing on single aspect, I show how differently banks are categorized based on each component of myopia. I first divide bank-year observations into two groups, one group of observations meet-or-beat analyst forecast consensus ( $Beat\_analyst=1$ ) and the other group does not ( $Beat\_analyst=0$ ). Then I categorize bank-year observations into three groups (high, medium, and low) based on their tail risk and short-term fund. Panel B of Table 2-1 reports the number of observations fall into each group. For instance, only 20 observations meet-or-beat analyst forecast consensus, have high tail risk, and have high ratio of short-term debt at the same time. However, 154 observations do not meet analyst forecast but have high tail risk and high ratio of short-term debt. This means that if we only focus on the earnings management aspect of myopia, we would miss a large number of cases when banks exhibited other aspects of myopic behaviour.

Table 2-1 Measure of Bank Short-termism

The table shows the characteristics of myopia index and its components. Panel A reports the correlation between each components of myopia index. Panel B reports bank-year observations in each group. I divide observations into two groups based on whether they meet-or-beat analyst forecast (*Beat\_analyst=1*) or not (*Beat\_analyst=0*). I construct three groups (high, medium, low) based on tail risk (*Tail\_risk*). I form three groups (high, medium, low) on the ratio of short-term debt divided total liability (*Stfund*).

<i>Panel A. Correlation between each components of myopia index</i>				
	Myopia	Beat_analyst	Tail_risk	Stfund
Myopia	1			
Beat_analyst	0.576	1		
Tail_risk	0.637	0.007	1	
Stfund	0.604	-0.022	0.168	1

<i>Panel B. Number of observations in each group</i>				
	Beat_analyst=1		Beat_analyst=0	
high Tail_risk & high Stfund	20		high Tail_risk & high Stfund	154
high Tail_risk & low Stfund	11		high Tail_risk & low Stfund	82
low Tail_risk & high Stfund	2		low Tail_risk & high Stfund	98
low Tail_risk & low Stfund	7		low Tail_risk & low Stfund	96

### 2.3.3 Corruption measure

I use the Corruption Perception Index (CPI) created by Transparency International as the primary measure of corruption as it is widely accepted and has been used in previous studies (e.g. (Barth, Lin, Lin, and Song, 2009; Djankov, La Porta, Lopez-de-Silanes, and Shleifer, 2002; Fisman, 2001). Transparency International is an anti-corruption organization that evaluates the level of public sector corruption based on surveys collected by reputable institutions. It publishes CPI every year for 180 countries. The CPI is a composite index that gives a single value for each country every year. The level of corruption has been seen to change only slightly throughout years.

I follow DeBacker et al. (2015) and reverse the scale of CPI for ease of interpretation. I calculate the average CPI from year 2012 to year 2016<sup>2</sup>. Then I subtract the CPI from 100 to obtain the corruption measure. Therefore, the higher the value of CPI in a country, the higher the level of corruption in that country.

Table 2-2 presents the list of countries in the sample together with their levels of short-termism and corruption. Based on the CPI, Russia is the country with the highest level of corruption in the sample. On average, banks headquartered in Russia are more likely to meet-or-beat analyst forecasts and have higher tail risk, however, the level of short term funding is lower than median level. On the contrary, Denmark is the least corrupt country in the sample. Banks headquartered in Denmark have much lower probabilities of beating analyst forecasts and have lower tail risk. The average proportion of short term debt of Danish banks is slightly below median level.

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<sup>2</sup> I start from year 2012 as the Corruption Perception Index has a scale from 0 to 10 before 2012.

Table 2-2 Mean Values of Myopia and Corruption in European Countries

This table reports the average myopic measure (*Myopia*), meet-or-beat analyst forecast (*Beat\_analyst*), tail risk (*Tail\_risk*), short-term debt out of total debt (*Stfund*), and corruption culture (*Corruption*) in each country. *Obs* is the total number of European bank-year observations included in the sample.

Country	Myopia	Beat_ analyst	Tail_risk	Stfund	Corruption	Obs.
Austria	0.402	0.067	0.040	0.201	28	60
Belgium	0.739	0.067	0.070	0.211	24	34
Croatia			0.041	0.048	52	9
Czech Republic	-1.498	0.000	0.039	0.053	48	6
Denmark	-0.002	0.039	0.043	0.147	9	147
Finland	1.125	0.250	0.062	0.178	11	18
France	0.436	0.060	0.038	0.316	30	172
Germany	0.319	0.196	0.047	0.156	20	87
Greece	2.672	0.140	0.098	0.268	58	66
Hungary	-0.650	0.000	0.053	0.104	48	16
Ireland	1.947	0.118	0.081	0.243	27	36
Italy	0.582	0.174	0.045	0.213	56	302
Netherlands	-0.074	0.000	0.043	0.109	16	17
Norway	-1.017	0.000	0.039	0.117	14	208
Poland	-0.413	0.087	0.048	0.108	39	119
Portugal	0.455	0.212	0.051	0.162	37	33
Romania	-0.706	0.000	0.048	0.101	55	10
Russia	0.253	0.167	0.074	0.170	72	54
Slovakia			0.074	0.069	51	27
Spain	0.786	0.184	0.045	0.243	40	97
Sweden	0.507	0.061	0.044	0.270	12	66
Switzerland	-0.269	0.064	0.032	0.109	14	286
UK	-0.249	0.018	0.052	0.149	22	119

### 2.3.4 Descriptive statistics

Based on previous studies, I control for various bank characteristics that might drive short-termism. I control for firm size (*SIZE*) and the square of size (*SIZE2*). *SIZE* is the natural logarithm of total assets. Banks may have a stronger incentive to behave myopically as they grow larger. However, once they reach a certain size, they would become more likely to be scrutinized by

regulators and to be subjected to stock market monitoring. Thus, I expect a nonlinear effect of firm size on short-termism. I control for the growth prospects of the banks by using the market-to-book ratio (*MB*), which is defined as the market value of equity divided by the total book value of equity. I control for firm performance by using return on assets (*ROA*), which is defined as the ratio of net income plus interest expenses to total assets. Firms with better performance have more investment opportunities and face a higher cost of reducing investment for short-term projects. I control for the total amount of loans divided by total assets (*LOAN*) and the amount of non-performing loans divided by total assets (*NPL*) as Beatty, Ke, and Petroni (2002) suggest that bank loans may affect nondiscretionary changes in earnings. Additionally, I include equity-to-assets ratio (*LEV*) and deposit-to-assets ratio (*DEPOSIT*). To take in to account for the shareholders' effect on myopia, I include total percentage institutional ownership (*TOTALOS*). In addition, I control for competition among banks within a country using a Herfindahl-Hirschman Index (*HHI*) of deposits among banks headquartered in the country during the year.

Moreover, I include a bunch of institutional environment measures in bank headquartered countries in the models. As national economic development is linked to the quality of institutions and is likely to affect firm behaviour, I control for the national logarithm of gross domestic product per capita (*LNGDP*). I include the creditor rights (*CR*) index developed by La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1997) and updated in Djankov, McLiesh, and Shleifer (2007). I control for the law enforcement index (*Enforce*) which measures the degree to which the law is fairly and effectively enforced in a country. It ranges

from 0 to 10 and higher values suggesting stronger enforcement. I control for the transparency of bank financial statement practices (*Transp*). I control for the restrictiveness of banking activities including securities market activities, insurance activities, and real estate activities (*Act\_res*). I control for the capital stringency index (*String*) which measures whether the capital requirement reflects certain risk elements and deducts certain market value losses from capital before minimum capital adequacy is determined. Higher values indicate greater capital stringency. I present summary statistics in Table 2-2. All continuous variables are winsorized at 1% in both tails.

Table 2-3 Summary Statistics

This table reports summary statistics for bank short-termism measures, corruption measure, bank-level variables, and country-level variables. I report statistics across the whole panel from 1998 to 2016. Variables are winsorized at the 1% and 99% levels.

	Mean	Std. Dev.	Min.	25th Pctl.	Median	75th Pctl.	Max.	Range	Obs.
<i>Short-termism measures:</i>									
Myopia	0.150	1.720	-2.708	-1.100	-0.160	0.864	9.001	11.710	1223
Beat_analyst	0.088	0.284	0.000	0.000	0.000	0.000	1.000	1.000	1233
Tail_risk	0.047	0.031	0.005	0.027	0.039	0.057	0.178	0.173	1980
Stfund	0.177	0.134	0.000	0.074	0.150	0.249	0.630	0.630	1976
<i>Corruption measure:</i>									
Domestic corruption	30.452	17.963	9.200	14.200	27.400	40.000	71.800	62.600	1989
<i>Bank-level variables:</i>									
SIZE	17.200	2.076	12.331	15.876	16.887	18.703	21.617	9.286	1989
MB	1.338	0.890	0.091	0.701	1.156	1.757	4.742	4.650	1989
ROA	1.013	0.901	-3.010	0.590	0.970	1.470	3.740	6.750	1989
LOAN	0.685	0.172	0.177	0.597	0.709	0.821	0.934	0.757	1989
LEV	0.071	0.040	0.007	0.043	0.062	0.090	0.253	0.245	1989
DEPOSIT	0.516	0.176	0.076	0.391	0.523	0.643	0.862	0.786	1989
NPL	0.047	0.084	0.000	0.008	0.020	0.051	0.677	0.677	1989
TOTALOS	0.329	0.314	0.000	0.000	0.241	0.613	1.000	1.000	1989
<i>Country-level variables:</i>									
HHI	0.415	0.205	0.136	0.268	0.351	0.533	1.000	0.864	1989
LNGDP	10.512	0.608	7.650	10.239	10.612	10.914	11.543	3.893	1989
CR	1.789	1.013	0.000	1.000	2.000	2.000	4.000	4.000	1989
Transp	5.216	0.705	2.400	5.000	5.000	6.000	6.000	3.600	1989
String	4.276	1.788	1.000	2.400	5.000	6.000	7.000	6.000	1989
Actres	6.721	1.617	3.000	6.000	7.000	8.000	9.000	6.000	1989
Enforce	5.537	1.318	3.330	4.130	5.960	6.370	7.750	4.420	1989

## 2.4 Bank short-termism and headquartered corruption culture

### 2.4.1 Empirical design

To study the relation between a bank's short-termism and the level of corruption of its headquartered country, I run the following panel regression model:

$$Myopia_{i,j,t} = \alpha + \beta_1 Corruption_j + \beta_2 BankControls_{i,j,t} + \beta_3 CountryControls_j + Year FE + \varepsilon_{i,j,t} \quad (2.2)$$

where  $i$  denotes the bank,  $j$  denotes the country where the bank is headquartered, and  $t$  denotes the year. The dependent variable  $Myopia_{i,j,t}$  is the multidimensional index of short termism. I also test each of the three components of the index in turn as dependent variables including meet-or-beat analyst forecast, tail risk, and short-term fund. Meet-or-beat analyst forecast regression uses probit estimation, as it is a binary variable. Tail risk and short-term funding use ordinary least square (OLS) estimations. The standard errors are clustered at the bank level to control for potential within firm correlation of the residuals.

The variable of interest,  $Corruption_j$  is the level of CPI of the country where the bank is located. I control for bank specific characteristics including firm size, market-to-book ratio, ROA, total loans, and leverage. I also control for non-performing loans, total deposit, total percentage of institutional ownership and HHI in models (5) to (8) of Table 2-4. For country characteristics, I control for GDP per capita, creditor rights, financial statement practices, capital stringency, bank activity restrictions, and law enforcement. I

include year dummies to control for macroeconomic status that could influence a firm's behaviour. I estimate the model on a panel of 23 European countries from 1998 to 2016.

#### **2.4.2 Baseline results**

I present the baseline results in Table 2-4. Model (1) to (4) include only basic control variables while model (5) to (8) include the full set of control variables. The coefficients on the corruption variable are positive and statistically significant at the 5% level or lower. In models (1) and (5), the dependent variable is the myopia index. The results are consistent with the first hypothesis that a bank's myopic behaviour is positively related to the level of corruption in the bank's home country.

In model (1), I examine the relationship between the myopia index and domestic corruption. One standard deviation (17.963) increase in bank headquartered corruption culture is associated with a 0.51 unit increase in the level of myopia index, which is equivalent to 30% of the standard deviation of the index values. In model (5), the myopia index is still the dependent variable and I include additional control variables, but the explanatory power of domestic corruption remains robust. One standard deviation increase in domestic corruption raises bank short-termism by 0.40 (23% of the standard deviation of the index).

In model (2) I focus on the earnings management component of the myopia index. *Beat\_analyst* is a binary variable that is equal to one if the bank-year beats analyst consensus forecast by no more than two cents. I report

marginal effects of the probit model. The coefficient on domestic corruption is 0.0018. A one standard deviation (17.963) increase in domestic corruption raises the probability of earnings management by 3.23%, which is 36.74% of the mean value of beat analyst forecast rate of 8.8%. The coefficient gets slightly larger in model (6) when I include additional firm characteristics. This effect is comparable to the effect of other variables related to culture such as individualism and uncertainty avoidance which are associated with 7.26% increase and 11.93% decrease in the probability of earnings management (measured by meet-or-beat prior year's earnings) for a one standard deviation increase in the culture measure according to Kanagaretnam et al. (2011).

Models (3) and (7) test the relation between corruption and tail risk. The coefficient of domestic corruption is 0.03% and significant at the 5% level in model (3). In terms of economic significance, a one standard deviation increase in corruption (17.963) raises the tail risk by 0.55%, which is 11.62% of the mean value of tail risk (0.047). Corruption seems to have a bigger effect on tail risk than the other social norm, namely religiosity, as Adhikari and Agrawal (2016) find that a one standard deviation increase in US county religiosity reduces tail risk by 0.15%.

Models (4) and (8) provide results on the ratio of bank short-term debt over total liabilities. The coefficient of domestic corruption is 0.34% in model (4). It goes down almost by half after controlling additional bank characteristics in model (8) but remains significant at the 1% level. According to the coefficient of corruption in model (8), *ceteris paribus*, the short-term funding ratio of a bank headquartered in Italy (whose CPI is 56) would be higher by 7.48%

compared to a bank headquartered in Switzerland (whose CPI is 14). This effect is very strong as it is 55.82% of the standard deviation of short-term funding ratio of 0.13.

Table 2-4 Bank Short-termism and Headquartered Corruption Culture

This table reports estimations of OLS regressions of short-termism on corruption culture from 1998 to 2016. The dependent variables are Myopia index (*Myopia*) and its components (*Beat\_analyst*, *Tail\_risk*, and *Stfund*). The main independent variable is the corruption culture of bank headquartered countries (*Country Corruption*). All regressions include year fixed effects, and standard errors are clustered at bank-level. In parentheses are the standard errors and the asterisks indicate a 10%(\*), 5%(\*\*), and 1%(\*\*\*) level of statistical significance. Numbers in column (3), (4), (7), and (8) are in percentage.

	(1) Myopia	(2) Beat_ analyst	(3) Tail_risk	(4) Stfund	(5) Myopia	(6) Beat_ analyst	(7) Tail_risk	(8) Stfund
Domestic	0.0285***	0.00179*	0.0304**	0.342***	0.0221**	0.00192**	0.0194*	0.178***
Corruption	(0.0107)	(0.00100)	(0.0144)	(0.0775)	(0.00912)	(0.000886)	(0.0110)	(0.0512)
SIZE	0.0770	0.0112*	0.00439	1.187**	1.479***	0.0650	-2.958***	14.886***
	(0.0594)	(0.00647)	(0.0746)	(0.540)	(0.542)	(0.0603)	(0.791)	(3.422)
MB	-0.175*	0.0173	-0.199	-1.373**	0.0551	0.00449	0.0300	0.111
	(0.102)	(0.0142)	(0.134)	(0.656)	(0.101)	(0.0111)	(0.115)	(0.539)
ROA	-0.314***	-0.00519	-1.01***	-0.504	-0.38***	-0.00355	-0.769***	-1.587***
	(0.0830)	(0.0133)	(0.192)	(0.549)	(0.0816)	(0.00829)	(0.156)	(0.512)
LOAN	-0.570	0.0734	-1.496**	-9.877	-0.238	0.0844	-0.594	-7.306*
	(0.738)	(0.0665)	(0.629)	(6.781)	(0.591)	(0.0670)	(0.666)	(3.983)
LEV	-4.065	0.193	-2.438	7.390	-3.117	0.190	-3.605	-7.611
	(2.511)	(0.348)	(5.462)	(18.363)	(2.395)	(0.267)	(4.120)	(14.491)
SIZE2					-0.04***	-0.00126	0.0840***	-0.46**
					(0.0159)	(0.00168)	(0.0228)	(0.102)
NPL					4.237***	-0.120*	11.020***	5.137
					(1.347)	(0.0627)	(1.823)	(4.635)
DEPOSIT					-3.55***	0.105	-1.673**	-50.295***
					(0.552)	(0.0817)	(0.729)	(4.015)

(continued next page)

TOTALOS					-0.115 (0.336)	0.0779** (0.0341)	-0.467 (0.398)	-2.806 (1.796)
HHI					0.372 (0.484)	0.0510 (0.0453)	1.542*** (0.536)	-1.629 (2.356)
LNGDP	0.0823 (0.254)	0.00925 (0.0214)	-0.679* (0.407)	4.559** (1.872)	0.0308 (0.228)	0.0273 (0.0195)	-0.360 (0.319)	0.0749 (1.643)
CR	-0.220* (0.121)	-.00810 (0.0118)	0.131 (0.148)	-3.045*** (0.861)	-0.180 (0.114)	-0.0109 (0.0103)	0.0149 (0.146)	-1.915*** (0.592)
Transp	0.352** (0.158)	0.0138 (0.0168)	-0.0224 (0.288)	3.599*** (1.134)	0.140 (0.137)	0.0256 (0.0169)	-0.343 (0.213)	1.288 (0.923)
String	-0.124 (0.0898)	0.00123 (0.00735)	-0.235* (0.133)	-1.513** (0.642)	-0.122 (0.0796)	0.00307 (0.00633)	-0.203* (0.107)	-1.447*** (0.505)
Actres	-0.203** (0.0986)	-0.00148 (0.00648)	-0.280* (0.144)	-1.712*** (0.640)	-0.26*** (0.0843)	0.000062 (0.00574)	-0.246** (0.120)	-2.442*** (0.496)
Enforce	0.119 (0.149)	-0.00274 (0.0175)	0.277 (0.201)	3.763*** (1.050)	0.0907 (0.158)	-0.00757 (0.0145)	0.0299 (0.197)	2.195*** (0.785)
Constant	-0.971 (2.482)	-9.68*** (2.459)	15.294*** (4.361)	-57.612*** (20.392)	-9.299* (4.930)	-18.53*** (5.702)	39.735*** (8.151)	-58.032* (33.691)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1223	1233	1980	1976	1223	1233	1980	1976
Adj R-sq	0.30	0.09	0.38	0.21	0.39	0.12	0.47	0.52

### 2.4.3 Instrumental variable

The baseline analysis does not take into consideration potential endogeneity issues. The purpose of this section is to address these issues. I can rule out reverse causality as a concern because the behaviour of a bank is unlikely to change the country-level corruption culture. I investigate whether the relationship I document between domestic corruption and myopic behaviour by banks is driven by an omitted variables bias. In particular, an endogenous relationship might exist between these two variables due to unobserved factors included in the disturbance term that are correlated with domestic corruption.

I address the endogeneity issue by using an instrumental variable approach. The instrument is the geographic distance between a bank's headquartered country and Denmark (which has the lowest value of CPI in the sample). This instrument satisfies the exogeneity condition as the distance between two countries is unlikely to have any direct effect on economic or behaviour outcomes. The instrument also satisfies the relevance condition as Hofstede (2001) points out that geography is one of the key determinants of culture differences across countries. The use of this instrument is similar in spirit to Kwok and Tadesse (2006) and Li et al. (2013) who use the continent a country belongs to as an instrumental variable for various dimensions of culture including uncertainty avoidance, individualism and harmony<sup>3</sup>.

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<sup>3</sup> Li et al. (2013) focus on 35 countries located in different continents. We cannot use continent as the instrumental variable as we only focus on European countries.

The first stage results (Panel A of Table 2-5) confirm that the geographic distance is highly related to the domestic corruption. The instrumental variable has a positive sign as expected and is strongly significant at the 1% level. A bank whose headquarters is geographically close to Denmark is expected to have a lower degree of domestic corruption than a bank whose headquarters is located far away from Denmark. The F-statistics for the weak instrument test suggests that the null hypothesis of a weak instrument is comfortably rejected at the conventional levels of significance. I report the results of the second stage regressions in panel B of Table 2-5. The effect of domestic corruption on short-termism remains significant. The two-stage estimates are larger in magnitude relative to the OLS estimates.

Table 2-5 Bank Short-termism and Headquartered Corruption Culture: Instrumental Variable

The table shows the regression results of using an instrumental variable (IV). *Distance* is the IV which is computed as the distance between Denmark (the cleanest country in terms of corruption) and bank headquartered country. Panel A reports the first stage results. Panel B reports the second stage results. All regressions include year dummies and standard errors are corrected for bank-level clustering. Standard errors are reported in parentheses. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels.

	(1) Myopia	(2) Beat_analyst	(3) Tail_risk	(4) Stfund
<b>Panel A. First stage results</b>				
Distance	23.265*** (2.251)	23.268*** (2.218)	22.642*** (1.649)	22.558*** (1.657)
IV F statistic	106.85	106.922	188.435	185.35
<b>Panel B. Second stage results</b>				
Domestic corruption	0.0461*** (0.0103)	0.0289*** (0.00971)	0.000466*** (0.000174)	0.00286*** (0.000764)
SIZE	1.434*** (0.538)	0.537 (0.536)	-0.0314*** (0.00785)	0.141*** (0.0335)
SIZE2	-0.0415*** (0.0157)	-0.00985 (0.0151)	0.000890*** (0.000226)	-0.00437*** (0.000999)
MB	0.0869 (0.0933)	0.0604 (0.105)	0.000509 (0.00115)	0.00195 (0.00514)
ROA	-0.374*** (0.0771)	-0.0374 (0.0728)	-0.00736*** (0.00151)	-0.0145*** (0.00500)
LOAN	-0.380 (0.593)	0.704 (0.665)	-0.00701 (0.00678)	-0.0772* (0.0399)
LEV	-2.556 (2.257)	2.393 (2.084)	-0.0358 (0.0404)	-0.0744 (0.144)
NPL	3.649*** (1.331)	-1.421** (0.637)	0.106*** (0.0178)	0.0345 (0.0446)
DEPOSIT	-3.506*** (0.565)	1.049 (0.714)	-0.0142* (0.00734)	-0.493*** (0.0418)
TOTALOS	-0.107 (0.331)	0.714** (0.286)	-0.00415 (0.00397)	-0.0259 (0.0174)
HHI	0.381 (0.537)	0.463 (0.442)	0.0162*** (0.00570)	-0.0132 (0.0257)
LNGDP	0.378 (0.235)	0.441** (0.220)	0.000906 (0.00405)	0.0187 (0.0211)
CR	-0.191* (0.113)	-0.106 (0.105)	-0.000343 (0.00146)	-0.0211*** (0.00603)
Transp	0.210 (0.137)	0.253* (0.148)	-0.00209 (0.00202)	0.0182** (0.00797)
String	-0.187** (0.0875)	-0.0101 (0.0672)	-0.00284** (0.00124)	-0.0177*** (0.00597)
Actres	-0.347*** (0.0841)	-0.0364 (0.0589)	-0.00367*** (0.00134)	-0.0292*** (0.00556)
Enforce	0.282* (0.149)	0.0187 (0.134)	0.00244 (0.00220)	0.0305*** (0.00803)
Constant	-13.54** (5.344)	-20.53*** (5.702)	0.352*** (0.0860)	-0.760** (0.379)
Year FE	Yes	Yes	Yes	Yes
Obs.	1223	1233	1980	1976
R-sq	0.37		0.47	0.51

## 2.5 Corruption during economic policy uncertainty

Recent studies show that culture could exert different effects on corporate decision making during different periods. For instance, CEO culture affects firm performance during periods of high competition (Nguyen, Hagendorff, and Eshraghi, 2017). Banks located in more religious US counties take less risk during the financial crisis period (Adhikari and Agrawal, 2016). Kanagaretnam, Lim, and Lobo (2013) show that individualism (uncertainty avoidance) is positively (negatively) associated with bank failure during the financial crisis.

In this section, I test the effect of corruption on bank short-termism during periods of economic policy uncertainty (EPU). By using a comprehensive European Economic Policy Uncertainty (EPU) index provided by Baker, Bloom and Davis (2016), I am able to precisely measure market uncertainty in Europe. To generate an annual uncertainty measure, I compute the average uncertainty during a year based on the monthly index and I take a natural logarithm of the annual value.

I test whether the effect of domestic corruption on bank short term varies across periods of high versus low economic policy uncertainty. Specifically, I separate the sample into two periods, one with high EPU level and the other with low EPU level. In both samples, I estimate OLS regressions using the same model as in the regression specification (2). Table 2-6 presents the results for banks during different uncertainty period. During the low EPU period, domestic corruption does not have a significant effect on the overall level of bank short-termism. On the contrary, domestic corruption has a significant positive effect on short-termism during high EPU period. One standard

deviation increase in bank headquartered country corruption level would increase myopic level by 0.64, which is 37% of the standard deviation of myopia index.

I further show results using instrumental variable in Table 2-7. Corruption has significant effect on short-termism during both low and high EPU, while the effect is stronger during high EPU. A one standard deviation increase in corruption level raises 73% myopia standard deviation during high EPU contrast to 29% during low EPU period. These findings can be interpreted as evidence that banks are more likely to focus on strategies with immediate benefits during financial market instability and a corrupt environment exacerbate the level of myopia.

Table 2-6 Bank Short-termism during European Economic Policy Uncertainty Periods

This table reports estimates of regressions of short-termism measures (*Myopia*, *Beat\_analyst*, *Tail\_risk*, and *Stfund*) on bank headquartered country corruption values during different economic policy uncertainty period. Column 1 to 4 report results during low uncertainty periods and column 5 to 8 report results during high uncertainty periods. All regressions include year dummies. Standard errors are clustered at bank-level and are shown in parentheses. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels.

	Low Economic Policy Uncertainty Period				High Economic Policy Uncertainty Period			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Myopia	Beat_analyst	Tail_risk	Stfund	Myopia	Beat_analyst	Tail_risk	Stfund
Domestic corruption	0.0110 (0.00743)	0.0015*** (0.000595)	0.000111 (0.000103)	0.00117* (0.000597)	0.0354** (0.0148)	0.00117 (0.00139)	0.000333 (0.000233)	0.00213*** (0.000701)
SIZE	0.844 (0.735)	-0.0367 (0.0489)	-0.0257*** (0.00745)	0.0947** (0.0368)	1.729*** (0.642)	0.316*** (0.120)	-0.0402*** (0.0127)	0.178*** (0.0410)
SIZE2	-0.0223 (0.0212)	0.00137 (0.00139)	0.000770*** (0.000215)	-0.00291*** (0.00107)	-0.0523*** (0.0185)	-0.00796** (0.00331)	0.00110*** (0.000363)	-0.00556*** (0.00121)
MB	0.106 (0.0847)	-0.00107 (0.00714)	0.00146 (0.00110)	0.00537 (0.00575)	0.169 (0.211)	0.0113 (0.0245)	-0.00347* (0.00190)	0.00636 (0.00756)
ROA	-0.241*** (0.0746)	0.00303 (0.00844)	-0.00467*** (0.00152)	-0.00937 (0.00718)	-0.301*** (0.0962)	0.0132 (0.0113)	-0.00770*** (0.00227)	-0.0193*** (0.00615)
LOAN	-0.361 (0.689)	0.0785 (0.0484)	-0.00663 (0.00669)	-0.0880* (0.0486)	-0.491 (0.648)	0.0176 (0.101)	-0.00633 (0.00884)	-0.0656 (0.0518)
LEV	0.717 (2.437)	0.355** (0.139)	0.0314 (0.0387)	-0.409** (0.168)	-10.21*** (3.053)	-1.112** (0.527)	-0.112* (0.0663)	0.204 (0.187)
NPL	-1.746 (1.376)	-0.350 (0.234)	-0.00475 (0.0218)	-0.207** (0.0948)	4.447*** (1.545)	-0.0222 (0.0945)	0.117*** (0.0212)	0.0594 (0.0498)
DEPOSIT	-3.611*** (0.723)	0.0849 (0.0677)	-0.0220*** (0.00719)	-0.470*** (0.0530)	-3.202*** (0.660)	0.165 (0.111)	-0.00326 (0.00931)	-0.521*** (0.0444)

TOTALOS	0.00358 (0.404)	0.0503** (0.0230)	-0.00235 (0.00411)	-0.0114 (0.0203)	-0.348 (0.419)	0.0539 (0.0495)	-0.00484 (0.00543)	-0.0393* (0.0206)
HHI	0.595 (0.510)	0.0700** (0.0304)	0.0123** (0.00501)	-0.00980 (0.0252)	0.549 (0.561)	-0.0381 (0.0688)	0.0185** (0.00799)	-0.0222 (0.0305)
LNGDP	0.110 (0.204)	0.0249 (0.0172)	-0.00679** (0.00308)	0.00794 (0.0206)	-0.0127 (0.290)	-0.0141 (0.0343)	0.000423 (0.00487)	-0.0115 (0.0167)
CR	-0.0457 (0.120)	-0.00101 (0.00712)	0.00199 (0.00140)	-0.00774 (0.00599)	-0.404*** (0.140)	-0.0177 (0.0155)	-0.00306 (0.00195)	-0.0293*** (0.00748)
Transp	0.0633 (0.134)	0.0158** (0.00778)	-0.00737*** (0.00223)	0.00755 (0.0130)	0.233 (0.189)	0.0182 (0.0240)	-0.000837 (0.00304)	0.0182** (0.00911)
String	-0.164** (0.0649)	0.000243 (0.00335)	-0.00154* (0.000804)	-0.0194*** (0.00631)	-0.0821 (0.107)	0.00683 (0.00889)	-0.00338* (0.00190)	-0.00658 (0.00486)
Act_res	-0.147** (0.0711)	0.00166 (0.00329)	-0.000994 (0.000816)	-0.0180*** (0.00581)	-0.379*** (0.119)	0.000957 (0.00914)	-0.00429* (0.00220)	-0.0265*** (0.00541)
Enforce	0.0845 (0.161)	-0.00553 (0.00730)	0.000547 (0.00177)	0.0199** (0.00998)	0.0334 (0.185)	-0.00498 (0.0206)	-0.000196 (0.00296)	0.0182** (0.00818)
Constant	-5.720 (6.689)	-11.46 (8.129)	0.388*** (0.0823)	-0.218 (0.408)	-10.19* (6.024)	-24.51*** (9.068)	0.461*** (0.117)	-0.774** (0.374)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	649.00	649.00	1040.00	1042.00	574.00	584.00	940.00	934.00
Adj R-sq	0.39	0.18	0.52	0.54	0.45	0.14	0.51	0.55

Table 2-7 Bank Short-termism during European Economic Policy Uncertainty Periods: Instrumental Variable

This table reports results using instrumental variable in the regressions of short-termism measures (*Myopia*, *Beat\_analyst*, *Tail\_risk*, and *Stfund*) on bank headquartered country corruption values during low (model 1-4) and low (model 5-8) economic policy uncertainty period. The instrumental variable is the geographic distance between bank headquartered country and the least corrupt country in Europe. All regressions include year dummies. Standard errors are clustered at bank-level.

	Low Economic Policy Uncertainty Period				High Economic Policy Uncertainty Period			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Myopia	Beat_analyst	Tail_risk	Stfund	Myopia	Beat_analyst	Tail_risk	Stfund
Domestic corruption	0.0282** (0.0112)	0.0391*** (0.0120)	0.000132 (0.000154)	0.00307*** (0.000988)	0.0707*** (0.0169)	0.0156 (0.0143)	0.000904*** (0.000329)	0.00261** (0.00106)
SIZE	0.786 (0.719)	-0.621 (0.859)	-0.0259*** (0.00734)	0.0815** (0.0369)	1.631** (0.638)	2.210** (0.929)	-0.0440*** (0.0131)	0.174*** (0.0408)
SIZE2	-0.0209 (0.0207)	0.0233 (0.0247)	0.000774*** (0.000211)	-0.00254** (0.00108)	-0.0498*** (0.0183)	-0.0555** (0.0256)	0.00120*** (0.000374)	-0.00546*** (0.00120)
MB	0.105 (0.0825)	-0.0131 (0.128)	0.00147 (0.00109)	0.00602 (0.00557)	0.244 (0.165)	0.0994 (0.178)	-0.00252 (0.00190)	0.00719 (0.00744)
ROA	-0.231*** (0.0767)	0.0690 (0.146)	-0.00464*** (0.00149)	-0.00668 (0.00701)	-0.282*** (0.0978)	0.0947 (0.0847)	-0.00704*** (0.00220)	-0.0187*** (0.00610)
LOAN	-0.426 (0.681)	1.322 (0.962)	-0.00670 (0.00656)	-0.0940* (0.0488)	-0.697 (0.661)	0.102 (0.764)	-0.00874 (0.00934)	-0.0676 (0.0513)
LEV	1.152 (2.310)	6.886** (2.678)	0.0314 (0.0380)	-0.408** (0.171)	-9.334*** (2.851)	-7.787** (3.940)	-0.114* (0.0649)	0.203 (0.185)
NPL	-2.018 (1.387)	-5.633 (3.840)	-0.00426 (0.0218)	-0.163** (0.0817)	3.095** (1.545)	-0.417 (0.822)	0.0996*** (0.0219)	0.0450 (0.0546)
DEPOSIT	-3.631***	1.557	-0.0218***	-0.458***	-3.109***	1.271	0.00166	-0.517***

	(0.722)	(1.044)	(0.00707)	(0.0542)	(0.682)	(0.841)	(0.00971)	(0.0438)
TOTALOS	-0.00296	0.884**	-0.00228	-0.00594	-0.378	0.398	-0.00461	-0.0390*
	(0.381)	(0.357)	(0.00407)	(0.0191)	(0.443)	(0.375)	(0.00551)	(0.0203)
HHI_C	0.588	1.247**	0.0123**	-0.00742	0.647	-0.279	0.0211**	-0.0201
	(0.536)	(0.570)	(0.00492)	(0.0300)	(0.653)	(0.528)	(0.00900)	(0.0308)
LNGDP	0.303	0.610*	-0.00643	0.0399	0.559	0.0218	0.00998	-0.00346
	(0.230)	(0.323)	(0.00397)	(0.0280)	(0.350)	(0.335)	(0.00627)	(0.0223)
CR	-0.0368	0.00502	0.00196	-0.0104	-0.455***	-0.142	-0.00415**	-0.0302***
	(0.118)	(0.129)	(0.00137)	(0.00634)	(0.148)	(0.122)	(0.00206)	(0.00737)
Transp	-0.00728	0.237	-0.00732***	0.0124	0.436**	0.164	0.00278	0.0212**
	(0.156)	(0.147)	(0.00209)	(0.0116)	(0.187)	(0.188)	(0.00312)	(0.00931)
String	-0.200***	-0.0261	-0.00159*	-0.0242***	-0.188	0.0260	-0.00522**	-0.00811
	(0.0720)	(0.0697)	(0.000936)	(0.00780)	(0.126)	(0.0806)	(0.00207)	(0.00583)
Actres	-0.199***	0.00162	-0.00108	-0.0260***	-0.522***	-0.0205	-0.00679***	-0.0286***
	(0.0749)	(0.0605)	(0.000972)	(0.00685)	(0.124)	(0.0850)	(0.00235)	(0.00661)
Enforce	0.225	0.000852	0.000725	0.0358***	0.261	0.00561	0.00350	0.0214**
	(0.168)	(0.142)	(0.00195)	(0.0108)	(0.189)	(0.167)	(0.00318)	(0.00889)
constant	-7.408	-14.05*	0.384***	-0.517	-17.25***	-24.66***	0.360***	-0.858**
	(6.936)	(7.957)	(0.0834)	(0.468)	(6.685)	(8.923)	(0.122)	(0.395)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	649	649	1,040	1,042	574	584	940	934
Adj R-sq	0.378		0.524	0.524	0.428		0.49	0.551

## 2.6 Robustness tests

I conduct a battery of tests to investigate whether the relationship between domestic corruption and bank myopia documented in the baseline results is robust. In particular, I investigate if the main results still hold using an alternative measure of corruption, removing large banks, and employing alternative measures of short-termism. Table 2-8 summarises these results.

### 2.6.1 Alternative corruption measure

First, I use an alternative measure for domestic corruptions. I employ the “control of corruption indicator” in the World Governance Indicators computed by the World Bank as the new measure of corruption which aggregates various surveys of firms, residents, and experts all over the world. The higher the value, the stronger control for corruption, the lower the corruption norms in the society. Panel A of Table 2-8 reports the results for the new measure of corruption. The coefficient for the alternative corruption measure (*controlcorruption*) is negative and significant which indicates that a strong control of corruption (less corrupt) is associated with less bank short-termism.

Table 2-8 Robustness Tests

This table shows the coefficient of bank headquartered country corruption from alternative specifications of the regressions of *Myopia*, *Beat\_analyst*, *Tail\_risk*, and *Stfund*. Columns 1 to 4 show OLS regression results and columns 5 to 8 show 2SLS regression results using instrumental variable. Panel A demonstrates results using the World Governance Indicator as an alternative measure of bank headquartered country corruption. Panel B shows the results after removing big banks each year in each country. Panel C shows the results of using different composites of myopia index. All regressions include bank-level control variables (size, square-root of size, market-to-book ratio, ROA, total loans out of total assets, total deposits out of total assets, total equity divided by total debt, non-performing loans out of total loans, and total large institutional shareholdings), bank headquartered country-level control variables (Herfindahl-Hirschman Index of deposits, logarithm of GDP, Transparency, stringency, activity restrictiveness, and law enforcement), and year dummies. Standard errors are clustered at the bank-level and are reported in parentheses.

Panel A: Alternative corruption measure								
	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Myopia	Beat_analyst	Tail_risk	Stfund	Myopia	Beat_analyst	Tail_risk	Stfund
control corruption	-0.507** (0.226)	-0.372* (0.194)	-0.00474* (0.00281)	-0.0383*** (0.0122)	-1.230*** (0.291)	-0.793*** (0.258)	-0.0123*** (0.00465)	-0.0770*** (0.0217)
Bank-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1159.00	1169.00	1874.00	1870.00	1159.00	1169.00	1874.00	1870.00
Adj R-sq	0.40	0.12	0.48	0.51	0.37	0.15	0.47	0.50

(continued next page)

(Table 2-8 continued.)

Panel B: remove large banks

	OLS				IV			
	(1) Myopia	(2) Beat_ analyst	(3) Tail_risk	(4) Stfund	(5) Myopia	(6) Beat_ analyst	(7) Tail_risk	(8) Stfund
Country corruption	0.031*** (0.0102)	0.0204** (0.00821)	0.00030** (0.000142)	0.0021*** (0.000649)	0.053*** (0.00887)	0.0281*** (0.00931)	0.00056*** (0.000195)	0.0030*** (0.000582)
Bank-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1035.00	997.00	1618.00	1611.00	1035.00	997.00	1618.00	1611.00
Adj R-sq	0.43	0.15	0.49	0.54	0.42		0.48	0.53

Panel C: Alternative short termism measures

	OLS			IV		
	(1) pca	(2) Myopia (allp)	(3) Myopia (downrisk)	(4) pca	(5) Myopia (allp)	(6) Myopia (downrisk)
Country corruption	0.0148** (0.00619)	0.0340*** (0.0116)	0.0243** (0.00985)	0.0286*** (0.00557)	0.0517*** (0.0131)	0.0479*** (0.00874)
Bank-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1035.00	1029.00	1035.00	1035.00	1029.00	1035.00
Adj R-sq	0.60	0.49	0.41	0.59	0.49	0.40

### **2.6.2 Remove large banks**

Second, I remove the largest banks in the sample. This test is to remove the influence of “too-big-to-fail” banks. Those banks are more likely to be short-termism as they believe they would be bailed out by the government if the long-term consequence realized. Therefore, I remove the largest bank in each country every year. In total, I drop 366 observations (almost 30% of the sample). Panel B of Table 2-8 shows that the results do not change. In fact, the effect of corruption on bank short-termism becomes even slightly stronger. The results are not driven by very large banks in each country.

### **2.6.3 Alternative measure for short-termism**

Third, I use an alternative method to aggregate different components of the bank short-termism measure. Instead of just summing up the standardized value of meet-or-beat analyst forecast, tail risk, and short-term debt ratio, I employ factor analysis on those three components. I extract the first principle component (*pca*) and use it as an alternative measure for short-termism. I report ordinary least square (OLS) results in column (1) of Panel C of Table 2-8 and instrumental variable results in column (4). The results are similar to the main results.

### **2.6.4 Alternative measure for earnings management**

Fourth, I use an alternative measure for earnings management. Instead of using meet-or-beat analyst consensus forecast, I use discretionary loan loss provisions as the proxy for earnings management. I estimate discretionary LLPs following Bushman and Williams (2012):

$$\begin{aligned}
LLP_{itj} = & \gamma_0 + \gamma_1 Eblp_{itj} + \gamma_2 \Delta NPL_{it+1,j} + \gamma_3 \Delta NPL_{it,j} + \gamma_4 \Delta NPL_{it-1,j} \\
& + \gamma_5 \Delta NPL_{it-2,j} + \gamma_6 CAP_{it-1,j} + \gamma_7 Size_{it-1,j} + \gamma_8 \% \Delta GDP_{tj} \\
& + Country Dummies + Year Dummies + \varepsilon_{itj}
\end{aligned} \tag{2.3}$$

$LLP_{itj}$  is the loan loss provision scaled by lagged total loans for bank  $i$ , in country  $j$ , for year  $t$ .  $Eblp_{itj}$  is earnings before loan loss provisions and taxes for period  $t$  scaled by lagged total loans.  $\Delta NPL$  is the change in non-performing loans scaled by lagged total assets.  $CAP_{it-1,j}$  is the book value of equity divided by lagged total assets.  $Size_{it-1,j}$  is the natural logarithm of total assets.  $\% \Delta GDP_{tj}$  is the percentage change in GDP per capital to control for macroeconomic status. I also include country dummies to account for any time-invariant country characteristics that could influence loan loss provisioning and year dummies to capture changes in loan loss provisioning over time. I report the results in Appendix 2.

The absolute value of the residuals ( $ALLP$ ) are the proxy for short-termism. The higher the value, more likelihood of myopic behaviour. I then replace meat-or-beat analyst forecast with standardized  $ALLP$ . The myopia ( $ALLP$ ) in Panel C of Table 2-8 is computed as below:

$$Myopia(ALLP) = STD(ALLP) + STD(Tailrisk) + STD(Stfund) \tag{2.4}$$

I report the results for ordinary least squares in model (2) of panel C and the results for instrumental variable (which is the geographic distance between bank headquartered country and Denmark) in column (5). The results are consistent with the main results.

## 2.6.5 Alternative risk measure

Next, I use an alternative measure for tail risk. Similar to tail risk, I wish to have a measure that captures the probability of returns falling below a disaster level with the consideration of general market condition. Thus, I employ the downside risk as an alternative. It measures the sensitivity of investors to downside losses relative to upside gains. Follow Ang, Chen, and Xing (2006), I compute downside risk as market betas over periods when the excess market return is below its mean:

$$\beta^- = \frac{cov(r_i, r_m | r_m < \mu_m)}{var(r_m | r_m < \mu_m)} \quad (2.5)$$

where  $r_i$  is bank  $i$ 's excess return,  $r_m$  is the market (the major stock index) excess return of bank  $i$ 's domiciled country,  $\mu_m$  is the average market excess return every year. I standardize downside risk and replace tail risk with it:

$$\begin{aligned} & Myopia(downrisk) \\ & = STD(Beat_{analyst}) + STD(Downrisk) + STD(Stfund) \end{aligned} \quad (2.6)$$

Column (3) and (6) of Panel C of Table 2-8 show the results for OLS and instrumental variable respectively. The results hold for a risk measure that controls market factor.

## 2.7 Bank short-termism and foreign shareholders' corruption

The findings that domestic corruption is significantly and positively associated with bank short-termism is consistent with the first hypothesis. I further investigate whether 'foreign corruption', which is the degree of corruption in countries where foreign shareholders are based could also

influences bank short-termism. I focus on foreign shareholders as they are a potential channel to import corruption culture from outside to the bank headquartered country. I only consider large foreign institutional investors that hold at least 5% of the bank's shares. I do this to reduce the noise caused by small shareholders who are likely to invest for diversification purposes and who would not have a significant influence on the behaviour of banks they invest in as a result. I collect institutional ownership data from the Thomson Reuters 13F ownership database.

### **2.7.1 Foreign shareholders**

Previous studies focus on two hypotheses on the effect of foreign shareholders on non-financial firm myopic behaviour. One hypothesis states that foreign shareholders are "locusts" that only search for short-run profits and care little about the long-term prospects of the firm. The other hypothesis proposes an opposite view, suggesting that foreign shareholders foster long-term investment as they are more effective monitors than domestic shareholders and bring in better governance. To my best knowledge, there is little evidence on the effect of shareholders in the banking sector.

I propose that foreign shareholders from different culture backgrounds may have different effects on the behaviour of their investees. For instance, the US has a higher corruption score than Norway but a lower corruption score than Italy. The effect of a US shareholder on a Norwegian bank should be different from its effect on an Italian bank. Therefore, I divide banks into two groups based on their level of corruption. One group contains banks headquartered in countries with lower than average corruption values. Those

countries are Austria, Belgium, Denmark, Finland, Germany, Ireland, Netherlands, Norway, Sweden, Switzerland, and the UK. The other group contains banks that are headquartered in countries with higher than average corruption values. Those countries include Croatia, Czech Republic, France, Greece, Hungary, Italy, Poland, Portugal, Romania, Russia, Slovakia, and Spain.

I report summary statistics of institutional ownership in Table 2-9. *TOTOS* is the total percentage ownership computed by summing up the shareholdings of all large institutional investors (with at least 5% shareholding) divided by the stock's total market capitalization. *FOROS* presents the total foreign ownership percentage calculated by summing up the shareholdings of all institutions domiciled outside bank headquartered country divided by the bank's market capitalization. On average, the total percentage of institutional ownership is 47% and the average total foreign ownership is 30%, which is more than half of the total ownership. In the sample, Slovakia has a very high proportion of ownership by foreign institutional investors, amounting to 90%. In contrast, I find very low foreign institutional ownership in Norway (10%), France (9%), and Finland (8%). I observe that banks headquartered in countries with lower than average corruption values have less foreign ownership and this may due to more restrictive policies in those countries. For instance, Finland has some tax policies that may make it unattractive to foreign investors.

In Column (3) of Table 2-9, *FOROS\_corrupt* represents the total percentage shareholdings by foreign institutions (with at least 5% shareholding) domiciled in countries with higher corruption value than bank-headquartered

countries as a fraction of market capitalization. For banks headquartered in area with high corruption norms (Czech Republic, France, Greece, Hungary, Romania, Russia, and Spain), they rarely have any shareholders from countries that have higher corruption values than their headquartered countries. *FOROS\_clean* represents the holdings by foreign institutions (with at least 5% shareholding) domiciled in countries with lower corruption value than bank-headquartered countries as a fraction of market capitalization. There is a concern of the offsetting effect of having both corrupt and clean shareholders. However, those statistics make it clear that banks headquartered in corrupt (clean) countries, they rarely have foreign shareholders domiciled in even more corrupt (clean) countries. The offsetting effect is tiny and should not affect the results.

To further illustrate the effect of large foreign shareholders, instead of computing percentage shareholdings as a percentage of market capitalization, I compute shareholdings as a percentage of large institutional investors in column (5) and (6). *SH\_corrupt* represents the total percentage ownership held by shareholders from countries with higher corruption values than bank-headquartered countries out of total percentage shareholdings by large shareholders (at least 5% shareholdings). For instance, on average only 68% shares of banks in Austria are held by large institutional investors, 36% of shares are held by foreign investors from countries with higher corruption scores than Austria. *SH\_clean* represents the ownership by institutions domiciled in countries with lower than bank headquartered countries as a fraction of large institutional investors (both domestic and foreign).

Table 2-9 Summary Statistics of European Bank Shareholders

The table reports summary statistics of average bank ownership by each country. I only consider large shareholders with at least 5% shareholdings. *TOTOS* is the total ownership. *FOROS* is the total foreign ownership. *FOROS\_corrupt* is the percentage ownership by shareholders from countries with higher corruption values than bank headquartered country divided by market capitalization. *FOROS\_clean* is the percentage ownership by shareholders from countries with lower corruption values than bank headquartered country divided by market capitalization. *SH\_corrupt* is computed as the total ownership by shareholders from countries with higher corruption values than bank headquartered country divided by total ownership of large shareholders (*TOTOS*). *SH\_clean* is computed as the total ownership by shareholders from countries with lower corruption values than bank headquartered country divided by total ownership of large shareholders (*TOTOS*).

Headquartered Country	TOTOS	FOROS	FOROS _corrupt	FOROS _clean	SH _corrupt	SH _clean
<i>Banks headquartered in countries with corruption score lower than average</i>						
Austria	67.76%	25.82%	25.01%	0.83%	35.72%	1.24%
Belgium	46.03%	10.29%	8.50%	1.79%	17.94%	3.89%
Denmark	30.73%	11.05%	7.72%	0.00%	36.76%	0.00%
Finland	59.07%	7.96%	7.96%	0.00%	13.48%	0.00%
Germany	49.59%	32.51%	32.23%	0.28%	61.52%	2.71%
Ireland	19.41%	14.62%	0.00%	14.62%	0.00%	84.19%
Netherlands	46.75%	13.52%	13.52%	0.00%	37.18%	0.00%
Norway	33.50%	9.55%	2.23%	7.32%	10.64%	30.27%
Sweden	30.72%	18.02%	0.42%	17.60%	1.80%	59.80%
Switzerland	49.38%	42.35%	33.43%	0.00%	74.44%	0.00%
UK	22.43%	14.97%	10.86%	4.46%	60.55%	22.07%
Total	38.55%	21.46%	15.94%	3.36%	43.94%	15.65%
<i>Banks headquartered in countries with corruption score higher than average</i>						
Croatia	61.68%	61.68%	48.36%	15.06%	49.87%	51.91%
Czech Republic	60.36%	59.62%	0.00%	59.62%	0.00%	98.51%
France	24.61%	8.62%	0.61%	8.05%	2.17%	41.67%
Greece	30.90%	30.90%	0.00%	30.90%	0.00%	100.00%
Hungary	43.55%	20.43%	0.00%	20.43%	0.00%	46.78%
Italy	29.61%	11.93%	0.00%	11.93%	0.00%	53.01%
Poland	69.61%	62.73%	14.32%	48.59%	22.68%	66.27%
Portugal	61.12%	53.42%	45.16%	8.38%	73.73%	15.86%
Romania	50.54%	45.66%	0.00%	45.66%	0.00%	90.85%
Russia	70.48%	32.14%	0.00%	32.14%	0.00%	41.94%
Slovakia	90.27%	90.27%	37.12%	53.15%	38.46%	61.54%
Spain	31.78%	10.75%	0.79%	10.52%	6.46%	45.34%
Total	55.31%	43.34%	12.09%	31.43%	17.10%	56.80%

As the banking-sector is highly regulated and closely monitored compared with the other sectors, I am not sure about whether foreign shareholders would have any effect on the behaviour of banks. Therefore, I first test the effect of foreign shareholders on bank short-termism as specified in equation (2.7):

$$Myopia_{i,j,t} = \alpha + \beta_1 FOROS_{i,j,t} + \beta_2 BankControls_{i,j,t} + Headquartered\ Country\ FE + Year\ FE + \varepsilon_{i,j,t} \quad (2.7)$$

I control for the same bank characteristics ( $BankControls_{i,j,t}$ ) as in equation (2.2) which includes size, the quadratic form of size, market-to-book ratio, ROA, total loans, leverage, total deposits, non-performing loans, total shareholders' ownership, HHI, and logarithm of GDP. I include year fixed effects to control for any time-specific factors. I also control for country fixed effects so that the results are not driven by country-level time-invariant factors. By doing so, the corruption level of bank headquartered country will not be a factor that would influence the results here.  $FOROS_{i,j,t}$  is the total percentage ownership by foreign large shareholders (with at least 5% shareholding) out of market capitalization. The results in Table 2-10 show that foreign shareholders induce short-termism in banks headquartered in countries with lower than average corruption values but not in banks headquartered in countries with higher than average corruption values.

For banks headquartered in relatively clean countries, one standard deviation (0.18) increase in the percentage of foreign shareholding would increase bank myopic level by 0.32, which is 20% standard deviation of the myopic index. The effect of foreign shareholders on short-termism only shows

up on the multidimensional myopia index but not on its components. The reason might be that each dimension is only one facet of myopia and no single dimension alone can fully capture the effect of foreign shareholders. Bernile, Bhagwat, and Yonker (2018) create a multidimensional measure of board diversity where they utilize the same method as the myopia index. They test the impact of diversity on corporate risk-taking and find that higher values in multidimensional diversity index lead to lower stock return volatility. Similar to the non-significant results of all components of the myopia index, Bernile, Bhagwat, and Yonker (2018) find that no single component of the diversity index has any impact on firm risk-taking. Only use the combined index could board diversity reveals its effect. They suggest that only the combined effect of different aspects of board diversity could influence corporate decision-making. This logic verifies the use of a multidimensional index when it is agnostic about which aspects would matter. The combined effect increases the probability of capturing different sources of short-termism.

Table 2-10 Bank Short-termism and Foreign Shareholders

This table shows estimations of panel regression of myopia measure (*Myopia*) and its components (*Beat\_analyst*, *Tail\_risk*, and *Stfund*) on foreign shareholding. The main independent variable (*FOROS*) is ownership by institutions domiciled in countries outside bank-headquartered countries. Column 1-4 reports results for banks headquartered in countries with lower than average corruption values and column 5 to 8 reports results for banks headquartered in countries with higher than average corruption values. All regressions include bank headquartered country and year dummies. Standard errors are clustered at the bank-level. \*, \*\*, \*\*\* indicate significance at the 10%, 5%, and 1% levels.

	Bank headquartered in clean countries				Bank headquartered in corrupt countries			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Myopia	Beat_analyst	Tail_risk	Stfund	Myopia	Beat_analyst	Tail_risk	Stfund
FOROS	1.803** (0.792)	0.183* (0.106)	0.0199 (0.0123)	0.00349 (0.0338)	-0.670 (0.621)	-0.135 (0.102)	-0.00216 (0.00589)	-0.0405 (0.0329)
SIZE	0.0779 (0.600)	-0.0815 (0.173)	-0.00508 (0.00767)	0.0871*** (0.0300)	0.832 (0.809)	-0.128 (0.131)	-0.0361*** (0.0120)	0.227*** (0.0858)
SIZE2	-0.00522 (0.0178)	0.00241 (0.00472)	0.000146 (0.000232)	-0.00266*** (0.000957)	-0.0207 (0.0224)	0.00509 (0.00361)	0.00107*** (0.000335)	-0.00703*** (0.00243)
MB	-0.0569 (0.0925)	0.00624 (0.0209)	-0.00418*** (0.00147)	0.00550 (0.00576)	0.0808 (0.148)	0.00538 (0.0266)	-0.000275 (0.00138)	0.00933 (0.00699)
ROA	-0.278*** (0.0830)	0.0177 (0.0164)	-0.0105*** (0.00161)	-0.0112** (0.00475)	-0.215*** (0.0726)	0.00975 (0.0191)	-0.00589*** (0.00190)	-0.0105 (0.00638)
LOAN	-1.374 (0.906)	-0.0753 (0.101)	-0.00879 (0.00703)	-0.0764 (0.0576)	0.464 (0.743)	0.725*** (0.205)	-0.00203 (0.00831)	-0.0893 (0.0666)
LEV	-0.539 (1.786)	0.0383 (0.428)	0.123*** (0.0335)	-0.299*** (0.110)	-8.112*** (2.594)	0.212 (0.904)	-0.0572 (0.0441)	-0.178 (0.250)
DEPOSIT	-3.622*** (0.773)	0.148 (0.0967)	-0.0291*** (0.0109)	-0.466*** (0.0417)	-4.014*** (0.808)	0.178 (0.140)	-0.0343*** (0.00691)	-0.547*** (0.0716)

NPL	2.149 (3.087)	-0.802 (0.508)	0.139*** (0.0360)	-0.0519 (0.110)	2.382* (1.315)	-0.213 (0.130)	0.0763*** (0.0183)	-0.0292 (0.0438)
TOTALOS	0.360 (0.377)	0.0969 (0.0638)	-0.00913* (0.00521)	0.0124 (0.0176)	0.533 (0.378)	0.220*** (0.0738)	0.000612 (0.00442)	-0.00176 (0.0356)
HHI	-0.327 (0.513)	0.0127 (0.119)	0.00570 (0.00517)	-0.0718*** (0.0266)	-0.664 (1.022)	-0.0231 (0.179)	-0.0177** (0.00723)	0.0378 (0.0583)
LNGDP	1.030 (0.634)	0.0692 (0.189)	0.0177* (0.00914)	0.0568 (0.0469)	-1.253 (0.948)	0.0247 (0.254)	-0.0328** (0.0130)	0.0385 (0.0409)
Constant	-5.751 (6.935)	-6.853 (20.64)	-0.0693 (0.101)	-0.652 (0.538)	7.022 (11.52)	-6.707 (16.190)	0.702*** (0.168)	-1.646* (0.852)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	666	440	1,071	1,065	557	526	909	911
Adj R-sq	0.512	0.225	0.531	0.599	0.396	0.158	0.617	0.555

### **2.7.2 Corrupt foreign shareholders**

I continue the investigation on the effect of different types of foreign shareholders on bank myopic behaviour. I conjecture that the positive relationship (that I found in Table 2-10) between foreign shareholdings and bank myopic behaviour in countries with higher than average corruption value is driven by foreign shareholders from countries that are more corrupt relative to the country where the bank is headquartered. If so, I would expect that for banks with higher percentage shareholdings from countries with corruption value higher than its headquartered countries behave more myopically. I only conduct tests on banks that are headquartered in countries with lower than average corruption values. The reason is that in 8 out of 12 countries with higher than average corruption scores, banks rarely have any foreign investors domiciled in countries with even higher corruption values than their headquartered countries.

Panel A of Table 2-11 reports the results for banks headquartered in countries with lower than average corruption level. I use the same bank-level control variables as in equation (2.2). I include bank headquartered country and year fixed effects in all regressions. I show that one standard deviation (0.13) increase in percentage shareholdings from countries that are more corrupt than the country where the bank is located increases bank short-termism by 0.13 standard deviation. This is consistent with the expectation that corruption corrupts and foreign shareholders are acting as the channel. These results justify the use of a multidimensional myopic index as it is the only measure that captures the effect. Using the myopia index increases the

probability that myopia is captured, since the manifestation of myopia may have various facets. If I only focus on individual dimension of myopia, I would not find any effect.<sup>4</sup>

Furthermore, I test if shareholders located in countries that are less corrupt relative to the country where the bank is headquartered bring in their culture, such that such foreign shareholders curb the short-termism of banks headquartered in countries with higher than average corruption values. I compute the total shareholding by institutions domiciled in countries with smaller corruption values than bank headquartered countries (*FOROS\_clean*). I only focus on banks that are headquartered in countries with higher than average corruption values as the rest of banks (headquartered in countries with lower than average corruption values) rarely have shareholders from countries with even lower corruption values. In Panel B of Table 2-11, the results show that a higher percentage of clean foreign shareholders have no effect on the bank short-termism.

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<sup>4</sup> We have less observations when using meet-or-beat analyst forecast rather than myopia index as the dependent variable. The reason is that many observations drop when dependent variable is a categorical variable. For instance, in year 2000, all our observations have *Beat\_analyst* values equal to zero. Once we use year fixed effect, observations drops for year 2000.

Table 2-11 Bank Short-termism and Foreign Shareholders' Corruption Culture

Panel A of the table focus on banks headquartered in countries with lower than average corruption values. I report estimates of regressions of bank short-termism index (*Myopia*) and its components (*Beat\_analyst*, *Tail\_risk*, and *Stfund*) on ownership by shareholders from countries that have higher corruption values than bank-headquartered countries (*FOROS\_corrupt*). Panel B of the table focus on banks headquartered in countries with higher than average corruption values. I report estimates of regressions of myopia (*Myopia*, *Beat\_analyst*, *Tail\_risk*, *Stfund*) on ownership by shareholders from countries that have lower corruption values than bank-headquartered countries (*FOROS\_clean*). Firm control variables are the same as in Table 2-10. All regressions include bank headquartered country and year dummies. Standard errors are clustered at the bank level and are reported in parentheses. \*, \*\* indicate significance at the 10% and 5% levels.

Panel A: foreign shareholders from countries with corruption values higher than bank headquartered countries

	Bank headquartered in clean countries			
	(1)	(2)	(3)	(4)
	Myopia	Beat_analyst	Tail_risk	Stfund
FOROS_corrupt	1.723** (0.829)	-0.001 (0.063)	0.023 (0.015)	0.010 (0.041)
Firm controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs	666	440	1,071	1,065
Adj R-sq	0.510	0.213	0.532	0.600

Panel B: foreign shareholders from countries with corruption values lower than bank headquartered countries

	Bank headquartered in corrupt countries			
	(1)	(2)	(3)	(4)
	Myopia	Beat_analyst	Tail_risk	Stfund
FOROS_clean	0.605 (0.472)	0.132 (0.134)	-0.003 (0.007)	-0.005 (0.026)
Firm controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs	557	526	909	911
Adj R-sq	0.396	0.158	0.617	0.554

## 2.8 Conclusion

Notwithstanding the large body of literature studying myopia in nonfinancial firms, the research that focuses on the measurement and the determinants of myopic behaviour in the banking sector is limited. In this study, I construct a multidimensional myopia index tailored for the banking sector to capture all aspects that could possibly reveal short-term oriented behaviour. I use this index to explore whether corruption has an influence on bank short-termism. I investigate this relationship using a large sample of European banks over the period running from 1998 to 2016.

The empirical results show that banks headquartered in relatively more corrupt countries behave in a more myopic way than those headquartered in relatively less corrupt countries. This effect is reflected in earnings management, tail risk-taking, and short-term debt ratio. The effect of corruption becomes even stronger during high economic uncertain period. I further show that not only the domestic corruption contributes to bank short-termism, but also the corruption culture of foreign shareholders matter. This study is subject to the limitation that the corruption measure is time-invariant. I assume that the country corruption level remains unchanged during the sample period. Also, although I have taken several steps to alleviate endogeneity concerns in the first part of the study, a lack of a valid instrument for the results on shareholders' corruption culture may not indicate causal relations.

Overall, the results provide evidence on the unexplored effect that informal institutions have on bank behaviour. This study offers important implications

for European bank legislators on curbing bank short-termism as corruption may be transmitted through foreign shareholders.

## Appendix 2-1 Variable Definitions

Variables	Definitions
<i>Bank Short-termism</i>	
<i>Myopia</i>	The sum of standardized meet-or-beat analyst forecast, tail risk, and short-term debt ratio
<i>Beat_analyst</i>	Indicator variable that equals 1 if bank either meet or beat analyst forecast consensus earnings per share by 2 cents, 0 otherwise.
<i>Tail_risk</i>	the negative value of mean return on the bank's stock over the 5% worst return days of each year
<i>Stfund</i>	short-term borrowing divided by total liability
<i>Corruption measures</i>	
<i>Country Corruption</i>	Corruption perception index
<i>Shareholder corruption</i>	weighted shareholders' corruption
<i>control_corruption</i>	world governance indicators
<i>Bank-level controls</i>	
<i>SIZE</i>	Nature logarithm of total assets. Source: Worldscope
<i>SIZE2</i>	square root of size
<i>MB</i>	market-to-book ratio
<i>ROA</i>	return on assets
<i>LOANS</i>	Ratio of total loans to total assets. Source: Worldscope
<i>LEV</i>	Equity-to-assets ratio
<i>DEPOSIT</i>	Ratio of total deposits divided by total assets

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*Country-level controls*

<i>LNGDP</i>	Log of annual gross domestic product (GDP) per capita. Source: World Bank's World Development Indicators database
<i>CR</i>	Creditor rights developed by La Porta et al. (1998) and updated in Djankov, Mcleish, and Shleifer (2007).
<i>Transp</i>	Measure of the transparency of bank financial statement practices. Source: Barth et al. (2006)
<i>String</i>	Capital Stringency Index measures the regulatory approach to assessing the degree of capital at risk in a bank.
<i>Actres</i>	It measures the extent to which banks are allowed by the regulator to engage in securities market activities, insurance activities, and real estate activities.
<i>Enforce</i>	an index of enforcement of contracts

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## Appendix 2-2 Calculation of earnings smoothing through loan loss provisions

The table reports OLS regression estimates of loan loss provisions (LLP) on earnings before provisions and tax (EBLLP), forward and lagged term of changes in non-performing loans ( $\Delta NPL$ ), lagged capital ( $CAP_{t-1}$ ), lagged total assets ( $SIZE_{t-1}$ ), and changes in GDP per capita ( $\Delta GDP_t$ ). I include country and year dummies. Results are in percentage

Dependent variable: LLP	
EBLLP <sub>t</sub>	-0.151*** (-14.08)
$\Delta NPL_{t+1}$	0.0241*** (4.52)
$\Delta NPL_t$	0.0512*** (10.11)
$\Delta NPL_{t-1}$	0.0350*** (7.38)
$\Delta NPL_{t-2}$	0.0336*** (6.56)
$CAP_{t-1}$	0.0209*** (2.77)
$SIZE_{t-1}$	0.000144 (1.03)
$\Delta GDP_t$	-0.000350*** (-2.89)
Constant	0.00894*** (2.87)
Country FE	YES
Year FE	YES
N	1317
adj. R-sq	0.574



# **Chapter 3 Macroeconomic and Political Uncertainty and Cross-sectional Return Dispersion around the World**

## **3.1 Introduction**

The financial crisis of 2008 made it clear that investors and regulators lack a simple and easy measure to capture macroeconomic and political uncertainty, let alone that one would be able to capture uncertainty in real-time. As a consequence, the number of papers trying to link different volatility measures to uncertainty has been growing (see for instance Jurado, Ludvigson, and Ng (2015), Cesa-Bianchi, JPesaran, Rebucci (2014), and the papers within).

The goal is a simple one. Can I find a measure that might capture uncertainty and can also be easily calculated in real time? Preferably, one that is simple to measure, simple to understand, useful to academics and which would give investors, financial regulators and other stakeholders a feel in real time for the level of uncertainty as perceived by financial markets. I am not looking for the perfect ex post uncertainty measure but a risk measure, just like duration for bonds, that could be a first proxy of uncertainty implied by prices set by market participants with their perception of risk in real time.

Of course, stock return volatility itself does not qualify because it cannot be observed in real time. Moreover, as Diebold and Yilmaz (2008) put it: “There are few studies attempting to link underlying macroeconomic fundamentals to stock return volatility, and the studies that do exist have been largely unsuccessful. P.4)” Implied volatility might be another candidate as it is traded directly. However, it is only available in a limited number of countries.<sup>5</sup>

An increasing number of studies suggest that cross sectional return dispersion, which is the cross-sectional standard deviation of stock returns, might be able to fill this gap and fulfil a role as a proxy for uncertainty. For instance, for US data return dispersion is associated with subsequent unemployment (Loungani, Rush, and Tave, 1990), the future business cycle (Loungani, Rush, and Tave, 1991), the state of the aggregate economy (Gomes, Kogan, and Zhang, 2003), and future stock market volatility (Stivers, 2003). Apart from this empirical evidence, it also intuitively seems a good measure for uncertainty. When there is good (bad) macroeconomic news on the general economy all stocks will go up (down) together and thus, return dispersion will be low. However, it will be high when the future is uncertain as some stocks may go up while others go down. Unfortunately, international evidence is scarce and even for the US we lack evidence on how well cross-sectional dispersion is linked to many variables that might capture uncertainty.

This chapter intends to fill this gap and investigate the usefulness of cross sectional dispersion as a simple and real time measure of uncertainty that does

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<sup>5</sup> Of course, one could extract implied volatilities from option prices, but apart from arbitrary model choices, this would be harder to understand.

not require a large amount of data. I embark on a comprehensive endeavour using a set of international data to verify whether return dispersion correlates with a broad set of alternative uncertainty proxies (which are hard to measure in real time). Essentially, I consider any international available uncertainty measures I can get my hands on. More specifically, I link return dispersion at a monthly level to different aspects of uncertainty including (local and international) business cycles, political crises, country risk, uncertainty measured by use of the words 'risk', 'uncertainty' and 'uncertainties' in the media, and uncertainty that relates to fiscal, regulatory and monetary policies (that is economic policy uncertainty). The tests rely on monthly data as these other measures are often at best available at the monthly level or precisely determined with the benefit of hindsight years later, like the international political crisis data I use. Use of monthly stock dispersion allows for a long sample starting in 1986. However, cross sectional return dispersion itself can of course be measured at higher frequencies. I consider cross-country data to test how robust is the return dispersion measure worldwide. I compute monthly return dispersion series of individual countries using the 50 largest market capitalization stocks in 18 respective countries. The focus on the fifty largest market capitalization stocks makes this measure even simpler and gives similar results to measures which include all stocks. Using the fifty largest stocks also assure that the series can easily be constructed and replicated for practical purposes. Last but not least, it is well-known (Lo and MacKinlay, 1990) that small stocks lag stocks of larger firms, hence focusing on the largest fifty stocks purges delayed trading effects of smaller stocks. I then link return

dispersion to the cross section of stock returns in each country, asking the question whether stocks that are more sensitive to (changes in<sup>6</sup>) return dispersion offer higher returns. For a limited number of countries where direct implied volatility data are available I compare both measures.

Based on general asset pricing models, return dispersion changes if asset pricing factors move, factor loadings vary or idiosyncratic volatility fluctuates (e.g., de Silva et al. 2001). Therefore, there are concerns that return dispersion may change when there is no change in uncertainty of the economy (also see the discussion in Jurado et al. 2015). First, return dispersion will vary over time if idiosyncratic or firm-specific risk varies over time. However, Herskovic et al. (2016) show that residual return volatility has effectively the same common factor structure as total return volatility, which implies fluctuation of idiosyncratic volatilities is systematic. Second, return dispersion will change if loadings are time-varying. Although Lewellen and Nagel (2006) find that betas vary over time with variables commonly used to measure business conditions such as term spread, they document that constant betas have similar explanatory power for the cross section of stock returns as time-varying betas, which suggests time-varying betas are unlikely to be an important driver of variation of return dispersion over time. Third, investors' sentiment may cause asset market fluctuations, whereby alters return dispersion. Nevertheless, sentiment (such as that discussed by Baker and Wurgler (2006)) tends to move

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<sup>6</sup> We measure changes as the residuals from an AR(1) process estimated for the levels.

stocks in similar directions. Taken together, fluctuation of return dispersion likely reflects variation of uncertainty of the economy over time.

Overall, the results suggest that return dispersion captures different kinds of macroeconomic and political uncertainty well. The latter is especially reassuring as recent studies on rare disasters and international political crises show that political uncertainty may be an important risk factor (see for instance, Berkman, Jacobsen and Lee, 2011). Furthermore, return dispersion (either measured in changes or levels) is strongly linked to cross-sectional stock returns in all countries. Stocks with higher sensitivities to return dispersion have higher average returns. I compare the return dispersion measure with implied volatility and find both measures respond differently to the proxies for different types of uncertainty. Return dispersion has a higher correlation with political uncertainty whereas, implied volatility seems stronger related to economic uncertainty. However, and somewhat surprisingly, I find no evidence that (levels or changes in) implied volatility correlate with the cross section of stock returns.

In the empirical analysis, I focus on five aspects of uncertainty. First, I test whether return dispersion correlates with contractions and expansions of local and global business cycles using the business cycle data from Fushing, Chen, Berge, and Jordà (2010). The results confirm that in 11 out of 18 countries, return dispersion is significantly higher during local contractions. However, once I include the global business cycle, results are stronger than for the local business cycle (even though on average a local business cycle effect persists). Return dispersion is significantly higher during global recessions in 13

countries. On average global recessions raise return dispersion by almost 50% (compared to expansions, assuming no local contractions) suggesting that international uncertainty might be more important than local uncertainty. To the best of my knowledge, this is a new finding.

Second, I test whether return dispersion captures international political instability after controlling for business cycle effects. I use International Crisis Behaviour (ICB) database that counts the number of crises starting in a month, ongoing in a month and ending in a month. This database includes rare disasters in various types such as military incidents, diplomatic conflicts, economic pressures, and cultural problems. According to the rare disaster risk literature (see among others Barro (2006), Gabaix (2012), Rietz (1988), Wachter (2013)), stock market returns correlate strongly with changes in international crisis risk. One would expect that the start of a crisis may resolve uncertainty or increase it. However, one would expect ongoing crises, plausibly reflecting severity of issues and implications, likely to be associated with higher uncertainty, hence higher return dispersion. I test this hypothesis and find that international political uncertainty is an important contributing factor to return dispersion. The evidence for crises starts is indeed mixed although significantly positive when I pool the data, suggesting that the changed probability of a crisis raises uncertainty. During international political crises, return dispersion is statistically significantly in all but one of the countries I consider.

Third, I assume that when general market uncertainty—regardless of the type of uncertainty or the reason for it—is higher, there are more media stories

mentioning words such as 'uncertainty' and 'risk'. I consider this as general uncertainty captured by the media, and I test if return dispersion is higher during general uncertainty. Even though this may be a crude test, results suggest that return dispersion is significant and positively related to the number of news articles with these words being used in Bloomberg. After controlling for business cycles and international political crises effects, return dispersion is significantly higher in 11 out of 18 countries during months where there are more news articles with words like 'uncertainty' and 'risk'.

Fourth, return dispersion seems linked to country risk based on the widely used International Country Risk Guide (ICRG) data. This data set provides political, financial and economic risk ratings. Again, after controlling for the aforementioned factors, the composite ICRG rating (as a proxy for each country's business and investment status) decreases return dispersion significantly in a number of countries.

Fifth, I consider uncertainty that relates to fiscal, regulatory and monetary policies. Baker, Bloom, and Davis (2016) construct an US economic policy uncertainty index which is computed by counting the number of articles with policy related keywords in the leading newspapers. They further developed a global economic policy uncertainty index and several indices for other countries.<sup>7</sup> I test if return dispersion is associated with both local and global economic policy uncertainty. Cross sectional return dispersion increases

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<sup>7</sup> The general media uncertainty measure captures all kinds of uncertainties such as firm operational uncertainty, environmental policy uncertainty, supply uncertainty etc. Whereas the index developed by Baker, Bloom, and Davis (2016) only focuses on uncertainties related to economic policies. The correlations between those two measures in all countries are not very high. For instance, the US economic policy uncertainty and media general uncertainty has a correlation of 0.57.

significantly during periods with high local economic policy uncertainty in Australia, Italy, Japan and US but not in France, Germany, Ireland, Netherlands, Spain and Sweden. Global economic policy uncertainty has strong and positive effect on return dispersion in seven out of eleven countries.<sup>8</sup>

As return dispersion seems to capture different aspects of international uncertainty, return dispersion might be able to explain the cross-section of stock returns. If so, stocks that are more sensitive to return dispersion should offer higher returns. Jiang (2010) builds a model that includes return dispersion directly in the pricing kernel. Chichernea, Holder, and Petkevich (2015) use Jiang's (2010) model to test the relation between return dispersion and the cross-sectional expected returns. Following those two papers and extending their US evidence, the results indicate a strong positive relation between high sensitive return dispersion stocks and stock returns in 18 countries, regardless whether I look at levels or changes in dispersion. The difference between stocks with the high sensitivity to return dispersion and the portfolios with low sensitivity to return dispersion is substantial (around 5% on average a month regardless whether I control for sensitivity to the market and other factors or not). The result holds for all 18 countries. Results are also highly significant

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<sup>8</sup> We also employ several economic forecast variables as proxies of uncertainty in the US. We find that the forecast dispersion of personal consumption expenditure, real non-residential investment growth, term spread and AAA ranked government bond yield are significantly and positively related to return dispersion. The forecast dispersion of personal consumption expenditure for current quarter accounts for more than one third of the variation in return dispersion. As we only have the economic forecast dispersion for the US market (data from the survey of professional forecasters provided by the Federal Reserve Bank of Philadelphia), we do not include those results in our main findings. For the US we also find a strong relation between macro uncertainty and financial uncertainty variables made available by Jurado, Ludvigson, and Ng (2015)

with an average t-value for the difference between the high-return dispersion portfolios minus the low return dispersion portfolios of 10.69, controlling for four risk factors (market, size, value and momentum). These t-values suggest that return dispersion easily passes the thresholds to account for datamining recently suggested by Harvey, Liu, and Zhu (2014).<sup>9</sup>

Finally, I compare return dispersion with the implied volatility in seven countries for which implied volatility data are available. Implied volatility is comparable to return dispersion as this measure can also be observed in real time and at any frequency unlike many other risk measures and has also been considered in the literature (for instance, Beber and Brandt (2009) and Baker et al. (2016)). The results show that implied volatility also captures uncertainty associated with business cycles, political crises, general market uncertainty, country risk, and economic policy. However, both measures are associated differently with these uncertainty measures. Return dispersion tends to strongly reflect global business cycles and world crisis risk. It does so even after controlling for implied volatility. Implied volatility significantly captures the global economic policy uncertainty in all six countries (for which I have economic policy and implied volatility data) but return dispersion does not.

This chapter makes the following contributions to the existing literature. First, I find that using international evidence in 18 countries that cross sectional return dispersion correlates strongly with (new) measures of general, macro and political proxies of uncertainty. Second, I link return dispersion to all sorts

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<sup>9</sup> They argue that many previously documented factors may not pass statistical significance tests once we take data mining into account and that we should use t-values cut-offs of 3 or higher.

of proxies of macroeconomic and political uncertainty that have not been considered in the literature before. For instance, establishing a link between the international political crisis and return dispersion, provides further empirical support for theoretical models that allow for time-varying rare disaster risk (Barro, 2006; Gabaix, 2012; Rietz, 1988; Wachter, 2013). The evidence indicates that cross sectional return dispersion differs from implied volatility as it captures political uncertainty better. Implied volatility seems to perform better capturing economic uncertainty. Third, I propose return dispersion to be a very useful measure for uncertainty especially for practitioners. Investors can track the financial market by observing return dispersion at any point of time and make decisions based on the levels of it. Four, I also consider international cross-sectional evidence and find that cross sectional return dispersion (both levels and changes) correlate with the cross section of returns internationally whereas, surprisingly, implied volatility (both levels and changes) does not.

In sum, the international comparison indicates that cross sectional return dispersion (based on a limited number of 50 stocks) is useful, simple and a real time proxy to gauge uncertainty in several countries. While it may not be perfect, it is easy to calculate and may be valuable to investors and regulators who continuously monitor financial markets and different economies.

### **3.2 A short literature review**

The financial crisis during 2007-2008 period and its subsequent prolonged recovery brings the topic of macroeconomic uncertainty back to the table. The literature suggests several proxies of uncertainty and among these, volatility is the most popular one. However, Gorman, Sapra, and Weigand (2010) suggest

that the cross-sectional variation of equity returns may be a more relevant way to measure risk rather than time-series volatility. Jiang's (2010) results are consistent with the notion that return dispersion can be considered to be a macro state variable which can be used to capture the risk contained in both business cycle fluctuations and macroeconomic restructuring.

### **3.2.1 Measuring macroeconomic uncertainty**

Knight (1921) distinguishes uncertainty from risk and defines uncertainty as a situation of not having ability to forecast the existing or future outcomes. The literature provides ample evidence of the negative effects that policy uncertainty has on the economy. For instance, economic policy uncertainty affects stock prices (Pastor and Veronesi, 2012), economic activities (Baker, Bloom, and Davis, 2013). Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012) find that uncertainty is strongly countercyclical at both the aggregate and the industry-level. They find that uncertainty shocks drive business cycles.

Therefore, it is important to measure uncertainty. Stock market volatility is a traditional measure that is commonly used. However, in a recent work, Cesa-Bianchi et al. (2014) explore the role of volatility on measuring economic uncertainty over 33 countries. They find that volatility significantly leads business cycles. However, volatility shocks have no or little direct effect on real GDP. They suggest that volatility might be more a result rather than a cause of economic uncertainty.

Baker et al. (2016) develop a relatively new measure of economic policy uncertainty (EPU). They count the frequency of articles that refer to economy uncertainty and use it to build a news-based EPU index. Baker et al. (2016) test their EPU index and find that it captures policy related economic uncertainty well over time. Other studies propose other proxies of EPU (e.g., Baker et al., 2013; Bali et al., 2016; Wang et al., 2015). Baker and Bloom (2013) list five proxies for uncertainty including stock index volatility, the cross-firm stock returns spread, bond yields volatility, exchange rate volatility and GDP forecast disagreement. Bali and Zhou (2016) consider the market variance risk premium (VRP) as a proxy for economic uncertainty. They find that the variance risk premium is strongly correlated with all the other sets of proxies including conditional variance of US output growth, the conditional variance of Chicago Fed National Activity Index (CFNAI), extreme downside risk in time-series and in cross-sectional financial firms' returns, the credit default swap (CDS) index, and the aggregate measure of investors' disagreement. Additionally, Wang, Zhang, Diao, and Wu (2015) use the changes in 23 commodity prices to predict EPU. Bekaert, Engstrom, and Xing (2009) measure economic uncertainty by the conditional volatility of dividend growth. Last but not least, Jurado, Ludvigson, and Ng (2015) suggest several promising new measures of uncertainty based on aggregated volatility of individual macro-economic and financial series in the US.

### **3.2.2 Return dispersion**

In the literature, there is an increasing focus on the cross sectional return dispersion as a measure of uncertainty. Theoretically, Christie and Huang

(1995) find that, return dispersion will increase during market stress according to the rational asset pricing models, as individual assets have different sensitivities to market returns. In the US market, they find that return dispersion is higher during periods of large return changes. Recently, Angelidis, Sakkas, and Tessaromatis (2015) show that return dispersion is able to predict the business cycles, business conditions and unemployment rates. A higher world dispersion over the last three months indicates a higher probability that the economy is currently in recession.

The literature suggests that return dispersion is closely linked to macroeconomic uncertainty. Loungani et al. (1990) find that return dispersion predicts high unemployment rates. A higher cross-industry dispersion in stock price growth leads to higher unemployment. This evidence conforms to the sectoral shifts hypothesis that higher dispersion of inter-sectoral shifts leads to higher unemployment by raising the required labour reallocation. Gomes et al. (2003) and Zhang (2005) formally establish the theoretical link between return dispersion and the state of the aggregate economy. Gomes et al. (2003) present a general equilibrium model where the conditional capital asset pricing model holds, where firm betas vary with the market state, and where firm betas are related to a firm's size and book-to-market ratio. Given that firm betas cannot be measured perfectly in practice, a firm's size and book-to-market ratio are likely to contain incremental information about the cross-sectional variation in mean returns, their model suggests that return dispersion may contain incremental information about the current state of the economy, beyond market-level returns. Zhang (2005) extends Gomes, Kogan and

Zhang's (2003) framework and features costly reversibility of capital investment, the countercyclical price of risk, and variation in the level of growth options across firms. His framework predicts that some seemingly idiosyncratic risk variables, for example, the average stock return variance, can affect firm-level systematic risk and expected returns because they can be used in predicting the future evolution of the output price. Zhang (2005) suggests that the market's cross-sectional stock return volatility may be positively related to the future industry cost of capital, based on simulation data.

Empirically, Loungani et al. (1991) find that return dispersion is associated with the business cycle. Jiang (2010) illustrates that time-varying return dispersion is able to capture economic restructuring, uncertainty shocks and business cycles. Jiang (2010) shows that periods during major technology shocks result in extremely high return dispersion. Grobys and Kolari (2015) use return dispersion to test whether changes in economic states would influence asset pricing anomalies. Last but not least, Bekaert and Harvey (2000) use return dispersion as a control variable for stock market integration. They suggest that when an economy becomes more developed, reliance on particular sectors would decrease and thus, increase cross sectional return dispersion.

### **3.2.3 Return dispersion and the cross section of returns**

Jiang (2010) considers return dispersion as a risk factor that plays an essential role in capturing the cross-sectional variation in expected returns. Stocks which are more sensitive to return dispersion tend to have higher returns. Demirer and Jategaonkar (2013) expand Jiang's (2010) study and

illustrate a systematic conditional relation between return dispersion and cross section of stock returns. Generally speaking, the higher the sensitivity of a stock to return dispersion, the higher its average return is. However, the premium on return dispersion disappears when the market faces large losses. Chen, Demirer, and Jategaonkar (2015) extend Jiang's (2010) work and find similar evidence in the Chinese market. Chang, Cheng, and Khorana (2000) examine the relationship between equity return dispersions and market returns internationally. They find that the return dispersions increase linearly in the US, Japan and Hong Kong when the prices move extremely high or low. However, in the South Korea and Taiwan, they find smaller return dispersion during periods of extreme price movements. In this chapter, I extend international evidence to 18 countries and all of them suggesting that more return dispersion sensitive stocks generate higher returns.

Return dispersion also seems related to asset pricing factors. Conrad and Kaul (1998) find that the profitability of a momentum strategy can be attributed to return dispersion. Bhootra (2011) confirms their result that return dispersion is a potential source of momentum profit. Connolly and Stivers (2003) link return dispersion with return momentum and reversal. Weeks with extremely high (low) dispersion are followed by a momentum (reversal) in weekly equity-index returns. Stivers and Sun (2010) suggest that return dispersion is positively related to subsequent value premiums and negatively related to subsequent momentum premiums. These intertemporal relations remain strong even after controlling for a wide range of state variables include the dividend yield, the default yield spread, the term yield spread and the short-

term treasury yield. Kim (2012) expands their results and shows that return dispersion has predictive power for the value premium in emerging countries but not in developed countries. Chichernea et al. (2015) find that return dispersion provides a risk-based explanation to accrual and investment anomalies. After 2008, low accrual and low-investment portfolios seem to get a high risk premium as a compensation for the increased risk as measured by return dispersion.

### **3.2.4 Return dispersion and other risk measures**

According to Jiang (2010) return dispersion relates to two dimensions of risk. One is related to business cycles and the other is related to fundamental economic restructuring. Return dispersion seems to be a better risk factor than time-series volatility (Gorman et al., 2010) (Jiang, 2010). Stivers (2003) and Connolly and Stivers (2006) show that return dispersion conveys information about future volatility, and Stivers (2003) shows that firm return dispersion is positively related to future market volatility in the US. Connolly and Stivers (2006) suggest that return dispersion is positively associated with both firm-level and portfolio-level future return volatilities. Angelidis et al. (2015) find that return dispersion is a good predictor of changes in market volatility. There is a positive and significant relation between world return dispersion and world market volatility. Gomes et al. (2003) confirm their results by showing that return dispersion has significant explanatory power for future aggregate return volatility even after controlling for the market returns.

Return dispersion is also related to idiosyncratic volatility. For instance, Garcia, Mantilla-Garcia, and Martellini (2014) use the cross-sectional variation

of stock returns as a measure of aggregate idiosyncratic volatility. Garcia et al. (2014) suggest that return dispersion is a consistent and asymptotically efficient proxy for idiosyncratic volatility. Additionally, de Silva, Sapra, and Thorley (2001) indicate that return dispersion is a function of stocks' cross-sectional variation in their sensitivity to market changes and the general level of idiosyncratic risk. Bloom (2014) shows graphically that five uncertainty measures, namely cross-firm daily stock return dispersion, stock index daily returns volatility, sovereign bond yields daily volatility, exchange rate daily volatility and GDP forecast disagreement, have similar negative relations with annual GDP growth for 60 developing and developed countries over the period 1970 to 2012. Overall, there lacks a comparison between return dispersion and implied volatility.

### 3.3 Data

I obtain the return data from Compustat Global for all countries except for the US where I use Center for Research in Security Prices (CRSP) stock return files. As noted before return dispersion is simply the cross sectional standard deviation of stock returns:

$$RD_t = \sqrt{\frac{1}{N-1} \sum_{i=1}^n (R_{i,t} - R_{M,t})^2} \quad (3.1)$$

where  $RD_t$  is the return dispersion at time  $t$ ,  $N$  is the number of stocks included,  $R_{i,t}$  is the return of individual stock  $i$  at time  $t$ , and  $R_{M,t}$  is the mean return of those  $N$  stocks at time  $t$ .<sup>10</sup>

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<sup>10</sup> Note, that we assume for simplicity no predictability in the underlying variables. As noted by Jurado, Ludvigson, and Ng (2015) as an uncertainty measure it could be improved upon by taking the

Although it is desirable to have a long series and a large number of countries, I am constrained by the quality of the data. Thus I restrict my analysis to countries for which I can find reliable business cycle data and for which I can obtain a considerable degree of dispersion. I use the international business cycle data derived by Fushing et al. (2010). An advantage is that their methodology also allows for the creation of global business cycles, so I can test whether the source of uncertainty may be global or local. As a result, the data period for all the countries starts from January 1986 to December 2013.

These criteria lead to return dispersions and business cycles jointly for 18 countries: Australia, Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, Norway, New Zealand, Spain, Sweden, Switzerland, the United Kingdom and the United States. For some countries, longer series are possible based on the constituents of the main indices in those countries and I use these as a robustness test in the analysis (I report those results in the Appendix C) This set consists of market indices for seven countries: Australia, Finland, France, Germany, Japan, Switzerland and the United States. These time series have at least 300 return dispersion observations based on all constituents of the main indices in these countries. I consider returns at a monthly frequency as these tend to be less noisy than high frequency data and many of the other variables are only available at

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predictability of the mean returns into account but that would open a discussion which variables to use as predictors and deviate from our requirement that the measure should be simple and easy to understand.

monthly frequency but return dispersion can of course be measured at higher frequencies.

The first thing I want to establish is whether the return dispersion of the 50 largest (market capitalization) stocks might be a good proxy for the more general market. Table 3-1 compares the basic characteristics for the full market return dispersion and return dispersion of the 50 largest firms. The last column contains the correlations between these two measures in each country. Generally, correlations tend to be very high ranging from 0.56 to 0.98. (I do not have a full return dispersion index for Ireland). Using the US stock market as an example, Figure 3-1 shows that cross sectional return dispersion of all available stocks and cross sectional return dispersion of the top 50 stocks are closely linked.<sup>11</sup> They peak at almost the same time all the way through with only a difference in magnitude. Unfortunately, it is hard to say which one would be the most accurate measure. As noted in the introduction, it is well-known (Lo and MacKinlay, 1990) that small stocks lag stocks of larger firms. If the full market is made up of a large number of stocks this may cause return dispersion of the full index to respond with a delay and essentially introduce noise. Still, differences are small and I focus on the return dispersion ( $RD_t$ ) of 50 largest firms ( $N=50$ ) in every country.<sup>12</sup> The advantage is that these series are relatively easy to replicate. This is not only useful from an academic point of view but might also make its use easier for practitioners to implement these

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<sup>11</sup> The US market could be a conservative benchmark as Bekaert and Harvey (2000) suggest that return dispersion of the top 50 stocks will be less representative of all stocks for more developed markets than for less developed markets.

<sup>12</sup> Connolly and Stivers (2003) also use large-firm portfolio (largest size-based decile portfolio) in calculating return dispersion as small firms add disruption because of high idiosyncratic volatility.

measures. Hence, from now on the analysis focuses on the cross-sectional return dispersion measure for the 50 largest stocks.

For the return dispersion of 50 largest stocks the mean values of the return dispersion series range from 5.68 percent to 10.61 percent and the median values are a bit lower from 5.12 percent to 9.21 percent. The US market has the lowest mean and median return dispersion. All the distributions show positive skewness and are leptokurtic. I reject the null hypothesis that return dispersion series follow normal distribution for all countries.

Table 3-1 Descriptive Statistics

This table reports the basic statistics (mean, median, max, min, standard deviation, skewness and kurtosis) of return dispersion made by 50 largest market capitalization stocks (RD 50) and return dispersion of all stocks (RD all). The return dispersion is calculated as the cross-sectional standard deviation of stock returns at time t. Both return dispersion series are computed from January 1986 to December 2013. I report the correlation between those two measures in the last column. The mean, median, maximum and minimum values are in percentage.

	Mean		Median		Max		Min		Std. Dev.		Skewness		Kurtosis		Obs		Corre- -lation
	RD 50	RD all	RD 50	RD all	RD 50	RD all	RD 50	RD all	RD 50	RD all	RD 50	RD all	RD 50	RD all	RD 50	RD all	
Australia	7.16	11.39	6.27	10.79	30.10	32.22	1.96	5.27	0.03	0.03	3.51	1.76	19.80	8.93	336	300	0.56
Austria	8.57	7.94	7.78	7.01	33.53	28.18	2.25	3.33	0.04	0.04	2.34	2.20	11.56	9.73	336	253	0.65
Belgium	6.86	6.77	6.13	5.70	28.59	36.86	1.82	1.85	0.03	0.04	2.32	3.06	11.92	19.24	336	276	0.84
Denmark	8.14	7.80	7.30	6.77	41.11	26.66	3.93	2.99	0.04	0.04	3.54	2.15	25.05	9.37	336	290	0.76
Finland	8.92	8.50	8.07	7.64	27.70	56.37	3.15	1.63	0.03	0.05	1.51	4.05	6.68	33.48	336	308	0.81
France	6.80	6.77	6.11	6.12	20.21	19.15	1.44	2.64	0.03	0.03	1.86	1.88	8.29	7.73	336	312	0.93
Germany	6.97	6.48	6.16	5.73	26.48	28.46	1.40	2.69	0.03	0.03	2.21	2.43	10.75	12.80	336	305	0.91
Ireland	10.61	-	9.21	-	41.04	-	3.56	-	0.05	-	1.96	-	8.37	-	336	0	-
Italy	7.43	7.02	6.77	6.41	44.83	17.66	3.31	3.22	0.03	0.03	5.02	1.28	53.08	4.73	336	196	0.58
Japan	7.43	7.98	6.58	7.53	25.35	17.60	2.98	3.24	0.03	0.03	1.89	0.79	7.80	3.60	336	336	0.78
Netherlands	7.65	8.93	6.64	6.99	40.13	58.21	1.59	2.65	0.04	0.06	3.18	3.52	20.04	22.61	336	238	0.70
Norway	9.96	11.24	8.91	9.81	42.86	38.06	1.71	4.47	0.04	0.06	2.54	2.21	14.82	9.05	336	158	0.84
New Zealand	9.10	6.73	7.91	6.09	32.80	20.67	2.60	3.55	0.04	0.03	2.09	2.32	9.37	10.85	336	126	0.83
Spain	7.85	7.23	6.84	6.39	65.08	26.84	1.43	2.71	0.05	0.03	6.31	1.85	73.13	9.33	336	300	0.72
Sweden	7.49	6.91	6.89	6.04	23.48	20.79	1.80	3.02	0.03	0.03	1.56	2.08	6.95	8.41	336	93	0.84

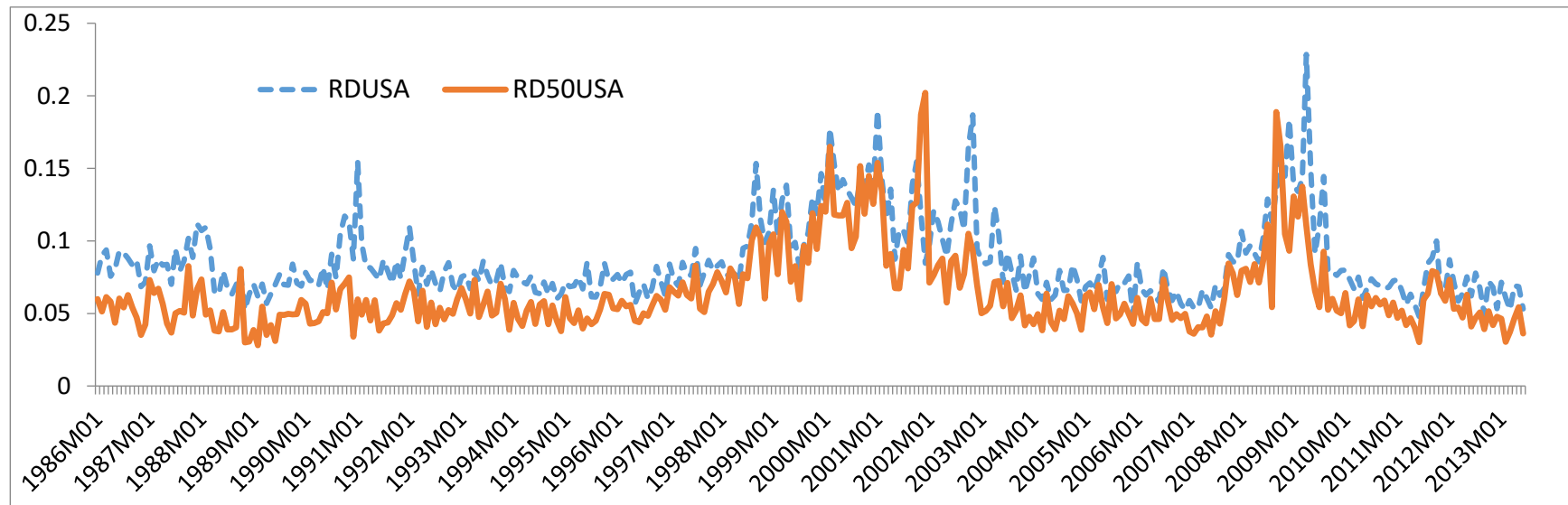
(continued next page)

(Table 3-1 continued)

Switzerland	6.80	6.41	6.11	5.75	36.60	18.41	1.89	1.94	0.03	0.03	3.79	1.58	30.53	6.26	336	306	0.76
UK	6.66	7.47	5.84	6.33	21.00	19.73	1.34	4.06	0.03	0.03	1.84	2.03	7.26	7.36	336	67	0.98
US	5.68	8.59	5.12	7.72	24.57	22.85	2.09	4.79	0.02	0.03	2.56	1.70	13.86	6.37	336	330	0.79

Figure 3-1 Return Dispersion of All Stocks Versus Return Dispersion of the Largest 50 Stocks in the US

Figure 3-1 plots two return dispersion indices in the US stock market. The dashed line (RDUSA) is the return dispersion made by all available US stocks. The solid line is the return dispersion computed using 50 largest (market capitalization) stocks.

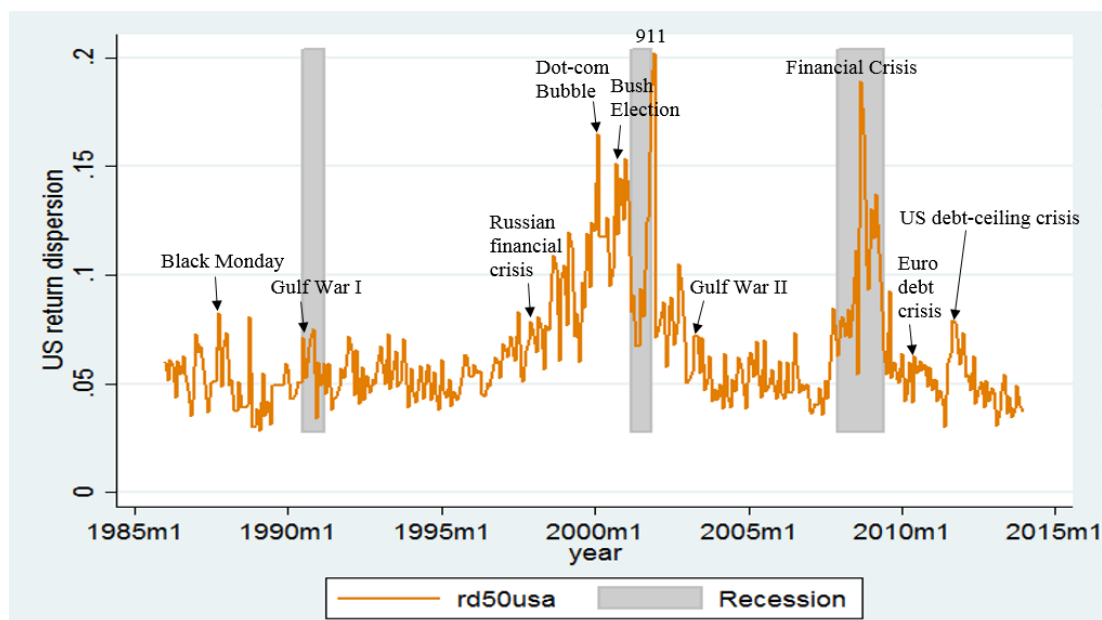


### 3.4 Return dispersion and macro economy

As a first eyeball test whether return dispersion is linked to macroeconomic uncertainty Figure 3-2 plots the monthly return dispersion of the US largest 50 stocks from January 1986 to December 2013. The graph shows how return dispersion increases during periods of macroeconomic news shocks, political events and stock market downturns. The shaded periods are NBER recessions. The US return dispersion spikes during major events such as the Gulf Wars and the Russian financial crisis, the Dot-com Bubble, the Bush Election, 9/11, Lehman brother's bankruptcy and the following crisis of 2008.

Figure 3-2 Return Dispersion in the US and Events

Figure 3-2 plots the return dispersion of the largest 50 US stocks from January 1986 to December 2013. The shaded areas are NBER recessions.



### 3.4.1 Business cycles

Does return dispersion vary over the business cycle in all countries as in the US? If so, it should be significantly higher during recessions. Based on the international business cycle data of Fushing et al. (2010), I create dummy variables for both the country specific local business cycle and the global business cycle (1= recession, 0 = expansion). I first regress return dispersion series on the country specific business cycle variable alone as shown in equation (3.2):

$$RD_t = \alpha + \beta_1 BC\_local_t + \varepsilon_t \quad (3.2)$$

where  $BC\_local_t$  is the dummy variable for local business cycle (1= recession, 0 = expansion). Then I include the global business cycle  $BC\_global_t$  as well in the second regression (equation 3.3):

$$RD_t = \alpha + \beta_1 BC\_local_t + \beta_2 BC\_global_t + \varepsilon_t \quad (3.3)$$

For both regressions, the data end in September 2009 because the (international) business cycle data I use end in that year. Table 3-2 and 3-3 contain these results. Considering only the local business cycle, the international evidence confirms to some extent the earlier US result that, the local business cycle is indeed important. Generally, return dispersion is higher during recessions. In thirteen out of eighteen countries return dispersion is significantly higher during recessions. However, many countries do not show as strong an effect as in the US where return dispersion is on average fifty percent higher (9.35 percent versus 6.13 percent in expansions). Also, return dispersion in Ireland, the Netherlands and Switzerland is more than 50 percent

higher during recessions. However, return dispersion in Japan is only about 10 percent higher. On average, I find that for other countries, the difference is around 27 percent (9.74 percent versus 7.65 percent).

Table 3-2 Return Dispersion over Local Business Cycles

This table reports the results of the univariate regressions of  $RD_t = \alpha + \beta_1 BC\_local_t + \varepsilon_t$ , where  $RD_t$  is the return dispersion of the largest 50 market capitalization stocks at time  $t$ . Local BC is a dummy variable that equals one if the country is in recession and zero otherwise. System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression. I use robust standard errors. Coefficients are in percentage.

	constant	t-value	local BC	t-value	Adjusted R2
Australia	7.26	<b>33.43</b>	1.50	<b>1.76</b>	0.01
Austria	8.29	<b>38.17</b>	3.59	<b>3.75</b>	0.09
Belgium	6.59	<b>34.16</b>	1.06	<b>1.72</b>	0.01
Denmark	7.96	<b>38.84</b>	0.77	1.22	0.00
Finland	8.86	<b>40.12</b>	3.30	<b>6.15</b>	0.08
France	6.33	<b>34.85</b>	1.81	<b>5.51</b>	0.10
Germany	6.99	<b>41.84</b>	2.17	1.52	0.03
Ireland	9.42	<b>30.35</b>	5.10	<b>5.49</b>	0.14
Italy	7.25	<b>34.13</b>	1.72	<b>2.90</b>	0.02
Japan	7.43	<b>31.37</b>	0.86	<b>1.92</b>	0.01
Netherlands	7.00	<b>38.42</b>	4.20	<b>4.83</b>	0.16
Norway	10.10	<b>37.24</b>	2.63	<b>2.79</b>	0.03
New Zealand	9.59	<b>36.14</b>	-0.40	-0.46	0.00
Spain	7.47	<b>35.84</b>	2.24	<b>3.62</b>	0.05
Sweden	7.89	<b>38.92</b>	-0.29	-0.73	0.00
Switzerland	6.51	<b>45.73</b>	3.55	<b>4.33</b>	0.16
UK	6.64	<b>36.77</b>	0.65	1.33	0.01
US	6.13	<b>39.89</b>	3.23	<b>5.74</b>	0.16
System			1.98	<b>12.82</b>	
Sur			0.71	<b>7.14</b>	

However, things change quite dramatically once return dispersion can fluctuate with the global business cycle as well. Table 3-3 reports results for both local and global business cycles. The local business cycle is still significant in 12 out of 18 countries but the size of the effect becomes much smaller compared to including the local business cycle only.

Given its significance level and the size of the coefficient, return dispersion is significantly higher (at the 10 percent level) during global recessions in 15 out of 18 countries. The size of the effect is large. On average a global recession seems to raise the return dispersion by almost 50% (11.05 percent versus 7.52 percent in expansions, assuming no local recession) and the effect of return dispersion is approximately 16 percent higher on average in a local recession (8.69 percent versus 7.52 percent in expansions assuming no global recession). Interestingly, these results also hold for the US. Return dispersion in the US seems to be associated more with global economic conditions than with economic conditions in the US only. In fact, once I control for global recessions, the US is one of the countries where local effects are – although still statistically significant, substantially reduced in economic terms as shown by the drop in the coefficient. Of course, part of this is caused because of the high correlations between some local country recessions and the global recession dummy (correlations range from -0.01 for New Zealand to 0.82 for the US (I report the correlations of variables in Appendix A1)). The higher return dispersion is associated with the global dummy rather than the local dummy in almost all regressions. Pooling the data and estimate it either as a

seemingly unrelated regression or as a system gives similar results. The local business cycle is significant but the global factor seems to weigh more heavily.

Table 3-3 Return Dispersion over Local and Global Business Cycles

This table reports the coefficients estimates and t-statistics of the regression in the form of  $RD_t = \alpha + \beta_1 local BC_t + \beta_2 global BC_t + \varepsilon_t$ , where  $RD_t$  is the return dispersion of the largest 50 market capitalization stocks at time t,  $local BC_t$  and  $global BC_t$  are the contemporaneous dummy variable for business cycle (1= recession, 0 = expansion) in local country and global respectively. System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression. I use robust standard errors. Coefficients are in percentage.

	consta nt	t- value	local BC	t- value	global BC	t- value	Adjusted R2
Australia	7.05	<b>32.46</b>	0.46	0.72	3.99	<b>3.88</b>	0.09
Austria	8.10	<b>36.99</b>	2.01	<b>2.85</b>	5.04	<b>4.03</b>	0.18
Belgium	6.31	<b>33.44</b>	0.17	0.41	5.72	<b>5.54</b>	0.22
Denmark	7.63	<b>35.38</b>	0.11	0.24	6.72	<b>4.29</b>	0.21
Finland	8.71	<b>41.55</b>	2.45	<b>3.78</b>	3.10	<b>2.96</b>	0.12
France	6.30	<b>35.35</b>	1.44	<b>4.16</b>	2.01	<b>3.12</b>	0.13
Germany	6.69	<b>42.45</b>	-0.13	-0.14	5.80	<b>6.07</b>	0.24
Ireland	9.28	<b>29.23</b>	3.75	<b>4.80</b>	5.34	<b>3.38</b>	0.19
Italy	7.18	<b>32.89</b>	1.20	<b>2.01</b>	1.42	<b>2.58</b>	0.02
Japan	7.36	<b>31.46</b>	0.01	0.03	3.04	<b>4.56</b>	0.05
Netherlands	6.97	<b>37.79</b>	3.76	<b>3.55</b>	1.47	1.33	0.17
Norway	9.88	<b>35.79</b>	2.06	<b>2.36</b>	3.44	<b>3.50</b>	0.06
New Zealand	9.54	<b>34.28</b>	-0.41	-0.47	0.68	0.96	0.00
Spain	7.43	<b>35.22</b>	1.58	<b>2.84</b>	1.70	<b>2.01</b>	0.06
Sweden	7.70	<b>38.35</b>	-0.74	<b>-2.14</b>	3.62	<b>6.19</b>	0.10
Switzerland	6.51	<b>45.65</b>	3.04	<b>1.98</b>	0.98	0.59	0.16
UK	6.51	<b>35.81</b>	-0.63	<b>-2.01</b>	5.45	<b>6.01</b>	0.21
US	6.13	<b>39.82</b>	1.01	<b>2.03</b>	4.15	<b>4.85</b>	0.24
System			0.86	<b>6.00</b>	3.82	<b>19.05</b>	
Sur			0.40	<b>4.37</b>	3.83	<b>9.62</b>	

### **3.4.2 International political crises**

Would return dispersion also be affected by international political uncertainty? According to the recent literature on rare disaster risk it should be. This literature introduced by Rietz (1988) and made popular by Barro (2006) suggests that rare disaster risk may be an important factor driving the equity premium. Indeed, empirical evidence by Berkman et al. (2011) suggests that the changes in the likelihood of international political crises have a strong impact on stock market returns. They find that stock market returns go down significantly at the start of perceived international crises based on the well-known International Crisis Behaviour (ICB) database. In this study, I also utilize the ICB dataset that records 476 crises from 1918 to 2015. A detailed discussion of the dataset can be found in Brecher and Wilkenfeld (1997) and they consider crisis as perceived changes in the probability of threat. Overall, The ICB dataset consists different types of disaster events such as military incidents, diplomatic conflicts, economic pressures, and cultural problems. Examples of crises are Panama Crisis, Israeli and Hizbullah forces in the Operation Accountability Crisis, North Korea Nuclear Crisis, Syria Chemical Weapons etc.

While return dispersion does not necessarily increase when a crisis starts (all stocks may go down together), it seems likely that ongoing international political crises raise uncertainty that may only go down when crises end. Although the end of crises effects might be less clear as 1) the end of a crisis in the ICB database may be easier to anticipate, and 2) while the end of crisis may reduce uncertainty it might also fuel uncertainty about the future.

I test this hypothesis using the international crises variables introduced by Berkman et al. (2011), which I extend to December 2013. In line with their approach, I use the variables that denote the number of crises starting in a month (start), ongoing crises in a month (during) and a variable indicating the number of crises ending (end). I also use their World Crisis Index (also constructed from the ICB database) which takes into account crisis severity, with more serious crises getting a stronger weight.<sup>13</sup> This may be a better proxy for actual perceived crisis risk. (I report the results where I just rely on the number of crises in the appendix A2).

Table 3-4 presents the descriptive statistics of the world crises variables and world crises index (WCI). The data range from January 1986 to December 2013. The number of ongoing crisis is 1.46 a month on average. The means of the world crisis index start, during and end are 1.02, 4.81 and 1.04.

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<sup>13</sup> The world crises index sums up six dummy variables that capture six dimensions of the severity of a crisis. Each dummy variable equals 1 if the crisis started with violence, if violence is used during the crisis, if it is a full-scale war, if there is severe value threat, if the crisis is part of a protracted conflict, and if superpower is involved in the crisis. The WCI index ranges from zero to six.

Table 3-4 Basic Statistics of International Political Crisis Data

This table reports the summary statistics for the international political crisis data from January 1986 to December 2013. Data is from the International Crisis Behaviour project (ICB) database. WORLD\_S, WORLD\_D and WORLD\_E represent the number of world crisis starting, during and ending in a month. I also use their World Crisis Index (also constructed from the ICB database) which takes into account crisis severity, with more serious crises getting a stronger weight. WCI\_Start, WCI\_During and WCI\_End are the World Crisis Index starting, during and ending in a month.

	Crisis _start	Crisis _during	Crisis _end	WCI _start	WCI _during	WCI _end
Mean	0.33	1.46	0.33	1.02	4.81	1.04
Median	0.00	1.00	0.00	0.00	4.00	0.00
Maximum	3.00	5.00	3.00	12.00	20.00	11.00
Minimum	0.00	0.00	0.00	0.00	0.00	0.00
Std. Dev.	0.57	1.11	0.61	1.98	4.01	2.02
Skewness	1.73	0.42	1.88	2.42	0.62	2.09
Kurtosis	5.98	2.67	6.32	9.85	2.75	7.11
Observations	336	336	336	336	336	336

I control the effect of both local and global business cycle and add three variables to equation (3.3) The first variable measures the WCI of crises starting in that month, ( $Start\_WCI_t$ ) the second one the WCI for ongoing crises during month t ( $During\_WCI_t$ ) and the last variable the WCI of crises ending in month t ( $End\_WCI_t$ ).

$$RD_t = \alpha + \beta_1 BC\_local_t + \beta_2 BC\_global_t + \beta_3 Start\_WCI_t + \beta_4 During\_WCI_t + \beta_5 End\_WCI_t + \varepsilon_t \quad (3.4)$$

Table 3-5 shows the estimation results for international political crises. Return dispersion is higher during times of crises. In all but four countries the effect is significant. The crisis index has a mean of 4.81 per month. This means

that on average during international political crises return dispersion is around 10 percent higher. There also seems to be a start of a crisis effect although less strong (significant in six out of the 18 countries). If I pool the data in a system, the overall effect also indicates significance. Crises start adds another two percent to return dispersion. The end of crises does not seem to add significantly to return dispersion.

Table 3-5 Return Dispersion and International Political Crises

Table 3-5 provides the results of return dispersion regressions on world crisis index with the control of business cycle in each country ( $RD_t = \alpha + \beta_1 BC_{local_t} + \beta_2 BC_{global_t} + \beta_3 Start\_WCI_t + \beta_4 During\_WCI_t + \beta_5 End\_WCI_t + \varepsilon_t$ ).  $RD_t$  is the return dispersion of the largest 50 market capitalization stocks in each country at time  $t$ .  $BC_{local_t}$  and  $BC_{global_t}$  are the dummy variables for business cycle (1= recession, 0 = expansion) in local country and global respectively.  $Start\_WCI_t$ ,  $During\_WCI_t$  and  $End\_WCI_t$  are ongoing crisis starting at month  $t$ , during month  $t$  and ending at month  $t$ . System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression. I use robust standard errors. Coefficients are in percentage.

	Constant	t-value	Local BC	t-value	Global BC	t-value	Start WCI	t-value	During WCI	t-value	End WCI	t-value	Adjusted R2
Australia	6.49	<b>21.71</b>	0.46	0.69	4.23	<b>4.15</b>	0.18	<b>1.65</b>	0.06	1.03	0.07	0.87	0.10
Austria	8.10	<b>22.54</b>	2.00	<b>2.74</b>	5.05	<b>4.06</b>	-0.05	-0.54	-0.02	-0.38	0.13	0.84	0.18
Belgium	5.93	<b>17.68</b>	0.21	0.50	5.85	<b>5.64</b>	0.07	0.81	0.04	1.10	0.06	0.71	0.22
Denmark	6.99	<b>28.67</b>	0.16	0.36	6.86	<b>4.40</b>	0.06	0.70	0.14	<b>3.63</b>	-0.16	<b>-2.41</b>	0.24
Finland	7.08	<b>22.15</b>	2.24	<b>3.47</b>	3.66	<b>3.45</b>	0.14	<b>1.74</b>	0.29	<b>6.29</b>	-0.01	-0.12	0.22
France	5.57	<b>28.38</b>	1.19	<b>3.31</b>	2.40	<b>3.59</b>	0.10	1.13	0.13	<b>3.57</b>	0.02	0.18	0.16
Germany	6.33	<b>28.01</b>	-0.19	-0.19	5.94	<b>6.20</b>	0.10	1.16	0.05	<b>1.67</b>	-0.03	-0.29	0.24
Ireland	7.95	<b>17.32</b>	3.91	<b>4.96</b>	5.66	<b>3.50</b>	0.25	1.38	0.22	<b>3.17</b>	-0.11	-0.90	0.22
Italy	6.79	<b>16.47</b>	1.01	<b>1.69</b>	1.59	<b>2.69</b>	-0.04	-0.44	0.08	1.35	0.05	0.52	0.02
Japan	6.35	<b>20.43</b>	-0.04	-0.08	3.39	<b>5.15</b>	0.15	1.44	0.16	<b>3.22</b>	0.00	-0.02	0.08
Netherlands	6.34	<b>19.27</b>	3.58	<b>3.33</b>	1.78	1.58	0.15	1.23	0.12	<b>2.50</b>	-0.12	-1.08	0.18
Norway	9.03	<b>17.52</b>	1.99	<b>2.20</b>	3.69	<b>3.65</b>	0.10	0.77	0.16	<b>2.49</b>	-0.09	-0.87	0.08
New Zealand	8.00	<b>16.11</b>	-0.26	-0.30	1.18	<b>1.65</b>	0.29	<b>1.70</b>	0.23	<b>4.00</b>	-0.01	-0.13	0.05
Spain	5.89	<b>22.98</b>	1.13	<b>2.08</b>	2.61	<b>2.97</b>	0.39	<b>3.47</b>	0.17	<b>3.90</b>	0.23	<b>1.97</b>	0.16

Sweden	6.02	<b>24.49</b>	-0.52	-1.62	4.08	<b>6.79</b>	0.22	<b>1.95</b>	0.24	<b>6.42</b>	0.11	1.18	0.23
Switzerland	5.91	<b>24.29</b>	3.08	<b>2.02</b>	1.13	0.69	0.02	0.23	0.09	<b>2.26</b>	0.09	0.97	0.17
UK	5.87	<b>24.66</b>	-0.48	-1.57	5.56	<b>6.21</b>	0.20	<b>2.48</b>	0.12	<b>3.70</b>	-0.19	<b>-2.87</b>	0.26
US	5.33	<b>31.70</b>	0.89	<b>1.79</b>	4.47	<b>5.24</b>	0.00	-0.05	0.15	<b>4.47</b>	0.01	0.15	0.28
System			0.83	<b>5.85</b>	4.11	<b>20.59</b>	0.13	<b>5.15</b>	0.14	<b>11.14</b>	0.00	0.12	
Sur			0.40	<b>4.36</b>	4.06	<b>10.69</b>	0.10	<b>2.01</b>	0.16	<b>6.34</b>	0.06	1.23	

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### 3.4.3 Uncertainty around the world

In order to cover all kinds of uncertainty, I consider another proxy. I assume that the word ‘risk’ and ‘uncertainty’ will occur more frequently in months with higher perceived risk and uncertainty of any kind. I consider it as market general uncertainty which would be caused by any type of event. I then test whether return dispersion captures this general uncertainty. This has the advantage that I can use it for all 18 countries. I count the number of Bloomberg reports in every month that contains these two words and add in turn one of these two variables to the regressions. In both cases, I take the log as the number of news articles seems to have grown exponentially over time.<sup>14</sup> I use this word count uncertainty as an explanatory variable with the control variable of business cycles and world crisis index as below:

$$RD_t = \alpha + \beta_1 BC_{local_t} + \beta_2 BC_{global_t} + \beta_3 Start\_WCI_t + \beta_4 During\_WCI_t + \beta_5 End\_WCI_t + \beta_6 WordCount_t + \varepsilon_t \quad (3.5)$$

Table 3-6 contains the results for the word ‘Uncertainty’ (as results are similar for the word “risk” these are in the Appendix A3). Particularly for the US results are with a t-value of over 7 highly significant and of the expected sign. In months when the use of the word ‘uncertainty’ is high, return dispersion tends to dramatically increase. Maybe not surprising because Bloomberg originates from the US. In many other countries, I find a positive significant effect as well, with the exception of Australia, New Zealand and Spain where,

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<sup>14</sup> We also use another method of counting articles: We count the number of articles that contain the word “uncertain” and divide by the number of all articles. As these results are qualitatively similar we do not report them here.

the word count for uncertainty seems significantly negative. Overall the effect is however significantly positive. The uncertainty effect is positively significant in 11 out of 18 countries.

#### **3.4.4 International country risk**

I further include the International Country Risk Guide (ICRG) risk ratings as a proxy for country-level uncertainty. ICRG provides rating regarding country's political, economic and financial risk every month. I use the Composite Risk Rating which including twelve political risk components, five financial risk components, and five economic risk components. The data ranges from 65 to 96. I test if return dispersion captures the movement of country risk. I add the ICRG composite risk index as an uncertainty measure as shown in equation (6):

$$RD_t = \alpha + \beta_1 BC\_local_t + \beta_2 BC\_global_t + \beta_3 Start\_WCI_t + \beta_4 During\_WCI_t + \beta_5 End\_WCI_t + \beta_6 WordCount_t + \beta_7 Country\_Risk_t + \varepsilon_t \quad (3.6)$$

Table 3-7 shows the regression results. The overall effect of individual country risk on return dispersion seems to be negative. However, in France, the Netherlands, Switzerland, UK and US, they exhibit a significantly positive relation.

Table 3-6 Return Dispersion and Word Count Uncertainty

Table 3-6 reports the regression of return dispersion on word count uncertainty around the world. I count the number of Bloomberg reports in every month that contains the word “uncertainty” and take a log of it. I consider these word counts as proxy for uncertainty. I run the regression in the form of  $RD_t = \alpha + \beta_1 local\_BC_t + \beta_2 global\_BC_t + \beta_3 Start_t + \beta_4 During_t + \beta_5 End_t + \beta_6 \ln(word\ count\ uncertainty)_t + \varepsilon_t$  where BC is the business cycle dummy, Start is crisis starting in month t, During is the ongoing crisis in month t and End is the crisis ending in month t. System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression. I use robust standard errors. Coefficients are in percentage.

	constant	t-stat	local BC	t-stat	global BC	t-stat	start WCI	t- stat	during WCI	t-stat	end WCI	t-stat	Word Count Uncertainty	t-stat	Adjusted R2
Australia	9.69	<b>7.21</b>	0.08	0.11	5.07	<b>4.83</b>	0.13	1.15	0.04	0.78	0.02	0.22	-0.48	<b>-2.45</b>	0.12
Austria	4.90	<b>4.09</b>	1.95	<b>2.72</b>	4.36	<b>3.46</b>	0.01	0.07	-0.01	-0.11	0.19	1.21	0.49	<b>2.80</b>	0.20
Belgium	1.60	1.22	0.70	1.55	4.73	<b>4.57</b>	0.15	<b>1.78</b>	0.06	1.49	0.14	1.63	0.64	<b>3.91</b>	0.27
Denmark	2.10	<b>2.39</b>	0.61	1.32	5.66	<b>3.69</b>	0.14	<b>1.71</b>	0.17	<b>4.18</b>	-0.07	-1.15	0.72	<b>5.72</b>	0.28
Finland	7.04	<b>5.21</b>	2.24	<b>3.25</b>	3.64	<b>3.23</b>	0.14	1.64	0.29	<b>6.14</b>	-0.01	-0.11	0.01	0.03	0.22
France	3.11	<b>3.56</b>	1.30	<b>3.73</b>	1.78	<b>2.49</b>	0.15	1.57	0.14	<b>3.81</b>	0.06	0.64	0.37	<b>2.91</b>	0.19
Germany	1.35	<b>1.65</b>	0.67	0.69	4.51	<b>4.86</b>	0.18	<b>2.16</b>	0.07	<b>2.34</b>	0.05	0.53	0.75	<b>6.09</b>	0.32
Ireland	5.71	<b>3.67</b>	3.73	<b>4.67</b>	5.24	<b>3.10</b>	0.29	1.51	0.23	<b>3.27</b>	-0.07	-0.59	0.35	1.48	0.22
Italy	4.29	<b>5.26</b>	1.30	<b>2.24</b>	0.91	1.31	0.00	0.04	0.08	1.52	0.09	0.92	0.38	<b>2.60</b>	0.04
Japan	3.04	<b>2.72</b>	0.06	0.12	2.58	<b>3.69</b>	0.20	<b>1.98</b>	0.18	<b>3.35</b>	0.06	0.62	0.50	<b>3.20</b>	0.11
Netherlands	0.86	0.71	3.47	<b>3.49</b>	0.62	0.52	0.24	<b>2.08</b>	0.14	<b>3.20</b>	-0.03	-0.25	0.83	<b>4.41</b>	0.24
Norway	7.12	<b>4.33</b>	1.94	<b>2.18</b>	3.27	<b>3.15</b>	0.14	0.96	0.17	<b>2.54</b>	-0.06	-0.53	0.29	1.33	0.08
New Zealand	16.65	<b>10.35</b>	0.07	0.09	3.14	<b>4.17</b>	0.15	0.87	0.20	<b>3.76</b>	-0.16	-1.55	-1.32	<b>-5.78</b>	0.19
Spain	9.51	<b>9.42</b>	1.23	<b>2.14</b>	3.36	<b>3.74</b>	0.32	<b>3.08</b>	0.16	<b>3.62</b>	0.16	1.41	-0.55	<b>-3.82</b>	0.20
Sweden	5.40	<b>6.37</b>	-0.56	<b>-1.71</b>	3.95	<b>6.21</b>	0.24	<b>2.03</b>	0.25	<b>6.46</b>	0.13	1.23	0.09	0.75	0.23
Switzerland	1.71	1.58	2.65	<b>1.90</b>	0.56	0.35	0.09	1.31	0.11	<b>2.56</b>	0.16	1.87	0.64	<b>4.36</b>	0.23
UK	1.46	<b>1.74</b>	0.04	0.14	4.30	<b>4.70</b>	0.27	<b>3.56</b>	0.14	<b>4.56</b>	-0.12	-1.81	0.65	<b>5.25</b>	0.33
US	0.05	0.07	1.12	<b>3.29</b>	3.06	<b>3.87</b>	0.09	<b>1.76</b>	0.17	<b>5.59</b>	0.10	1.39	0.80	<b>7.33</b>	0.40
System			0.89	<b>6.30</b>	3.64	<b>17.43</b>	0.16	<b>6.41</b>	0.15	<b>11.75</b>	0.04	1.50	0.30	<b>7.37</b>	
Sur			0.41	<b>4.51</b>	3.91	<b>9.85</b>	0.11	<b>2.18</b>	0.16	<b>6.41</b>	0.07	1.48	0.23	<b>2.84</b>	

Table 3-7 Return Dispersion and International Country Risk

Table 3-7 presents the relation between return dispersion and international country risk. I take the International Country Risk Guide (ICRG) composite index as another measure of country-level uncertainty. I run the regression in the form of  $RD_t = \alpha + \beta_1 BC\_local_t + \beta_2 BC\_global_t + \beta_3 Start\_WCI_t + \beta_4 During\_WCI_t + \beta_5 End\_WCI_t + \beta_6 WordCount_t + \beta_7 Country\_Risk_t + \varepsilon_t$ .  $BC\_local_t$  and  $BC\_global_t$  are the dummy variables for business cycle (1= recession, 0 = expansion) in local country and global respectively.  $Start\_WCI_t$ ,  $During\_WCI_t$  and  $End\_WCI_t$  are ongoing crisis starting at month t, during month t and ending at month t.  $WordCount_t$  is the log number of the counts of Bloomberg reports in every month that contains the word “uncertainty”. System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression. I use robust standard errors. Coefficients are in percentage.

	constant	t-stat	local BC	t-stat	global BC	t-stat	start WCI	t-stat	during WCI	t-stat	end WCI	t-stat	word count uncertainty	t-stat	Country Risk	t-stat	Adj R2
Australia	48.24	<b>5.61</b>	0.45	0.69	3.68	<b>3.77</b>	0.04	0.43	0.00	0.05	0.00	-0.04	-0.10	-0.56	-0.50	<b>-4.81</b>	0.17
Austria	0.06	0.01	1.98	<b>2.77</b>	4.40	<b>3.49</b>	0.01	0.10	-0.01	-0.14	0.19	1.22	0.51	<b>2.85</b>	0.05	0.52	0.20
Belgium	38.08	<b>4.16</b>	0.21	0.47	3.92	<b>4.39</b>	0.11	1.31	-0.02	-0.44	0.11	1.25	0.80	<b>5.32</b>	-0.45	<b>-4.30</b>	0.32
Denmark	15.21	<b>2.33</b>	0.64	1.39	5.46	<b>3.62</b>	0.14	1.77	0.16	<b>4.08</b>	-0.07	-1.12	0.92	<b>5.39</b>	-0.17	<b>-2.00</b>	0.29
Finland	8.63	1.13	2.25	<b>3.24</b>	3.63	<b>3.19</b>	0.15	1.65	0.29	<b>6.04</b>	-0.01	-0.08	0.04	0.17	-0.02	-0.21	0.22
France	-15.56	<b>-2.16</b>	1.15	<b>3.18</b>	2.04	<b>2.75</b>	0.17	<b>1.83</b>	0.12	<b>3.41</b>	0.07	0.81	0.49	<b>3.34</b>	0.23	<b>2.75</b>	0.21
Germany	-10.32	-1.24	2.32	<b>2.07</b>	3.26	<b>3.68</b>	0.08	0.69	0.18	<b>4.54</b>	0.02	0.14	1.63	<b>7.53</b>	0.06	0.62	0.39
Ireland	32.52	<b>4.34</b>	3.39	<b>4.44</b>	4.29	<b>2.73</b>	0.30	1.55	0.18	<b>2.52</b>	-0.05	-0.45	1.10	<b>4.25</b>	-0.38	<b>-3.93</b>	0.26
Italy	3.03	0.59	1.34	<b>2.16</b>	0.90	1.30	0.00	0.02	0.08	1.50	0.09	0.91	0.38	<b>2.59</b>	0.02	0.25	0.03
Japan	-3.68	-0.57	0.11	0.25	2.64	<b>3.74</b>	0.21	<b>2.02</b>	0.19	<b>3.54</b>	0.06	0.66	0.60	<b>3.46</b>	0.07	1.04	0.11
Netherlands	-30.10	<b>-2.78</b>	2.75	<b>3.08</b>	0.67	0.56	0.21	<b>1.89</b>	0.14	<b>3.33</b>	-0.04	-0.41	1.09	<b>4.78</b>	0.34	<b>2.97</b>	0.26
Norway	4.22	0.39	1.93	<b>2.16</b>	3.31	<b>3.20</b>	0.14	0.94	0.18	<b>2.58</b>	-0.06	-0.53	0.24	0.88	0.04	0.27	0.08
NZ	50.14	<b>4.33</b>	0.43	0.54	2.19	<b>2.87</b>	0.09	0.51	0.16	<b>3.08</b>	-0.17	<b>-1.65</b>	-1.69	<b>-6.30</b>	-0.38	<b>-2.98</b>	0.22
Spain	21.98	<b>3.68</b>	1.06	<b>1.87</b>	3.02	<b>3.73</b>	0.32	<b>2.99</b>	0.15	<b>3.42</b>	0.16	1.38	-0.36	<b>-2.23</b>	-0.18	<b>-2.17</b>	0.21
Sweden	19.87	<b>3.72</b>	-0.64	<b>-1.90</b>	3.96	<b>6.51</b>	0.24	<b>2.05</b>	0.21	<b>5.54</b>	0.12	1.21	0.17	1.30	-0.17	<b>-2.76</b>	0.24
Switzerland	-43.27	<b>-3.27</b>	2.26	<b>1.89</b>	1.07	0.74	0.06	1.02	0.14	<b>2.99</b>	0.13	<b>1.81</b>	1.10	<b>4.64</b>	0.47	<b>3.57</b>	0.29
UK	-9.94	<b>-1.92</b>	-0.08	-0.25	4.62	<b>4.78</b>	0.28	<b>3.68</b>	0.14	<b>4.75</b>	-0.12	<b>-1.88</b>	0.69	<b>5.51</b>	0.14	<b>2.27</b>	0.34
US	-20.66	<b>-5.57</b>	1.33	<b>4.65</b>	2.64	<b>3.36</b>	0.08	<b>1.68</b>	0.13	<b>4.41</b>	0.10	1.34	1.25	<b>9.13</b>	0.22	<b>5.85</b>	0.44
System			0.88	<b>6.23</b>	3.70	<b>17.59</b>	0.16	<b>6.29</b>	0.15	<b>11.93</b>	0.04	1.51	0.29	<b>7.03</b>	0.05	<b>3.84</b>	
Sur			0.41	<b>4.35</b>	3.88	<b>9.81</b>	0.11	<b>2.46</b>	0.15	<b>6.36</b>	0.06	1.22	0.27	<b>3.67</b>	0.05	<b>5.51</b>	

### 3.4.5 Economic policy uncertainty

Policy-related uncertainties such as taxes, government spending, regulations, interest rate etc. have played an essential role in slowing down the recovery of the great depression of 2007-2009 (Baker et al., 2013). As return dispersion has been considered to be an economic state variable (see for instance Angelidis et al. (2015)), it may reflect economic policy uncertainty. To test this hypothesis, I employ the economic policy uncertainty (EPU) index developed by Baker et al. (2013). This index relies on monthly counts of articles in leading newspapers that references to the economic, uncertainty and policy.<sup>15</sup> Baker et al. (2013) first establish their index in the US and evaluate its impact on the macro economy. They find that the EPU index spikes around major political shocks including the Gulf Wars, 9/11, presidential elections, financial crisis etc.

Baker et al. (2013) also construct an EPU index for eleven countries. I employ the EPU index in seven countries (France, Germany, Italy, Japan, Spain, UK and US) which overlap with the sample of countries. Additionally, I include their global EPU index date back to January 1997. The global EPU index is a composite index reflecting 18 countries' uncertainty. These EPU indices have been used in several studies as proxy of economic policy uncertainty (for instance, Pástor and Veronesi (2013), Wang et al. (2015), Antonakakis, Chatziantoniou, and Filis (2013), Karnizova and Li (2014)). The

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<sup>15</sup> Baker, Bloom, and Davis (2015) construct the economic policy uncertainty index based on three components in their early draft paper. The components include the media coverage of references to economic uncertainty and policy, the number of federal tax code provision set to expire, and the degree of disagreement among economic forecasters. But in their latest draft they only include the newspaper coverage frequency.

data are from their website (<http://www.policyuncertainty.com/>). France economic policy uncertainty fluctuated most among all seven countries. The standard deviation of the EPU index in France is 72.55 compared to 32.82 for the US.

To test if return dispersion is influenced by macroeconomic policies, I again extend the previous regression to include both (the log of) local economic policy for each country ( $EPU\_local_t$ ) and (the log of) global economic policy uncertainty (equation 3.7).

$$\begin{aligned}
 RD_t = & \alpha + \beta_1 BC\_local_t + \beta_2 BC\_global_t + \beta_3 Start\_WCI_t + \beta_4 During\_WCI_t \\
 & + \beta_5 End\_WCI_t + \beta_6 WordCount_t + \beta_7 Country\_Risk_t \\
 & + \beta_8 \ln(EPU\_local)_t + \beta_9 \ln(EPU\_global)_t + \varepsilon_t
 \end{aligned} \tag{3.7}$$

Table 3-8 shows the results. The overall effect of both country specific EPU and global EPU on return dispersion is statistically significant and positive. Return dispersion is larger during higher country specific economic policy uncertainty in Australia, Italy, Japan, and the US. The effect is economically small. For instance, 10 percent increase in economic policy uncertainty will raise return dispersion around 37 basis points in the US and 25 basis points in Japan. Global EPU has larger effect than local one. Global economic policy uncertainty has a statistically significant effect on return dispersion in eight out of eleven countries I tested. However, the effect in Australia is negative and is insignificant in the US.

Table 3-8 Return Dispersion and Economic Policy Uncertainty

Table 3-8 presents the characteristics of economic policy uncertainty. I show the results for the regression:  $RD_t = \alpha + \beta_1 BC\_local_t + \beta_2 BC\_global_t + \beta_3 Start\_WCI_t + \beta_4 During\_WCI_t + \beta_5 End\_WCI_t + \beta_6 WordCount_t + \beta_7 Country\_Risk_t + \beta_8 \ln(EPU\_local)_t + \beta_9 \ln(EPU\_global)_t + \varepsilon_t$   $RD_t$  is the return dispersion of the largest 50 market capitalization stocks in each country at time t.  $BC\_local_t$  and  $BC\_global_t$  are the dummy variables for business cycle (1= recession, 0 = expansion) in local country and global respectively.  $Start\_WCI_t$ ,  $During\_WCI_t$  and  $End\_WCI_t$  are ongoing crisis starting at month t, during month t and ending at month t.  $WordCount_t$  is the log number of the counts of Bloomberg reports in every month that contains the word “uncertainty”.  $Country\_Risk_t$  represents the ICRG composite risk index for each country. I include two economic policy index, one is the country specific index ( $EPU\_local$ ) and the other is the global index ( $EPU\_global$ ). System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression. I use robust standard errors. Coefficients are in percentage.

Country	Coefficient	Constant	Local BC	Global BC	Start WCI	during WCI	end WCI	Word Count Uncertainty	Country Risk	ln(Local EPU)	ln(Global EPU)	N	Adjusted R2
<i>Australia</i>	Coeff. (%)	7.19	2.29	2.14	0.09	-0.09	0.22	0.34	-0.09	3.60	-2.48	144	0.35
	t-Stat	0.53	1.10	<b>2.26</b>	0.61	-1.03	1.30	0.62	-0.58	<b>4.06</b>	<b>-1.80</b>		
<i>France</i>	Coeff. (%)	-28.61	0.49	1.12	0.06	0.29	-0.02	-0.19	0.19	-0.41	5.09	156	0.43
	t-Stat	<b>-2.03</b>	0.55	1.45	0.38	<b>3.59</b>	-0.12	-0.36	1.36	-0.83	<b>4.72</b>		
<i>Germany</i>	Coeff. (%)	-9.71	2.22	2.46	-0.07	0.24	0.01	-0.04	-0.11	0.59	5.21	156	0.46
	t-Stat	-0.77	1.11	<b>2.60</b>	-0.51	<b>3.96</b>	0.06	-0.09	-0.81	0.85	<b>4.73</b>		
<i>Ireland</i>	Coeff. (%)	-8.05	2.63	3.33	0.40	0.09	-0.01	1.02	-0.19	1.76	4.16	156	0.29
	t-Stat	-0.48	<b>2.84</b>	<b>2.33</b>	0.97	0.76	-0.03	1.29	-1.38	1.57	<b>2.13</b>		
<i>Italy</i>	Coeff. (%)	-2.24	1.22	0.96	-0.06	0.15	0.05	-0.82	-0.05	2.16	2.13	156	0.07
	t-Stat	-0.21	1.34	1.60	-0.47	1.37	0.20	<b>-1.75</b>	-0.45	<b>2.70</b>	<b>1.98</b>		
<i>Japan</i>	Coeff. (%)	-17.71	0.23	2.23	0.08	0.41	-0.09	0.71	0.16	2.49	-1.36	156	0.18
	t-Stat	-1.51	0.34	<b>2.65</b>	0.51	<b>4.39</b>	-0.67	1.04	1.61	<b>2.51</b>	-0.89		
<i>Netherland</i>	Coeff. (%)	10.51	3.29	0.93	-0.07	0.02	-0.26	-1.71	-0.15	-0.74	5.71	82	0.53
	t-Stat	0.71	<b>1.86</b>	0.97	-0.44	0.16	<b>-1.92</b>	<b>-2.22</b>	-0.96	-0.81	<b>3.62</b>		

<i>Spain</i>	Coeff. (%)	14.50	1.19	1.56	0.18	0.22	0.22	-1.24	-0.23	-0.85	4.92	108	0.41
	t-Stat	1.06	1.60	1.51	0.86	<b>2.35</b>	1.04	-1.43	<b>-1.76</b>	-1.33	<b>3.53</b>		
Sweden	Coeff. (%)	13.45	-0.51	2.70	0.08	0.18	0.15	1.24	-0.34	1.29	1.64	156	0.39
	t-Stat	1.22	-1.16	<b>4.55</b>	0.55	<b>3.17</b>	0.78	<b>2.03</b>	<b>-2.95</b>	0.99	1.53		
<i>UK</i>	Coeff. (%)	-16.71	-0.11	2.88	0.17	0.22	-0.25	0.21	-0.02	-2.36	7.66	156	0.48
	t-Stat	<b>-2.06</b>	-0.23	<b>3.37</b>	1.31	<b>4.28</b>	<b>-2.18</b>	0.46	-0.33	<b>-3.17</b>	<b>6.40</b>		
<i>US</i>	Coeff. (%)	-39.18	1.22	1.65	0.01	0.25	0.11	0.58	0.31	3.74	-0.02	156	0.49
	t-Stat	<b>-6.40</b>	<b>2.74</b>	<b>2.32</b>	0.07	<b>3.88</b>	0.68	1.42	<b>6.25</b>	<b>2.27</b>	-0.01		
System	Coeff. (%)		1.23	2.35	0.07	0.24	0.03	0.06	0.13	0.64	3.21		
	t-Stat		<b>4.87</b>	<b>7.90</b>	1.17	<b>9.57</b>	0.49	0.28	<b>5.69</b>	<b>2.60</b>	<b>7.74</b>		
Sur	Coeff. (%)		0.53	2.70	0.03	0.21	0.09	-0.05	0.11	0.49	3.21		
	t-Stat		<b>3.15</b>	<b>6.91</b>	0.31	<b>6.11</b>	1.24	-0.19	<b>7.13</b>	<b>2.87</b>	<b>6.31</b>		

### 3.5 Return dispersion and the cross section of returns

As return dispersion seems to capture uncertainty well, one can easily relate it to returns. I consider whether returns of stocks depend on their sensitivity with respect to return dispersion. Jiang (2010) documents that return dispersion is a priced factor in the US and stocks with higher sensitivities to return dispersion have higher average returns. I consider not only levels but also changes in cross sectional return dispersion. Results for changes are similar (although not as strong as for the levels and I report these in the Appendix B). I provide evidence for 13 international stock markets, Australia, Belgium, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, the UK and the US.<sup>16</sup> The sample period starts from January 1986 to March 2014. I exclude very small firms. For each market in each year, I consider the 90% largest common stocks based on the market capitalization at the end of the previous year.<sup>17</sup> I also identify the largest 50 stocks by the same market capitalization measure.

The first step is to estimate the sensitivity of individual stocks to return dispersion. For each market for each month for each stock with more than 15 daily return observations, I run a time-series regression. Specifically, I regress the daily stock return on the mean return of the largest 50 stocks (as a proxy

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<sup>16</sup> We exclude five markets from this analysis because these markets have been small markets such that there are not enough observations in the early months for analysis. These five markets are Finland, Denmark, Austria, New Zealand and Ireland.

<sup>17</sup> We only focus on stocks that are traded in the domestic currency, which usually accounts for more than 90% of all stocks.

for the market-wide movement) and the return dispersion of the largest 50 stocks:

$$R_{i,t} = \alpha_i + \beta_{i,RMRF}RMRF_t + \beta_{i,RD}RD_t + \varepsilon_{i,t} \quad (3.8)$$

where  $R_{i,t}$  is the return of the individual stock at time  $t$ ,  $RMRF_t$  is the mean return of the largest 50 stocks at time  $t$  and  $RD_t$  is the return dispersion of the largest 50 stocks at time  $t$ . The estimated coefficient ( $\beta_{i,RD}$ ) is the estimated sensitivity of the stock with respect to cross sectional return dispersion measures.

In the second step, I form quintile portfolios based on this estimated coefficient  $\beta_{i,RD}$ . For each market for each month, I sort all the stocks by the estimated  $\beta_{i,RD}$ . Portfolio 1 consists of stocks with the smallest 20 percent  $\beta_{i,RD}$  whereas Portfolio 5 consists of stocks with the largest 20 percent  $\beta_{i,RD}$ .

In the third step, I calculate monthly returns for these portfolios. For each market for each month for each portfolio, I calculate the monthly value-weighted portfolio return using the monthly return, of the same month as the portfolio formation month, of all individual stocks constituting the portfolio where the weighting is the market capitalization as of the end of the previous month.

In the last step, I consider whether stocks with higher sensitivities to return dispersion have higher average returns. I present two sets of results, one is the average monthly CAPM alphas and the other is the four-factor alphas. The

CAPM alphas are returns after controlling for the mean return of the largest 50 stocks ( $RMRF_t$ , as a proxy for the “market” factor). The four-factor alphas are the returns after controlling for the Fama-French three factors (market, size and value) and the momentum factor.

Table 3-9 reports the results for CAPM alphas and Table 3-10 reports the four-factor alphas. The results for raw returns are non-tabulated. I plot the CAPM alphas of the value weighted portfolios in Figure 3-3. Stock returns are positively related to their sensitivity with respect to return dispersion. The returns increase monotonically as their sensitivities increase, regardless whether I consider CAPM alphas or four-factor alphas. For all the markets, the average alphas of the portfolios with the smallest return dispersion sensitivities (Group 1) are negative except for the equal-weighted US stocks. The mean returns of portfolios with the largest return dispersion sensitivities (Group 5) are positive and also highly statistically significant. For the middle groups, there is generally at least one group with a mean return that is statistically insignificantly different from zero: for raw returns, it is usually Group 2; for CAPM alphas, it is usually Group 3. The differences in the mean return between Group 5 and Group 1 range from 4.4% to 6.4% for the raw returns. For the CAPM alphas, average differences range from 3.5% to 6.4%. Again t-values for these differences indicate that the differences are highly significant. On average, I find a t-value of around 9 for the raw returns and approximately a t-value of 15 for the CAPM alphas. In short, stocks that are more sensitive to return dispersion generate substantially higher abnormal returns.

In order to test whether these results are not caused by construction, I conduct the Monte Carlo simulation. I generate daily random samples, estimate monthly return series by cumulating the daily stimulations and repeat the process 100 times. The detailed procedure are as follows. First, I take the full sample market index to estimate market index sample mean and standard deviation. Use those characteristics of the original market index, I generate simulated market return series. I use the randomly generated market index as the return of the market portfolio. Second, I use the original individual stock returns regress on the original market index according to the CAPM model in order to estimate constant, beta, standard deviation of error term for each stock over the full sample. Then I generate individual stock return series using simulated market return series and the estimations from CAPM model. Third, I use the randomly generated market index as the return of the market portfolio. I construct return dispersion from the randomly generated stock returns of all individual stocks. Forth, I cumulate the daily returns to get the monthly data. I calculate the return dispersion using all individual stocks. Finally, I sort equal-weighted quintile portfolios every month based on stocks' exposure to return dispersion as what I done using real data. The results of the simulated data are if anything go against those using the real dataset: the higher the exposure to return dispersion the lower return. This suggests that the methodology does not cause the effect I observe in the real data. These results are available on request from the author.

Table 3-9 CAPM Alphas of Portfolios Sorted by Their Sensitivity to Return Dispersion

This table reports the CAPM alphas of portfolios sorted by their sensitivity to return dispersion. I report the monthly value-weighted portfolio returns in panel A and equal-weighted portfolio returns in panel B.

<i>Panel A: value weighted portfolio returns</i>												
	Low		Group 2		Group 3		Group 4		High		High - Low	
	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value
Australia	-0.038	<b>-11.90</b>	-0.007	<b>4.29</b>	0.001	0.69	0.010	<b>7.49</b>	0.023	<b>7.07</b>	0.061	<b>13.40</b>
Belgium	-0.025	<b>-7.33</b>	-0.002	-1.37	0.001	0.76	0.009	<b>5.59</b>	0.021	<b>8.40</b>	0.046	<b>10.87</b>
France	-0.026	<b>-12.28</b>	-0.007	<b>-5.86</b>	0.001	0.56	0.007	<b>6.30</b>	0.023	<b>13.81</b>	0.050	<b>18.21</b>
Germany	-0.026	<b>-9.14</b>	-0.008	<b>-5.56</b>	-0.001	-0.97	0.007	<b>4.94</b>	0.024	<b>9.07</b>	0.050	<b>12.87</b>
Italy	-0.022	<b>-11.12</b>	-0.007	<b>-4.70</b>	-0.001	0.74	0.006	<b>4.32</b>	0.025	<b>14.15</b>	0.047	<b>17.70</b>
Japan	-0.025	<b>-12.10</b>	-0.001	<b>-10.02</b>	-0.004	<b>-3.27</b>	0.008	<b>6.90</b>	0.029	<b>14.50</b>	0.054	<b>18.79</b>
Netherlands	-0.033	<b>-11.30</b>	-0.003	-1.34	0.002	1.15	0.008	<b>5.17</b>	0.025	<b>10.99</b>	0.058	<b>15.69</b>
Norway	-0.031	<b>-9.83</b>	-0.001	-0.28	0.003	1.24	0.015	<b>7.25</b>	0.033	<b>11.24</b>	0.064	<b>14.85</b>
Spain	-0.026	<b>-9.92</b>	-0.004	<b>-2.25</b>	-0.001	-0.31	0.005	<b>2.19</b>	0.027	<b>11.28</b>	0.035	<b>14.93</b>
Sweden	-0.035	<b>-10.38</b>	-0.006	<b>-3.31</b>	0.001	0.74	0.009	<b>5.28</b>	0.028	<b>11.91</b>	0.063	<b>15.34</b>
Switzerland	-0.025	<b>-10.00</b>	-0.003	<b>-2.29</b>	0.002	1.09	0.007	<b>4.30</b>	0.024	<b>11.95</b>	0.048	<b>15.26</b>
UK	-0.030	<b>-10.85</b>	-0.005	<b>-4.51</b>	0.000	0.11	0.006	<b>5.60</b>	0.021	<b>14.94</b>	0.052	<b>16.52</b>
US	-0.025	<b>-10.80</b>	-0.006	<b>-5.05</b>	0.001	0.57	0.006	<b>5.58</b>	0.018	<b>8.07</b>	0.044	<b>13.39</b>
average	-0.028		-0.005		0.000		0.008		0.025		0.052	
min	-0.038		-0.008		-0.004		0.005		0.018		0.035	
max	-0.022		-0.001		0.003		0.015		0.033		0.064	
median	-0.026		-0.005		0.001		0.007		0.024		0.050	

(Continued on next page)

(Table 3-9 Continued)

Panel B: equally weighted portfolio returns

	Low		Group 2		Group 3		Group 4		High		High - Low	
	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value
Australia	-0.019	<b>-4.75</b>	-0.007	<b>-3.50</b>	-0.004	<b>-2.00</b>	-0.003	-1.50	0.006	1.50	0.025	<b>5.00</b>
Belgium	-0.010	<b>-5.00</b>	-0.001	-1.00	-0.000	0.00	0.005	<b>5.00</b>	0.014	<b>7.00</b>	0.024	<b>8.00</b>
France	-0.008	<b>-4.00</b>	-0.005	<b>-5.00</b>	-0.001	-1.00	0.001	1.00	0.008	<b>4.00</b>	0.016	<b>5.33</b>
Germany	-0.012	<b>-6.00</b>	-0.006	<b>-6.00</b>	-0.004	<b>-4.00</b>	-0.004	<b>-4.00</b>	-0.003	-1.50	0.009	<b>3.00</b>
Italy	-0.010	<b>-5.00</b>	-0.008	<b>-8.00</b>	-0.005	<b>-5.00</b>	-0.000	0.00	0.015	<b>7.50</b>	0.025	<b>8.33</b>
Japan	-0.004	-1.33	-0.007	<b>-3.50</b>	-0.004	<b>-2.00</b>	0.002	1.00	0.020	<b>6.67</b>	0.024	<b>6.00</b>
Netherland	-0.011	<b>-5.50</b>	-0.002	<b>-2.00</b>	0.001	1.00	0.002	<b>2.00</b>	0.012	<b>6.00</b>	0.023	<b>7.67</b>
Norway	-0.018	<b>-6.00</b>	-0.001	-0.50	0.002	1.00	0.010	<b>5.00</b>	0.023	<b>7.67</b>	0.041	<b>10.25</b>
Spain	-0.016	<b>-8.00</b>	-0.005	<b>-2.50</b>	-0.003	<b>-3.00</b>	0.003	1.50	0.019	<b>9.50</b>	0.035	<b>11.67</b>
Sweden	-0.018	<b>-6.00</b>	-0.007	<b>-3.50</b>	-0.003	<b>-3.00</b>	0.003	<b>3.00</b>	0.011	<b>3.67</b>	0.028	<b>7.00</b>
Switzerland	-0.013	<b>-6.50</b>	-0.003	<b>-3.00</b>	0.001	1.00	0.003	<b>3.00</b>	0.014	<b>7.00</b>	0.027	<b>13.50</b>
UK	-0.010	<b>-3.33</b>	-0.003	-1.50	-0.003	<b>-3.00</b>	-0.001	-1.00	0.004	1.33	0.014	<b>3.50</b>
US	-0.003	-1.00	-0.001	-0.50	0.001	0.50	0.002	1.00	0.011	<b>3.67</b>	0.014	<b>3.50</b>
average	-0.012		-0.004		-0.002		0.002		0.012		0.023	
min	-0.019		-0.008		-0.005		-0.004		-0.003		0.009	
max	-0.003		-0.001		0.002		0.010		0.023		0.041	
median	-0.011		-0.005		-0.003		0.002		0.012		0.024	

Table 3-10 Four-factor Alphas (in percentage) of Portfolios Sorted by Their Sensitivity to Return Dispersion

Table 3-10 reports the four factor alphas of portfolios sorted by their sensitivity to return dispersion. The four factors are market, size, value and momentum factors. I report the monthly value-weighted portfolio returns in panel A and equal-weighted portfolio returns in panel B. The coefficients are in percentage.

<i>Panel A: value weighted portfolio returns</i>												
	Low		Group 2		Group 3		Group 4		High		High - Low	
	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value
Australia	-3.82	<b>-10.63</b>	-0.86	<b>-3.87</b>	0.23	1.42	0.86	<b>4.19</b>	2.15	<b>6.65</b>	5.97	<b>12.33</b>
Belgium	-2.60	<b>-4.83</b>	-0.33	-1.18	0.04	0.17	0.71	<b>2.72</b>	1.98	<b>4.54</b>	4.58	<b>6.61</b>
France	-2.81	<b>-7.88</b>	-0.97	<b>-3.92</b>	-0.12	-0.58	0.63	<b>2.65</b>	2.42	<b>7.80</b>	5.23	<b>11.05</b>
Germany	-2.74	<b>-5.63</b>	-0.87	<b>-3.14</b>	-0.37	-1.59	0.61	<b>2.40</b>	2.45	<b>6.62</b>	5.19	<b>8.49</b>
Italy	-3.05	<b>-7.29</b>	-1.29	<b>-3.96</b>	-0.52	<b>-1.74</b>	0.04	0.12	2.07	<b>5.57</b>	5.12	<b>9.14</b>
Japan	-3.22	<b>-11.00</b>	-1.60	<b>-8.02</b>	-0.79	<b>-4.29</b>	0.21	1.12	2.07	<b>8.35</b>	5.30	<b>13.79</b>
Netherland	-3.60	<b>-8.33</b>	-0.62	<b>-1.88</b>	-0.14	-0.54	0.91	<b>3.36</b>	2.53	<b>6.56</b>	6.13	<b>10.57</b>
Norway	-4.28	<b>-8.17</b>	-1.05	<b>-2.70</b>	-0.36	-0.98	0.75	<b>2.28</b>	2.69	<b>5.48</b>	6.97	<b>9.71</b>
Spain	-3.28	<b>-6.96</b>	-0.69	<b>-2.42</b>	-0.24	-0.91	0.23	0.69	2.64	<b>7.08</b>	5.91	<b>9.85</b>
Sweden	-3.08	<b>-6.20</b>	-0.20	-0.58	0.56	<b>1.75</b>	1.03	<b>3.02</b>	3.60	<b>8.10</b>	6.68	<b>10.02</b>
Switzerland	-2.63	<b>-6.28</b>	-0.35	-1.37	0.06	0.25	0.77	<b>2.33</b>	2.46	<b>5.89</b>	5.10	<b>8.61</b>
UK	-3.35	<b>-8.07</b>	-0.64	<b>-3.28</b>	0.07	0.37	0.68	<b>3.31</b>	2.47	<b>9.32</b>	5.82	<b>11.83</b>
US	-2.38	<b>-12.78</b>	-0.68	<b>-6.76</b>	0.01	0.09	0.64	<b>8.58</b>	2.05	<b>11.12</b>	4.42	<b>16.95</b>
average	-3.14		-0.78		-0.12		0.62		2.43		5.57	
min	-4.28		-1.60		-0.79		0.04		1.98		4.42	
max	-2.38		-0.20		0.56		1.03		3.60		6.97	
median	-3.08		-0.69		-0.12		0.68		2.45		5.30	

(Continued on next page)

(Table 3-10 Continued)

	Low		Group 2		Group 3		Group 4		High		High - Low	
	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value
Australia	-1.47	<b>-3.71</b>	-0.94	<b>-4.45</b>	-0.37	<b>-2.10</b>	-0.39	<b>-1.80</b>	0.49	1.36	1.96	<b>3.67</b>
Belgium	-0.85	<b>-2.68</b>	-0.13	-0.62	-0.10	-0.49	0.38	<b>1.68</b>	1.35	<b>4.41</b>	2.21	<b>5.00</b>
France	-0.66	<b>-2.19</b>	-0.59	<b>-2.91</b>	-0.38	<b>-2.20</b>	-0.08	-0.40	0.84	<b>3.08</b>	1.50	<b>3.69</b>
Germany	-1.02	<b>-3.24</b>	-0.66	<b>-3.42</b>	-0.63	<b>-4.07</b>	-0.57	<b>-3.04</b>	-0.41	-1.36	0.61	1.39
Italy	-1.41	<b>-3.86</b>	-1.32	<b>-4.59</b>	-0.88	<b>-3.65</b>	-0.66	<b>-2.30</b>	0.95	<b>2.51</b>	2.36	<b>4.49</b>
Japan	-1.16	<b>-4.18</b>	-1.32	<b>-7.17</b>	-1.00	<b>-6.06</b>	-0.51	<b>-2.98</b>	1.05	<b>4.37</b>	2.21	<b>6.01</b>
Netherland	-0.97	<b>-3.15</b>	-0.33	-1.50	-0.19	-0.92	-0.07	-0.32	1.02	<b>3.32</b>	2.00	<b>4.58</b>
Norway	-2.12	<b>-4.21</b>	-0.86	<b>-2.26</b>	-0.21	-0.60	0.37	1.09	1.78	<b>3.51</b>	3.90	<b>5.46</b>
Spain	-1.78	<b>-4.67</b>	-0.85	<b>-3.32</b>	-0.60	<b>-2.77</b>	-0.18	-0.71	1.44	<b>4.15</b>	3.22	<b>6.25</b>
Sweden	-1.10	<b>-2.50</b>	-0.41	-1.27	0.10	0.33	0.33	1.06	1.59	<b>3.49</b>	2.69	<b>4.25</b>
Switzerland	-1.05	<b>-3.37</b>	-0.27	-1.18	0.02	0.09	0.25	1.06	1.40	<b>4.62</b>	2.45	<b>5.64</b>
UK	-0.89	<b>-2.92</b>	-0.31	-1.48	-0.29	-1.51	-0.10	-0.45	0.72	<b>2.21</b>	1.61	<b>3.61</b>
US	-0.40	<b>-2.56</b>	-0.34	<b>-3.20</b>	-0.11	-1.30	0.03	0.39	1.03	<b>6.34</b>	1.43	<b>6.33</b>
average	-1.15		-0.64		-0.36		-0.09		1.02		2.16	
min	-2.12		-1.32		-1.00		-0.66		-0.41		0.61	
max	-0.40		-0.13		0.10		0.38		1.78		3.90	
median	-1.05		-0.59		-0.29		-0.08		1.03		2.21	

Figure 3-3 Four-factor Alphas of Portfolios Sorted by Return Dispersion Betas

Figure 3-3a: Four-factor alphas of value-weighted portfolios sorted by return dispersion betas

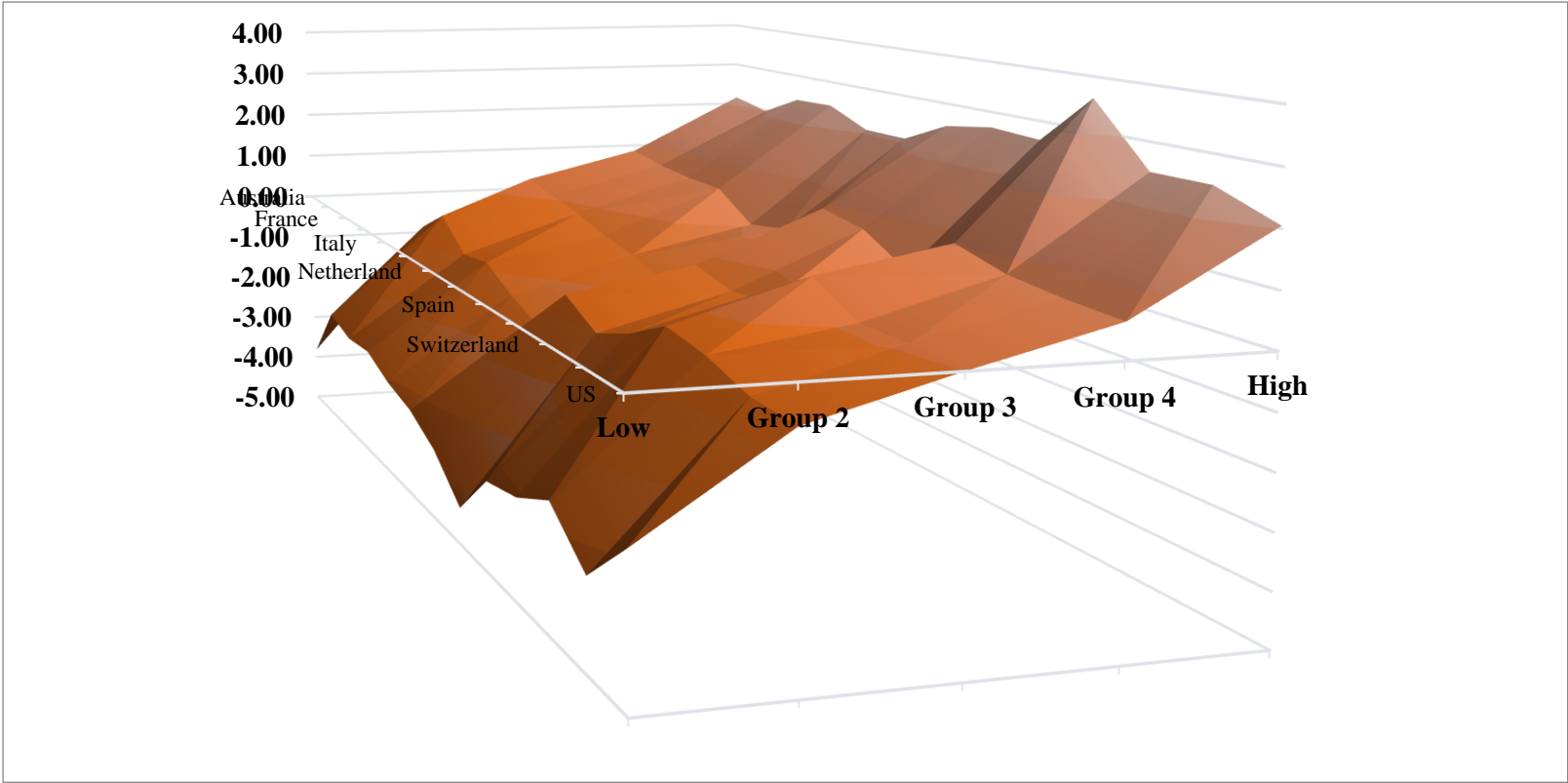
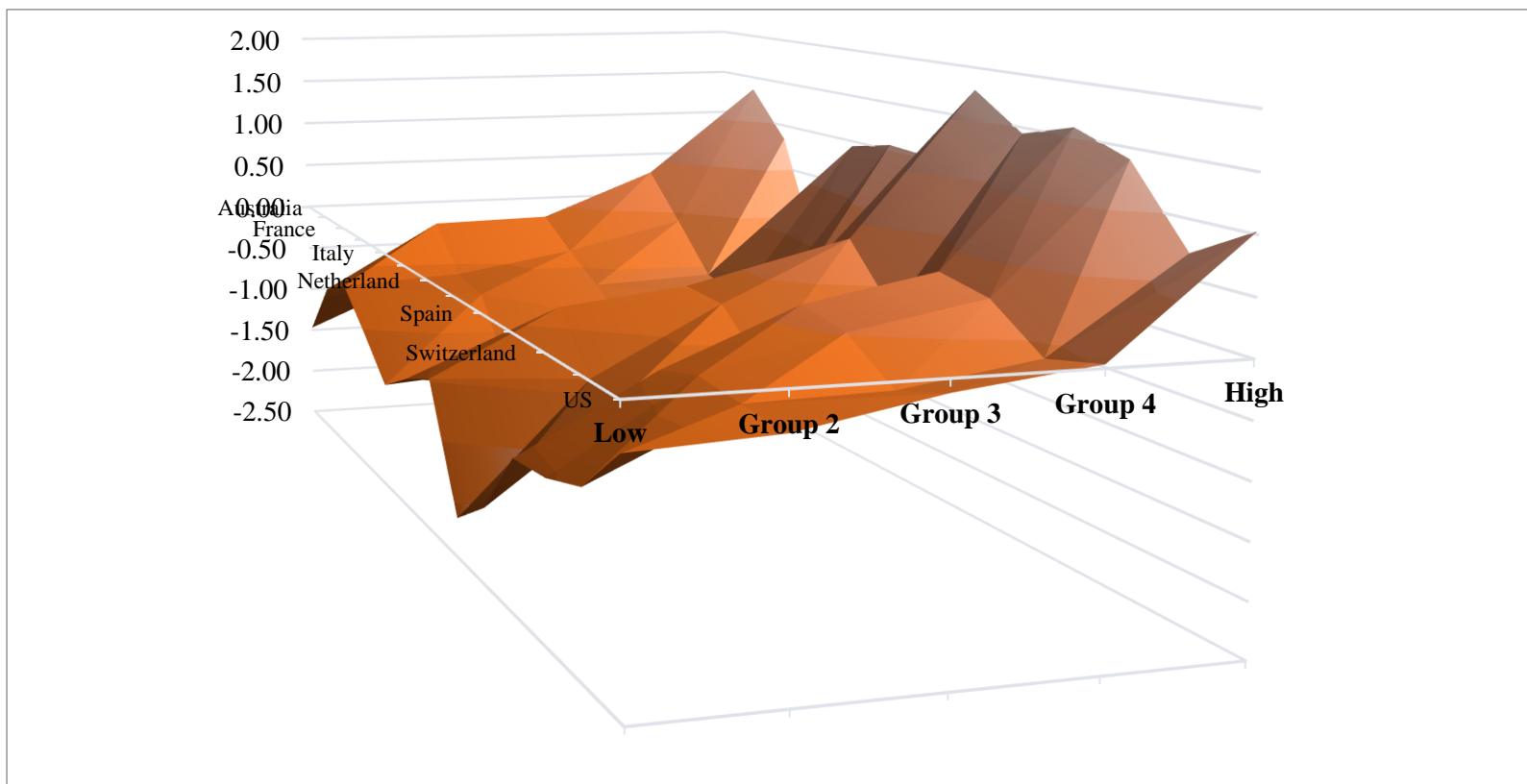


Figure 3-3b: Four-factor alphas of equal-weighted portfolios sorted by return dispersion betas



### **3.6 Return dispersion and implied volatility**

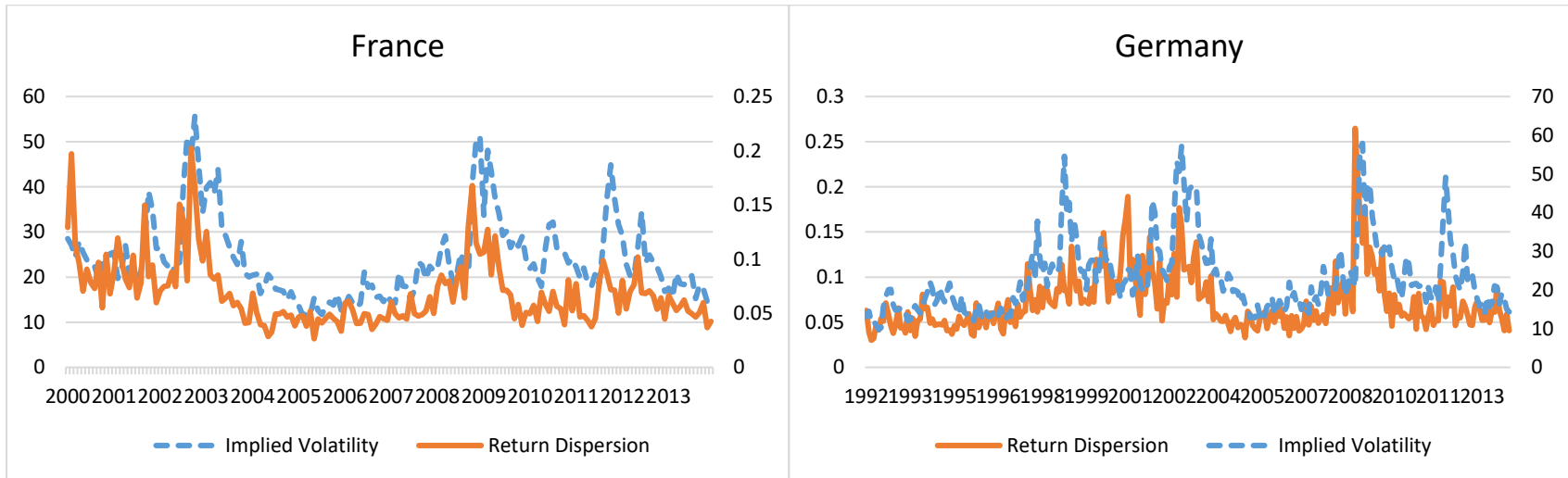
Implied volatility derived from an option contract is often used as a proxy for overall economic uncertainty. It is a forward-looking volatility measure that contains information about expected market fluctuations. In the G5 countries implied volatility is nowadays traded. The previous literature shows a close link between the implied volatility and the economic uncertainty. For instance, Beber and Brandt (2009) suggest that a high macroeconomic uncertainty period is followed lower implied bond futures volatility. Also, Stivers (2003) finds that the dispersion in firm returns provide incremental information about US market-level future volatility during period 1927 to 1995. I compare return dispersion with implied volatility. Just like return dispersion it is easy to observe in at least the five countries for which these data are available.

#### **3.6.1 Implied volatility and macroeconomic uncertainty**

I first compare co-movements between implied volatility and return dispersion visually. I obtain the implied volatility indices in G5 countries include CAC40 Volatility Index (France), VDAX New Volatility Index (Germany), NIKKEI Stock Average Volatility Index (Japan), FTSE 100 Volatility Index (UK) and CBOE SPX Volatility VIX (US). Figure 3-4 plots the return dispersion series and implied volatility index for each country. Although these two measures correlate, there still exists certain periods that they deviate from each other.

Figure 3-4 Return Dispersion and Implied Volatility

Figure 3-4 plots the return dispersion and its contemporaneous implied volatility index for each country. The return dispersion is calculated using the largest 50 stock returns. The implied volatility indices I use include CAC40 Volatility Index (France), VDAX New Volatility Index (Germany), NIKKEI Stock Average Volatility Index (Japan), FTSE 100 Volatility Index (UK) and CBOE SPX Volatility VIX (US).



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(Figure 3-4 Continued)

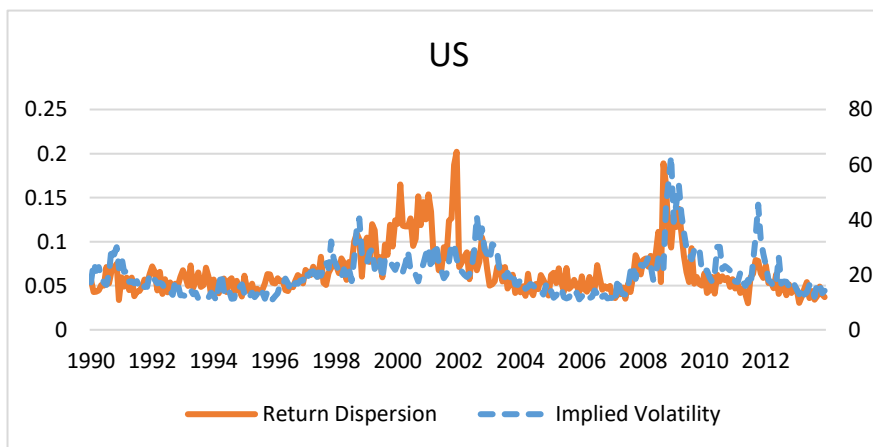
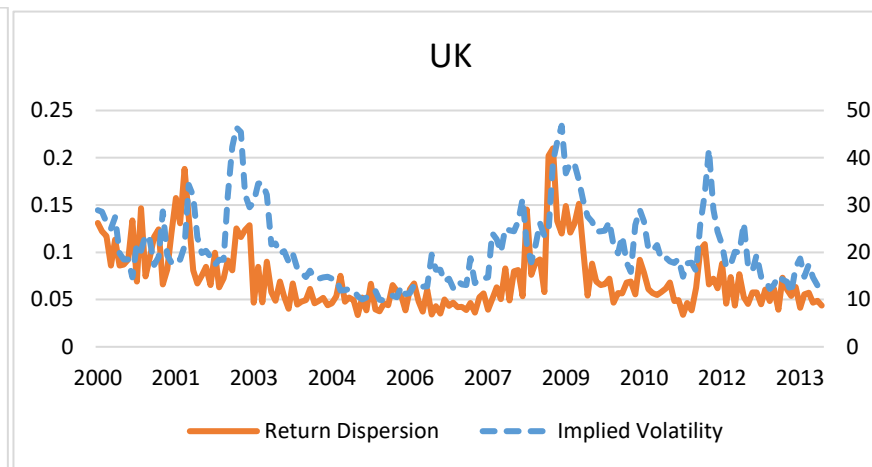
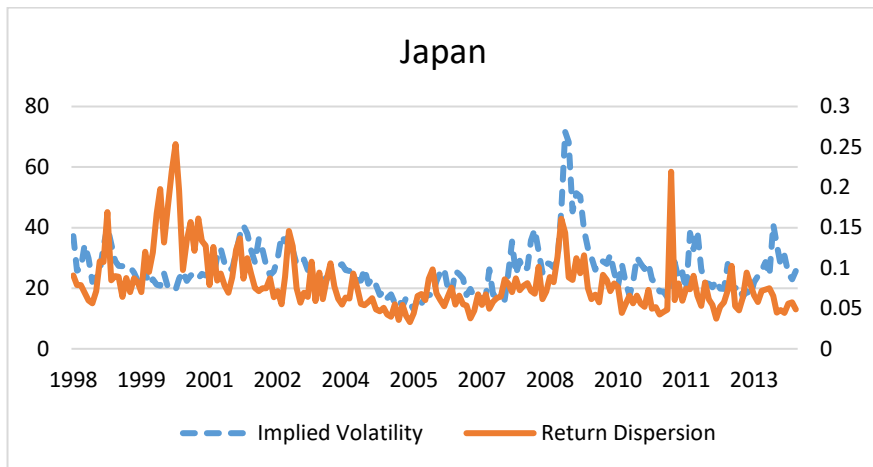


Table 3-11 reports the basic characteristics of the implied volatility. The implied volatility in G5 countries indeed correlates with the corresponding countries' return dispersion, but the correlation is not high. The average correlation is less than 0.6 especially for Japan where the correlation is only 0.2. The first-order autocorrelations,  $\rho(1)$  shows that a high implied volatility this month increases the likelihood of a high implied volatility next month for all five countries. As the first-order autocorrelations are relatively high, I further test if there exist unit root by using Dicky-Fuller test. I reject the hypothesis of having a unit root for all series.

Table 3-11 Basic Characteristics of Implied Volatility

This table reports the summary statistics of the implied volatility series in five countries. For France I use the CAC40 volatility index from January 2000 to December 2013. For Germany I use the VDAX new volatility index from January 1992 to December 2013. For Japan I use the NIKKEI stock average volatility index from January 1998 to December 2013. For the UK I use the FTSE 100 volatility index from January 2000 to December 2013. For the US I use the CBOE SPX volatility vix from January 1990 to December 2013. All series are obtained from Datastream.

	France	Germany	Japan	UK	US
Mean	23.80	22.95	26.20	20.66	20.09
Median	22.03	20.74	25.30	18.68	18.20
Max	55.71	57.90	71.62	46.78	62.98
Min	11.60	9.73	12.89	9.83	10.08
Std. Dev.	8.88	9.50	8.13	8.07	7.76
Skewness	1.33	1.51	2.06	1.16	1.81
Kurtosis	4.63	5.21	10.80	4.09	8.20
Jarque-Bera	90.70	183.94	698.49	61.39	549.76
Probability	0.00	0.00	0.00	0.00	0.00
Sum	4069.59	6126.43	5109.17	3533.08	5845.45
Sum Sq. Dev	13312.19	23946.27	12760.98	10992.2	17390.56
Correlation with RD	0.62	0.59	0.20	0.57	0.54
$\rho(1)$	0.85***	0.87***	0.77***	0.86***	0.84***
Dicky-Fuller test	-3.59***	-4.26***	-4.91***	-3.56***	-4.88***
Observations	171	267	195	171	291

The next is whether implied volatility is also a risk measure for macroeconomic uncertainty. Equation 3.9 shows the regression on business cycles, international political crisis, word count uncertainty, country risk, and economic policy uncertainty, similar to return dispersion but now the dependent variable is the implied volatility at month  $t$  ( $VIX_t$ ):

$$\begin{aligned}
 VIX_t = & \alpha + \beta_1 BC\_local_t + \beta_2 BC\_global_t + \beta_3 Start\_WCI_t + \beta_4 During\_WCI_t \\
 & + \beta_5 End\_WCI_t + \beta_6 WordCount_t + \beta_7 Country\_Risk_t \\
 & + \beta_8 \ln(EPU\_local)_t + \beta_9 \ln(EPU\_global)_t + \varepsilon_t
 \end{aligned} \tag{3.9}$$

Panel A of Table 3-12 has the regression results for G5 countries from January 2000 to December 2013 and the pooled OLS (system) and seemingly unrelated regression (sur) that considers these G5 countries as a system. Implied volatility seems to capture the uncertainty associated with these variables well. Implied volatility series correlate with the global business cycles but not local business cycles. The ongoing political crisis and country risk positively affects implied volatility as well in all G5 countries. However, word count uncertainty has a negative effect on implied volatility. Moreover, implied volatility series are significantly affected by the global economic policy uncertainty but not the local one. For instance, 10% increase in Global economic policy uncertainty will raise implied volatility by 2.4 units which is around 10% of the average implied volatility level. In fact, results for implied volatility seems strongly indicating that implied volatility is able to capture economic policy uncertainty better than return dispersion.

Table 3-12 Compared Implied Volatility and Return Dispersion in G5 Countries

This table compares the results of implied volatility regressions on uncertainties (Panel A) and results of return dispersion regressions on uncertainties (Panel B). Regressions are in the form of  $VIX_t/RD_t = \alpha + \beta_1 local BC_t + \beta_2 global BC_t + \beta_3 Start\_WCI_t + \beta_4 During\_WCI_t + \beta_5 End\_WCI_t + \beta_6 WordCount_t + \beta_7 Country\_Risk_t + \beta_8 \ln(local EPU)_t + \beta_9 \ln(global EPU)_t + \varepsilon_t$ .  $VIX_t$  is the implied volatility indices and  $RD_t$  is the return dispersion at time t in each country.  $BC\_local_t$  and  $BC\_global_t$  are the dummy variables for business cycle (1= recession, 0 = expansion) in local country and global respectively.  $Start\_WCI_t$ ,  $During\_WCI_t$  and  $End\_WCI_t$  are ongoing crisis starting at month t, during month t and ending at month t.  $WordCount_t$  is the log number of the counts of Bloomberg reports in every month that contains the word “uncertainty”.  $Country\_Risk_t$  represents the ICRG composite risk index for each country. I include two economic policy index, one is the country specific index ( $EPU\_local$ ) and the other is the global index ( $EPU\_global$ ). Our testing period is from January 2000 to December 2013. System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression.

<i>Panel A: Implied volatility and uncertainties in G5 countries</i>										
	Local BC	Global BC	Start WCI	during WCI	end WCI	Word Count Uncertainty	Country Risk	ln(Local EPU)	ln(Global EPU)	N
<i>System</i>										
Coeff. (%)	0.05	2.75	0.14	0.58	-0.20	-6.21	0.19	0.76	24.91	600
t-Statistic	0.06	<b>3.25</b>	0.73	<b>6.35</b>	-1.27	<b>-6.27</b>	<b>2.62</b>	0.88	<b>18.39</b>	
<i>Sur</i>										
Coeff. (%)	0.36	3.02	0.30	0.64	-0.12	-5.63	0.16	0.38	23.32	600
t-Statistic	1.14	<b>2.46</b>	0.93	<b>4.12</b>	-0.44	<b>-3.31</b>	<b>5.77</b>	1.17	<b>12.57</b>	
<i>Panel B: Return dispersion and uncertainties in G5 countries</i>										
<i>System</i>										
Coeff. (%)	0.23	2.56	0.14	0.41	0.01	-0.25	0.15	0.33	3.99	600
t-Statistic	0.65	<b>6.62</b>	1.60	<b>9.96</b>	0.20	-0.56	<b>4.49</b>	0.84	<b>6.44</b>	
<i>Sur</i>										
Coeff. (%)	0.04	2.64	0.17	0.44	0.05	-0.59	0.14	0.69	3.84	600
t-Statistic	0.15	<b>5.01</b>	1.25	<b>6.92</b>	0.43	-0.85	<b>5.52</b>	<b>2.20</b>	<b>4.77</b>	

For ease of comparison, Panel B of Table 3-12 contains the results for return dispersion during the same period with G5 countries. Return dispersion is able to capture global business cycles, ongoing political crisis, country risk, local economic policy uncertainty (for seemingly unrelated regressions only), and global economic policy uncertainty as well.

### 3.6.2 Implied volatility and cross-sectional stock returns

As implied volatility does a good job in capturing macroeconomic uncertainties, a logical question to ask is whether or not the implied volatility also relates to the cross section of stock returns. Similarly to section 3.5. I test whether stocks with higher sensitivities to implied volatility produce higher average returns. (again I report levels and also consider changes in Appendix B, but the latter are similar to the level). I run the following time-series regression:

$$R_{i,t} = \alpha_i + \beta_{i,RMRF}RMRF_t + \beta_{i,vix}VIX_t + \varepsilon_{i,t} \quad (3.10)$$

where  $R_{i,t}$  is the individual firm return,  $RMRF_t$  is the equal-weighted average return of the largest 50 firm and  $VIX_t$  is the implied volatility. Every year I use the largest 90% market capitalisation stocks (ranked at the end of the previous year). At the end of each month, I sort stocks into quintile portfolios based on the value of implied volatility risk loadings over the month. Panel A of Table 3-13 presents the average returns of the value-weighted portfolios and Panel B reports the average returns of the equal-weighted portfolios. For all the portfolios, I report the raw return, CAPM alphas and four-factor (market, size, value and momentum factors) alphas. For most the

countries, the difference between portfolios that are most sensitive to implied volatility and portfolios that are least sensitive to implied volatility are statistically zero except for the value-weighted portfolios in the UK and the US. For the US, the value-weighted portfolio with stocks that have the highest sensitivity generates an average higher four-factor alpha of 0.66 percent than portfolio with stocks that have the lowest sensitivity. For the UK, the difference is 1.54 percent and statistically significant with a t-value of 2.52.

Table 3-13 Implied Volatility and Cross-sectional Stock Returns

This table reports the average raw returns, CAPM alphas and four factor alphas for the portfolios sorted by implied volatility loadings. I run the time-series regression using individual stock return regress on market return and implied volatility:  $R_{i,t} = \alpha_i + \beta_{i, RMR} RMR_t + \beta_{i, vix} VIX_t + \varepsilon_{i,t}$ . Then I sort portfolios based on the implied volatility loadings. "Low" and "High" represent the portfolios that contains stocks that are most and least sensitive to implied volatility loadings. The results for the four factor alphas are in percentage.

<i>Panel A: value weighted</i>																			
	Raw average return						CAPM - alpha						4 factors - alpha (coefficient in %)						
	Low	2	3	4	High	H-L	Low	2	3	4	High	H-L	Low	2	3	4	High	H-L	
<i>France</i>																			
Coeff.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.67	-0.48	-0.40	-0.17	-0.28	0.39	
t-stat	-0.30	-0.17	-0.05	0.52	0.31	0.43	-0.98	-1.17	-0.78	0.64	0.11	0.82	-1.30	-1.51	-1.48	-0.58	-0.69	0.60	
<i>Germany</i>																			
Coeff.	0.00	0.00	0.00	0.00	0.00	0.01	-0.01	0.00	0.00	0.00	0.00	0.01	-0.97	-0.40	-0.30	-0.25	-0.07	0.90	
t-stat	-0.38	0.52	0.93	1.19	1.10	0.97	<b>-2.18</b>	-1.00	-0.24	0.11	0.30	<b>1.85</b>	<b>-1.74</b>	-1.25	-1.11	-0.81	-0.17	1.30	
<i>Japan</i>																			
Coeff.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	-0.41	-0.77	-0.83	-0.75	-0.19	0.22	
t-stat	-0.12	-1.07	-1.11	-0.81	0.54	0.46	0.96	-0.89	-1.07	-0.28	<b>2.51</b>	0.81	-1.16	<b>-3.16</b>	<b>-3.78</b>	<b>-2.93</b>	-0.55	0.44	
<i>United Kingdom</i>																			
Coeff.	-0.01	0.00	0.00	0.00	0.00	0.01	-0.01	0.00	0.00	0.00	0.00	0.01	-1.34	-0.65	-0.12	-0.07	0.20	1.54	
t-stat	-1.38	-0.57	0.72	0.94	0.74	1.56	<b>-2.74</b>	<b>-1.95</b>	0.68	1.28	0.70	<b>2.73</b>	<b>-2.53</b>	<b>-2.24</b>	-0.44	-0.31	0.66	<b>2.52</b>	
<i>United States</i>																			
Coeff.	0.01	0.01	0.01	0.01	0.01	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	-0.62	0.07	0.12	0.12	0.04	0.66	
t-stat	1.47	<b>4.01</b>	<b>4.13</b>	<b>3.76</b>	<b>3.20</b>	0.82	<b>-1.99</b>	1.64	<b>1.97</b>	1.07	-0.06	<b>1.69</b>	<b>-2.85</b>	0.70	<b>1.76</b>	0.94	0.26	<b>2.55</b>	

(Continued on next page)

(Table 3-13 Continued)

<i>Panel B: Equally weighted</i>																			
	Raw average return						CAPM - alpha						4 factors - alpha (coefficient in %)						
	Low	2	3	4	High	H-L	Low	2	3	4	High	H-L	Low	2	3	4	High	H-L	
<i>France</i>																			
Coeff.	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.22	-0.78	-0.82	-0.76	-0.16	-0.37
t-stat	0.63	-0.96	-1.37	-1.05	0.21	-0.37	-0.58	<b>-2.32</b>	<b>-3.00</b>	<b>-2.37</b>	-0.02	-0.48	0.45	<b>-3.02</b>	<b>-3.78</b>	<b>-2.97</b>	-0.46	-0.63	
<i>Germany</i>																			
Coeff.	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	-0.70	-0.85	-0.89	-0.89	-0.72	-0.02	
t-stat	-0.71	<b>-1.76</b>	<b>-2.34</b>	<b>-1.91</b>	-0.85	-0.10	<b>-2.08</b>	<b>-5.34</b>	<b>-6.50</b>	<b>-5.38</b>	<b>-2.51</b>	-0.17	<b>-1.76</b>	<b>-3.89</b>	<b>-5.17</b>	<b>-4.30</b>	<b>-1.89</b>	-0.04	
<i>Japan</i>																			
Coeff.	0.01	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.02	0.00	0.01	-1.19	-1.08	-0.99	0.42	0.41	
t-stat	1.43	-1.27	-1.31	0.01	<b>2.19</b>	0.48	<b>2.89</b>	-1.04	-1.13	-0.43	<b>4.05</b>	0.68	0.04	<b>-5.70</b>	<b>-5.82</b>	<b>-4.76</b>	-1.29	0.90	
<i>United Kingdom</i>																			
Coeff.	0.00	-0.01	0.00	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	-0.60	-0.87	-0.78	-0.72	-0.57	0.02	
t-stat	-0.55	-1.37	-1.36	-1.29	-0.72	-0.04	-1.06	<b>-2.82</b>	<b>-3.15</b>	<b>-2.81</b>	-1.44	-0.03	<b>-1.69</b>	<b>-4.21</b>	<b>-4.34</b>	<b>-3.62</b>	<b>-1.89</b>	0.05	
<i>United States</i>																			
Coeff.	0.02	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.30	-0.16	-0.23	-0.11	0.34	0.04	
t-stat	<b>3.81</b>	<b>3.14</b>	<b>2.99</b>	<b>3.19</b>	<b>4.06</b>	-0.27	<b>1.76</b>	0.43	0.14	0.55	<b>2.00</b>	-0.04	<b>1.72</b>	<b>-1.83</b>	<b>-2.90</b>	-1.07	<b>2.22</b>	0.18	

Figure 3-5 Four-factor Alphas of Portfolios Sorted Based on Sensitivities to Implied Volatility

Figure 3-5a: Four factor alphas of value-weighted portfolios sorted based on sensitivities to implied volatility

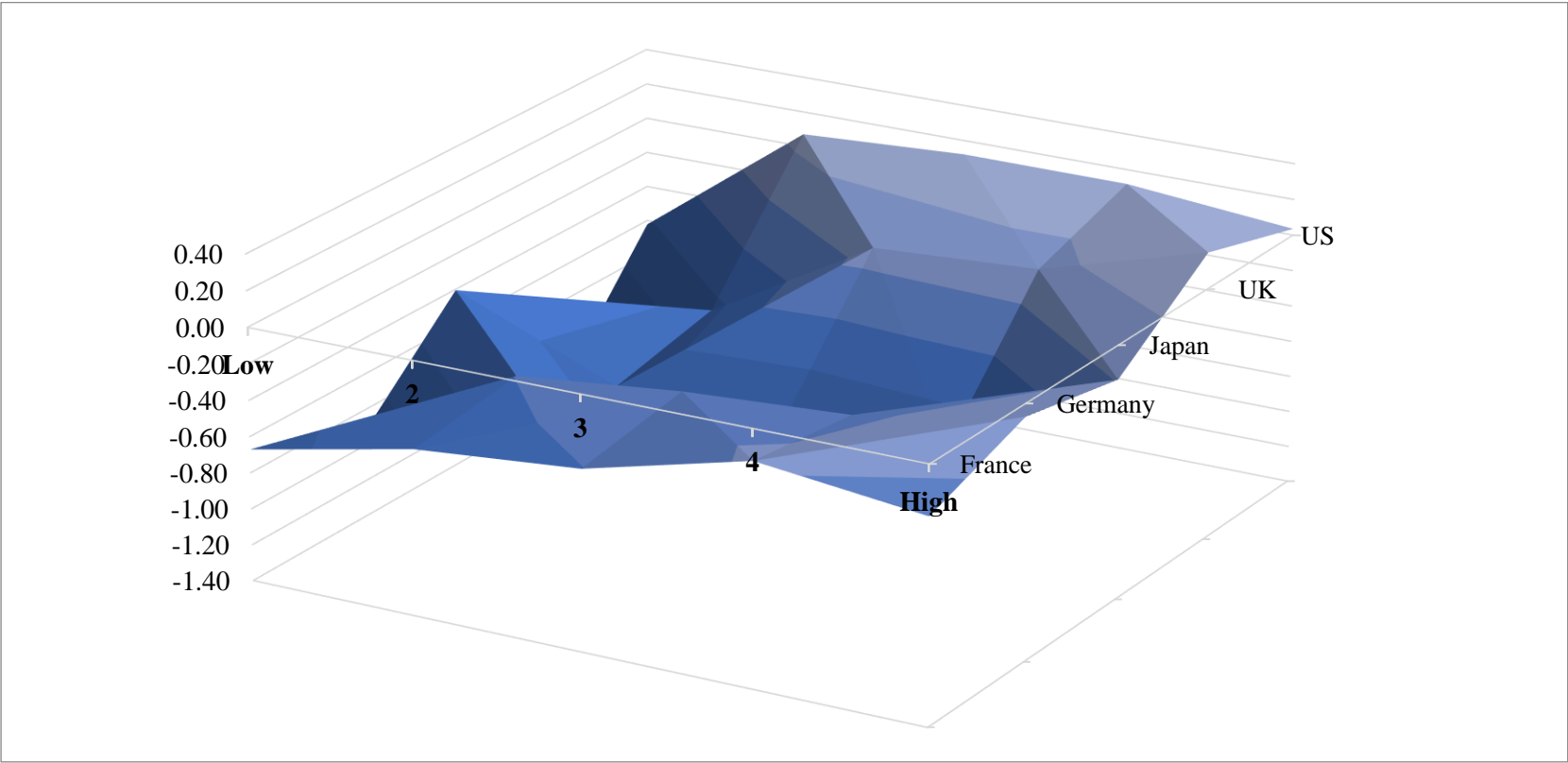
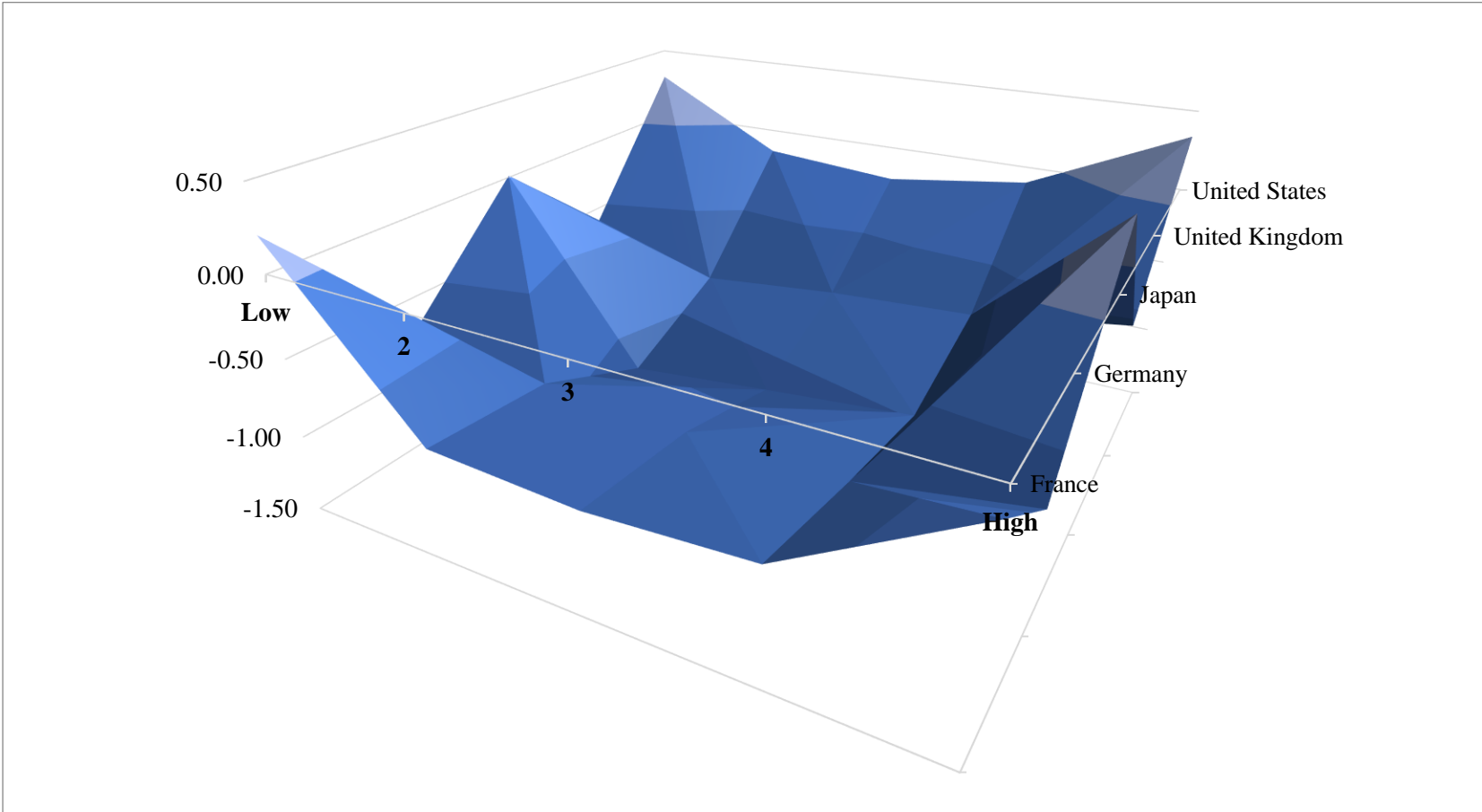


Figure 3-5b: Four factor alphas of equal-weighted portfolios sorted based on sensitivities to implied volatility



The difference between Figure 3-3 and Figure 3-5 is striking. I have two proxies that seem to capture both macroeconomic and political uncertainty. However, one (return dispersion) shows a strong relation with the cross section of returns whereas the other shows no relation whatsoever. I have done a number of tests but find no clear explanation what drives this difference. I have not been able to explain it, other than the obvious conclusion which is that the differences between the two measures is what they are and return dispersion captures the uncertainty related to the cross section of returns whereas implied volatility does not.

### **3.6.3 A horserace between return dispersion and implied volatility**

In order to see more explicitly whether return dispersion and implied volatility are linked with certain types of uncertainty, I run a horse race between the two measures. I use each type of uncertainty as the dependent variable and use both return dispersion ( $RD_t$ ) and implied volatility ( $IV_t$ ) as explanatory variable (equation 3.11).

$$Uncertainty_t = \alpha + \beta_1 RD_t + \beta_2 IV_t + \varepsilon_t \quad (3.11)$$

where  $Uncertainty_t$  is the local business cycle dummy, global business cycle dummy, start crises, ongoing crises, ending crises, word count uncertainty, international country risk, local economic policy uncertainty, and global economic policy uncertainty in turn. Table 3-14 contains the results for pooled OLS (system) and seemingly unrelated regressions (sur) on G5 countries. The system results demonstrate that return dispersion and implied volatility are significantly different. With regard to political risk (political crisis

and country risk), return dispersion seems to be more sensitive to this type of risk compared to implied volatility. With respect to the uncertainty that computed by media coverage (word count uncertainty and economic policy uncertainty), implied volatility does a better job than return dispersion.

Moreover, I test whether once I control for implied volatility, return dispersion is still a measure of uncertainty. I add implied volatility as a control variable in equation (3.7). Panel A of Table 3-15 reports the results. The effect of return dispersion is reduced but not eliminated. After controlling for implied volatility, return dispersion is higher during global recession, political crisis and higher country risk period. The effect of economic policy uncertainty on return dispersion is eliminated. I further test if implied volatility could capture those uncertainties well with the control of return dispersion. Panel B of Table 3-15 shows the regression that using implied volatility as dependent variable. It seems that the effect of business cycles on implied volatility is eliminated by return dispersion. In both tests, return dispersion is strongly and positively associated with implied volatility.

Table 3-14 Horserace between Return Dispersion and Implied Volatility in G5 Countries

Table 3-14 shows the horserace between return dispersion (RD) and implied volatility (IV) in G5 countries. I use each uncertainty proxy regress on both return dispersion and implied volatility.  $Uncertainty_t = \alpha + \beta_1 RD_t + \beta_2 IV_t + \varepsilon_t$  where  $Uncertainty_t$  is the local business cycle dummy (Local BC), global business cycle dummy (Global BC), world political crisis index (Crisis), word count uncertainty, ICRG country risk (Country Risk) and economic policy uncertainty (EPU) in turn. I report the p-value of the null hypothesis that the coefficient of return dispersion equals the coefficient of implied volatility in each regression. System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression.

	Local BC		Global BC		During_crisis		Word Count Uncertainty		Country Risk		local EPU		global EPU	
	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
<i>System</i>														
RD	2.616	<b>4.70</b>	3.308	<b>6.70</b>	26.654	<b>6.98</b>	-1.368	<b>-2.40</b>	29.413	<b>5.94</b>	-2.755	<b>-4.49</b>	-1.214	<b>-3.11</b>
VIX	0.005	<b>2.18</b>	0.006	<b>3.30</b>	0.020	1.42	0.011	<b>5.07</b>	-0.014	-0.73	0.022	<b>9.38</b>	0.022	<b>15.26</b>
p-value (diff)		<b>0.00</b>		<b>0.00</b>		<b>0.00</b>		<b>0.02</b>		<b>0.00</b>		<b>0.00</b>		<b>0.00</b>
<i>Sur</i>														
RD	0.497	1.02	0.279	<b>1.76</b>	1.196	1.12	-0.051	-0.68	12.881	<b>4.97</b>	0.066	0.16	-0.029	-0.25
VIX	0.006	<b>2.83</b>	0.002	<b>1.97</b>	0.001	0.14	0.001	1.40	0.001	0.15	0.012	<b>6.41</b>	0.003	<b>3.31</b>
p-value (diff)	0.32			<b>0.08</b>		0.26		0.49		<b>0.00</b>		0.90		0.79

**Table 3-15 Return Dispersion, Implied Volatility and Uncertainties**

Panel A of table 3-15 reports the results of the regression:  $RD_t = \alpha + \beta_1 BC\_local_t + \beta_2 BC\_global_t + \beta_3 Start\_WCI_t + \beta_4 During\_WCI_t + \beta_5 End\_WCI_t + \beta_6 WordCount_t + \beta_7 Country\_Risk_t + \beta_8 \ln(EPU\_local)_t + \beta_9 \ln(EPU\_global)_t + \beta_{10} VIX_t + \varepsilon_t$ . I use return dispersion ( $RD_t$ ) regress on the global business cycle dummy ( $BC\_global_t$ ), international political crisis starting in a month ( $Start\_WCI_t$ ), during a month ( $During\_WCI_t$ ), ending in a month ( $End\_WCI_t$ ), log value of the word count uncertainty ( $WordCount_t$ ), ICRG country risk ( $Country\_Risk_t$ ), log value of the local ( $local\_EPU_t$ ) and global economic policy uncertainty ( $global\_EPU_t$ ) and implied volatility ( $VIX_t$ ). Coefficients are in percentage. In panel B I use implied volatility ( $VIX_t$ ) regress on the above mentioned uncertainties and return dispersion. System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression.

<i>Panel A: Return dispersion and uncertainties with the control of implied volatility</i>												
	Constant	Local BC	Global BC	Start WCI	during WCI	end WCI	Word Count Uncertainty	Country Risk	ln(local EPU)	ln(global EPU)	VIX	N
<i>System</i>												
Coeff	-13.75	0.23	2.12	0.12	0.32	0.05	0.74	0.12	0.21	0.01	0.16	600
t-stat	<b>-3.63</b>	0.67	<b>5.80</b>	1.44	<b>7.99</b>	0.68	<b>1.69</b>	<b>3.79</b>	0.57	0.01	<b>9.06</b>	
<i>Sur</i>												
Coeff	-11.84	0.11	2.17	0.14	0.34	0.05	0.19	0.10	0.42	0.62	0.14	600
t-stat	<b>-2.72</b>	0.40	<b>4.72</b>	1.25	<b>6.10</b>	0.53	0.30	<b>4.05</b>	1.42	0.72	<b>7.29</b>	
<i>Panel B: Implied volatility and uncertainties with the control of return dispersion</i>												
	Constant	Local BC	Global BC	Start WCI	during WCI	end WCI	Word Count Uncertainty	Country Risk	ln(local EPU)	ln(global EPU)	RD	N
<i>System</i>												
Coeff	-42.57	-0.13	0.79	0.03	0.26	-0.21	-6.02	0.07	0.50	21.86	76.50	600
t-stat	<b>-5.20</b>	-0.18	0.96	0.18	<b>2.83</b>	-1.43	<b>-6.48</b>	1.10	0.63	<b>16.64</b>	<b>9.06</b>	
<i>Sur</i>												
Coeff	-49.53	0.04	1.78	0.21	0.55	-0.09	-6.28	0.13	0.21	23.68	27.59	600
t-stat	<b>-5.16</b>	0.11	1.66	0.75	<b>4.03</b>	-0.38	<b>-4.31</b>	<b>3.62</b>	0.50	<b>14.40</b>	<b>4.52</b>	

### **3.7 Conclusion**

The goal of this chapter is a simple one. Can I find a measure that might capture uncertainty and which can also be easily calculated in real time? Preferably one that is simple to measure and easy to understand and that would give, academics, investors, financial regulators and other stake holders a feel in real time for the level of uncertainty as implied by perception of financial markets.

This study links cross sectional return dispersion with different aspects of uncertainties in 18 countries. I show that return dispersion is large during local and global recessions, international political crisis, high economic policy uncertain periods and high general market uncertain periods in most countries. Contrary to implied volatility cross sectional return dispersion also seems strongly linked to the cross section of returns. It also captures different aspect than implied volatility does, with a stronger link to political risk. All in all, the evidence suggests that investors are able to gauge at least some of the macro economic and political uncertainty in real time by closely monitoring cross sectional return dispersion.

It would be interesting to see whether cross sectional return dispersion is linked to financial or aggregate firm level specific uncertainty. For the US, I have data on financial risk available from the study by Jurado, Ludvigson, and Ng (2015) and I find a strong relation. However, gathering those data internationally is beyond the scope of this study.

Moreover, what I cannot explain is why both implied volatility and cross sectional return dispersion seem both intuitively appealing risk measures, and are correlated – although not to the extreme) one has a strong link to the cross section of returns (cross sectional return dispersion) whereas the other (implied volatility) does not. I leave this as a puzzle to be explained.

## Appendix A

### Appendix A 1 Correlations of Uncertainty Variables in Each Country

This table shows the correlations across all variables in each country (shown in separate panels).

<i>Panel A: Australia</i>										
	RD	Local BC	Global BC	Start WCI	During WCI	End WCI	Word Count	Country Risk	ln(local EPU)	ln(global EPU)
RD	1.00									
Local BC	0.37	1.00								
Global BC	0.47	0.63	1.00							
Start WCI	0.05	-0.13	-0.10	1.00						
During WCI	-0.03	-0.01	-0.10	0.04	1.00					
End WCI	0.09	-0.04	-0.04	0.09	0.01	1.00				
Word Count	0.28	0.28	0.35	-0.14	-0.15	-0.15	1.00			
Country Risk	-0.27	-0.20	-0.36	-0.10	-0.18	0.04	-0.04	1.00		
ln(local EPU)	0.51	0.23	0.36	0.12	0.15	0.02	0.41	-0.42	1.00	
ln(global EPU)	0.42	0.30	0.36	0.11	0.02	0.04	0.47	-0.44	0.84	1.00

<i>Panel B: Austria</i>										
	RD	Local BC	Global BC	Start WCI	During WCI	End WCI	Word Count	Country Risk	ln(global EPU)	
RD	1.00									
Local BC	0.49	1.00								
Global BC	0.43	0.60	1.00							

Start WCI	-0.01	-0.04	-0.08	1.00					
During WCI	0.10	-0.02	-0.07	0.05	1.00				
End WCI	0.12	-0.01	-0.03	0.09	0.02	1.00			
Word Count	0.35	0.25	0.35	-0.06	0.01	-0.08	1.00		
Country Risk	-0.19	-0.37	-0.24	0.07	-0.21	0.02	-0.30	1.00	
In(global EPU)	0.48	0.29	0.36	0.13	0.05	0.04	0.42	0.12	1.00

*Panel C: Belgium*

	RD	Local BC	Global BC	Start WCI	During WCI	End WCI	Word Count	Country Risk	In(global EPU)
RD	1.00								
Local BC	0.34	1.00							
Global BC	0.50	0.40	1.00						
Start WCI	0.04	-0.19	-0.08	1.00					
During WCI	0.15	0.15	-0.07	0.05	1.00				
End WCI	0.11	-0.10	-0.03	0.09	0.02	1.00			
Word Count	0.30	0.11	0.35	-0.06	0.01	-0.08	1.00		
Country Risk	-0.40	-0.51	-0.27	0.02	-0.46	-0.02	-0.04	1.00	
In(global EPU)	0.55	0.12	0.36	0.13	0.05	0.04	0.42	-0.05	1.00

*Panel D: Denmark*

	RD	Local BC	Global BC	Start WCI	During WCI	End WCI	Word Count	Country Risk	In(global EPU)
RD	1.00								
Local BC	0.29	1.00							

Global BC	0.46	0.38	1.00						
Start WCI	-0.01	-0.14	-0.08	1.00					
During WCI	0.17	-0.27	-0.07	0.05	1.00				
End WCI	-0.07	-0.06	-0.03	0.09	0.02	1.00			
Word Count	0.29	0.24	0.35	-0.06	0.01	-0.08	1.00		
Country Risk	-0.10	0.01	-0.09	0.06	-0.02	-0.01	-0.17	1.00	
In(global EPU)	0.44	0.28	0.36	0.13	0.05	0.04	0.42	0.07	1.00

*Panel E: Finland*

	RD	Local BC	Global BC	Start WCI	During WCI	End WCI	Word Count	Country Risk	In(global EPU)
RD	1.00								
Local BC	0.29	1.00							
Global BC	0.41	0.56	1.00						
Start WCI	0.03	-0.02	-0.08	1.00					
During WCI	0.35	-0.12	-0.07	0.05	1.00				
End WCI	-0.04	0.00	-0.03	0.09	0.02	1.00			
Word Count	0.28	0.26	0.35	-0.06	0.01	-0.08	1.00		
Country Risk	0.14	0.16	-0.03	0.07	0.04	0.06	0.13	1.00	
In(global EPU)	0.38	0.29	0.36	0.13	0.05	0.04	0.42	0.02	1.00

*Panel F: France*

	RD	Local BC	Global BC	Start WCI	During WCI	End WCI	Word Count	Country Risk	In(local EPU)	In(global EPU)	VIX
RD	1.00										
Local BC	0.41	1.00									
Global BC	0.32	0.53	1.00								
Start WCI	0.14	-0.02	-0.08	1.00							
During WCI	0.42	0.32	0.00	-0.06	1.00						
End WCI	0.03	0.01	-0.02	0.20	-0.09	1.00					
Word Count	0.27	0.36	0.33	-0.07	0.17	-0.10	1.00				
Country Risk	0.40	0.46	-0.02	0.01	0.32	0.04	0.19	1.00			
In(local EPU)	0.04	-0.33	0.01	0.12	-0.32	0.01	0.23	-0.20	1.00		
In(global EPU)	0.55	0.31	0.38	0.10	0.08	0.05	0.61	0.26	0.54	1.00	
VIX	0.77	0.18	0.24	0.15	0.29	0.06	0.32	0.30	0.37	0.77	1.00

*Panel G: Germany*

	RD	Local BC	Global BC	Start WCI	During WCI	End WCI	Word Count	Country Risk	In(local EPU)	In(global EPU)	VIX
RD	1.00										
Local BC	0.38	1.00									
Global BC	0.46	0.60	1.00								
Start WCI	0.02	-0.01	-0.08	1.00							
During WCI	0.22	-0.13	-0.07	0.05	1.00						
End WCI	0.02	0.04	-0.03	0.09	0.02	1.00					
Word Count	0.31	0.16	0.35	-0.06	0.01	-0.08	1.00				

Country Risk	0.16	0.41	0.30	0.04	0.14	0.04	-0.02	1.00			
In(local EPU)	0.46	0.22	0.21	0.11	0.16	0.02	0.40	0.14	1.00		
In(global EPU)	0.60	0.31	0.36	0.13	0.05	0.04	0.42	0.09	0.67	1.00	
VIX	0.66	0.24	0.15	0.14	0.26	0.05	0.16	-0.01	0.52	0.73	1.00

*Panel H: Ireland*

	RD	Local BC	Global BC	Start WCI	During WCI	End WCI	Word Count	Country Risk	In(local EPU)	In(global EPU)
RD	1.00									
Local BC	0.38	1.00								
Global BC	0.40	0.37	1.00							
Start WCI	0.07	-0.02	-0.08	1.00						
During WCI	0.02	-0.06	-0.07	0.05	1.00					
End WCI	0.01	0.03	-0.03	0.09	0.02	1.00				
Word Count	0.33	0.27	0.35	-0.06	0.01	-0.08	1.00			
Country Risk	-0.24	-0.21	-0.24	0.09	0.11	0.09	-0.28	1.00		
In(local EPU)	0.31	0.17	0.18	-0.16	-0.08	0.06	0.18	-0.24	1.00	
In(global EPU)	0.43	0.26	0.36	0.13	0.05	0.04	0.42	-0.06	0.42	1.00

*Panel I: Italy*

	RD	Local BC	Global BC	Start WCI	During WCI	End WCI	Word Count	Country Risk	In(local EPU)	In(global EPU)
RD	1.00									
Local BC	0.14	1.00								
Global BC	0.14	0.63	1.00							

Start WCI	0.00	-0.03	-0.08	1.00						
During WCI	0.13	-0.14	-0.07	0.05	1.00					
End WCI	0.04	0.02	-0.03	0.09	0.02	1.00				
Word Count	0.03	0.18	0.35	-0.06	0.01	-0.08	1.00			
Country Risk	0.08	-0.21	-0.17	0.11	0.02	0.03	-0.33	1.00		
In(local EPU)	0.24	-0.05	-0.03	0.02	0.04	0.02	0.06	0.41	1.00	
In(global EPU)	0.27	0.35	0.36	0.13	0.05	0.04	0.42	0.18	0.55	1.00

*Panel J: Japan*

	RD	Local BC	Global BC	Start WCI	During WCI	End WCI	Word Count	Country Risk	In(local EPU)	In(global EPU)	VIX
RD	1.00										
Local BC	0.08	1.00									
Global BC	0.22	0.58	1.00								
Start WCI	-0.01	0.07	-0.10	1.00							
During WCI	0.40	-0.15	-0.10	0.04	1.00						
End WCI	-0.03	0.00	-0.04	0.09	0.01	1.00					
Word Count	0.15	0.11	0.35	-0.14	-0.15	-0.15	1.00				
Country Risk	-0.17	-0.12	-0.21	-0.05	-0.30	-0.03	-0.05	1.00			
In(local EPU)	0.21	0.31	0.18	0.06	0.11	0.08	0.18	-0.39	1.00		
In(global EPU)	0.16	0.38	0.36	0.11	0.02	0.04	0.47	-0.16	0.63	1.00	
VIX	0.31	0.42	0.45	0.04	0.02	-0.03	0.26	-0.23	0.45	0.73	1.00

*Panel K: Netherlands*

	RD	Local BC	Global BC	Start WCI	During WCI	End WCI	Word Count	Country Risk	In(local EPU)	In(global EPU)
RD	1.00									
Local BC	0.65	1.00								
Global BC	0.60	0.77	1.00							
Start WCI	-0.03	0.02	0.04	1.00						
During WCI	0.03	-0.07	0.00	-0.07	1.00					
End WCI	-0.11	0.04	0.01	0.09	-0.06	1.00				
Word Count	0.31	0.31	0.27	-0.11	0.08	-0.11	1.00			
Country Risk	-0.05	0.01	0.11	0.04	-0.31	-0.03	-0.22	1.00		
In(local EPU)	0.52	0.60	0.43	-0.03	-0.05	-0.08	0.52	-0.32	1.00	
In(global EPU)	0.67	0.61	0.58	-0.04	0.03	-0.05	0.65	-0.08	0.73	1.00

*Panel L: Norway*

	RD	Local BC	Global BC	Start WCI	During WCI	End WCI	Word Count	Country Risk	In(global EPU)
RD	1.00								
Local BC	0.26	1.00							
Global BC	0.29	0.20	1.00						
Start WCI	0.12	0.06	-0.08	1.00					
During WCI	0.29	0.02	-0.07	0.05	1.00				
End WCI	0.05	0.07	-0.03	0.09	0.02	1.00			
Word Count	0.41	0.24	0.35	-0.06	0.01	-0.08	1.00		

Country Risk	-0.13	-0.09	-0.13	0.06	-0.54	0.02	-0.03	1.00	
ln(global EPU)	0.61	0.44	0.36	0.13	0.05	0.04	0.42	-0.04	1.00

*Panel M: New Zealand*

	RD	Local BC	Global BC	Start WCI	During WCI	End WCI	Word Count	Country Risk	ln(global EPU)
RD	1.00								
Local BC	-0.02	1.00							
Global BC	0.26	-0.01	1.00						
Start WCI	0.08	-0.11	-0.08	1.00					
During WCI	0.26	-0.02	-0.07	0.05	1.00				
End WCI	0.01	-0.11	-0.03	0.09	0.02	1.00			
Word Count	0.25	-0.24	0.35	-0.06	0.01	-0.08	1.00		
Country Risk	-0.32	0.21	-0.40	-0.15	-0.39	-0.07	-0.38	1.00	
ln(global EPU)	0.34	-0.14	0.36	0.13	0.05	0.04	0.42	-0.30	1.00

*Panel N: Spain*

	RD	Local BC	Global BC	Start WCI	During WCI	End WCI	Word Count	Country Risk	ln(local EPU)	ln(global EPU)
RD	1.00									
Local BC	0.49	1.00								
Global BC	0.47	0.66	1.00							
Start WCI	0.11	0.01	-0.06	1.00						
During WCI	0.20	-0.11	-0.06	0.04	1.00					

End WCI	0.11	0.01	-0.06	0.21	-0.03	1.00				
Word Count	0.25	0.20	0.32	-0.06	0.17	-0.12	1.00			
Country Risk	-0.36	-0.49	-0.35	0.08	0.06	0.10	-0.19	1.00		
In(local EPU)	0.17	0.09	0.02	0.11	0.18	0.06	0.40	0.24	1.00	
In(global EPU)	0.50	0.40	0.41	0.08	0.25	0.01	0.64	-0.12	0.71	1.00

*Panel O: Sweden*

	RD	Local BC	Global BC	Start WCI	During WCI	End WCI	Word Count	Country Risk	In(local EPU)	In(global EPU)
RD	1.00									
Local BC	0.02	1.00								
Global BC	0.41	0.21	1.00							
Start WCI	0.07	-0.05	-0.08	1.00						
During WCI	0.32	-0.05	-0.07	0.05	1.00					
End WCI	0.10	0.01	-0.03	0.09	0.02	1.00				
Word Count	0.26	0.22	0.35	-0.06	0.01	-0.08	1.00			
Country Risk	-0.35	0.11	-0.03	-0.03	-0.42	-0.07	0.28	1.00		
In(local EPU)	0.24	-0.04	-0.02	0.20	0.28	0.08	-0.37	-0.43	1.00	
In(global EPU)	0.44	0.19	0.36	0.13	0.05	0.04	0.42	-0.20	0.39	1.00

*Panel P: Switzerland*

	RD	Local BC	Global BC	Start WCI	During WCI	End WCI	Word Count	Country Risk	In(global EPU)
RD	1.00								
Local BC	0.46	1.00							
Global BC	0.27	0.79	1.00						
Start WCI	0.04	-0.01	-0.08	1.00					
During WCI	0.22	-0.06	-0.07	0.05	1.00				
End WCI	0.08	0.04	-0.03	0.09	0.02	1.00			
Word Count	0.36	0.45	0.35	-0.06	0.01	-0.08	1.00		
Country Risk	0.21	0.05	-0.15	0.03	-0.17	0.08	0.24	1.00	
In(global EPU)	0.65	0.49	0.36	0.13	0.05	0.04	0.42	0.04	1.00

*Panel Q: UK*

	RD	Local BC	Global BC	Start WCI	During WCI	End WCI	Word Count	Country Risk	In(local EPU)	In(global EPU)	VIX
RD	1.00										
Local BC	0.24	1.00									
Global BC	0.48	0.54	1.00								
Start WCI	0.09	-0.07	-0.08	1.00							
During WCI	0.29	-0.03	0.00	-0.06	1.00						
End WCI	-0.09	0.00	-0.02	0.20	-0.09	1.00					
Word Count	0.45	0.23	0.33	-0.07	0.17	-0.10	1.00				
Country Risk	-0.07	-0.14	-0.25	0.01	0.16	-0.02	-0.13	1.00			

In(local EPU)	0.30	0.09	0.27	0.02	-0.14	0.03	0.44	-0.39	1.00		
In(global EPU)	0.60	0.16	0.38	0.10	0.08	0.05	0.61	-0.16	0.75	1.00	
VIX	0.69	0.10	0.36	0.10	0.29	0.02	0.38	-0.23	0.54	0.78	1.00

*Panel R: US*

	RD	Local BC	Global BC	Start WCI	During WCI	End WCI	Word Count	Country Risk	In(local EPU)	In(global EPU)	VIX
RD	1.00										
Local BC	0.43	1.00									
Global BC	0.44	0.82	1.00								
Start WCI	0.01	-0.07	-0.08	1.00							
During WCI	0.39	-0.04	-0.07	0.05	1.00						
End WCI	0.05	-0.03	-0.03	0.09	0.02	1.00					
Word Count	0.25	0.42	0.35	-0.06	0.01	-0.08	1.00				
Country Risk	0.35	-0.04	0.01	0.02	0.40	0.02	-0.39	1.00			
In(local EPU)	0.41	0.41	0.42	0.04	0.00	0.00	0.57	-0.23	1.00		
In(global EPU)	0.42	0.33	0.36	0.13	0.05	0.04	0.42	-0.07	0.90	1.00	
VIX	0.56	0.39	0.44	0.09	0.24	-0.02	0.21	0.11	0.70	0.74	1.00

Appendix A 2 Return Dispersion and Number of Crisis Starting in a Month (*Crisis start*), during a Month (*Crisis during*), and Ending in a Month (*Crisis end*)

This table shows the results of return dispersion regressions on international political crisis with the control of business cycle in each country ( $RD_t = \alpha + \beta_1 BC\_local_t + \beta_2 BC\_global_t + \beta_3 Crisis\_start_t + \beta_4 Crisis\_during_t + \beta_5 Crisis\_end_t + \varepsilon_t$ ).  $RD_t$  is the return dispersion of the largest 50 market capitalization stocks in each country at time  $t$ .  $BC\_local_t$  and  $BC\_global_t$  are the dummy variables for business cycle (1 = recession, 0 = expansion) in local country and global respectively.  $Crisis\_start_t$ ,  $Crisis\_during_t$  and  $Crisis\_end_t$  are numbers of crisis starting at month  $t$ , during month  $t$  and ending at month  $t$ . System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression. I use robust standard errors. Coefficients are in percentage.

	Constant	t-value	Local BC	t-value	Global BC	t-value	Crisis start	t-value	Crisis during	t-value	Crisis End	t-value	Adjusted R2
Australia	6.45	<b>20.68</b>	0.43	0.65	4.24	<b>4.20</b>	0.40	1.33	0.17	0.84	0.54	1.59	0.10
Austria	8.04	<b>20.04</b>	1.97	<b>2.68</b>	5.11	<b>4.06</b>	-0.26	-0.84	-0.03	-0.21	0.59	1.00	0.18
Belgium	6.17	<b>16.71</b>	0.21	0.48	5.77	<b>5.55</b>	-0.02	-0.06	0.02	0.13	0.30	0.96	0.21
Denmark	7.28	<b>27.31</b>	0.10	0.22	6.76	<b>4.35</b>	0.06	0.19	0.31	<b>2.39</b>	-0.44	<b>-1.69</b>	0.22
Finland	7.38	<b>20.56</b>	2.14	<b>3.24</b>	3.57	<b>3.36</b>	0.39	1.33	0.72	<b>4.30</b>	0.22	0.80	0.17
France	5.91	<b>25.39</b>	1.37	<b>3.80</b>	2.16	<b>3.27</b>	0.11	0.38	0.22	<b>1.70</b>	0.08	0.25	0.13
Germany	6.76	<b>25.13</b>	-0.11	-0.12	5.78	<b>6.07</b>	0.07	0.23	-0.06	-0.47	-0.03	-0.09	0.23
Ireland	7.59	<b>15.15</b>	3.85	<b>4.81</b>	5.71	<b>3.58</b>	0.68	1.21	0.94	<b>3.54</b>	-0.07	-0.15	0.22
Italy	7.37	<b>16.06</b>	1.27	<b>2.13</b>	1.33	<b>2.26</b>	-0.36	-1.17	-0.08	-0.39	0.18	0.53	0.02
Japan	6.88	<b>18.57</b>	-0.05	-0.10	3.23	<b>4.71</b>	0.53	1.44	0.21	1.20	-0.09	-0.29	0.05
NL	6.74	<b>18.10</b>	3.72	<b>3.46</b>	1.56	1.39	0.32	0.73	0.12	0.70	-0.20	-0.47	0.16
Norway	9.58	<b>16.41</b>	2.06	<b>2.27</b>	3.50	<b>3.46</b>	0.20	0.46	0.20	0.86	-0.25	-0.64	0.06
NZ	7.92	<b>15.97</b>	0.00	0.00	1.12	1.58	1.09	<b>1.76</b>	0.76	<b>3.50</b>	-0.06	-0.16	0.04
Spain	6.07	<b>20.76</b>	1.06	<b>1.93</b>	2.55	<b>2.89</b>	0.99	<b>2.57</b>	0.48	<b>2.89</b>	0.82	<b>2.42</b>	0.13
Sweden	6.22	<b>23.83</b>	-0.77	<b>-2.24</b>	4.05	<b>6.65</b>	0.51	1.47	0.74	<b>5.17</b>	0.42	1.29	0.19
Switzerland	6.23	<b>25.01</b>	3.08	<b>2.00</b>	1.03	0.62	-0.08	-0.33	0.13	1.07	0.29	0.96	0.15
UK	6.29	<b>22.04</b>	-0.61	<b>-1.94</b>	5.49	<b>6.14</b>	0.57	<b>2.23</b>	0.13	1.18	-0.54	<b>-2.20</b>	0.23
US	5.88	<b>28.03</b>	0.93	<b>1.85</b>	4.27	<b>4.97</b>	-0.11	-0.54	0.20	<b>1.99</b>	-0.03	-0.15	0.24
System	6.92	<b>68.85</b>	0.84	<b>5.86</b>	4.01	<b>19.89</b>	0.28	<b>3.07</b>	0.30	<b>6.59</b>	0.11	1.26	
Sur	6.70	<b>32.75</b>	0.40	<b>4.34</b>	4.00	<b>10.17</b>	0.18	0.95	0.35	<b>3.63</b>	0.27	1.60	

### Appendix A 3 Return Dispersion and Word Count Uncertainty for Word “Risk”

This table shows the regression of return dispersion on word count uncertainty around the world. I count the number of Bloomberg reports in every month that contains the word “risk” and take a log of it (Word Count Risk). I run the regression in the form of  $RD_t = \alpha + \beta_1 local\_BC_t + \beta_2 global\_BC_t + \beta_3 Start\ Crisis_t + \beta_4 During\ Crisis_t + \beta_5 End\ Crisis_t + \beta_6 Word\ Count v Risk_t + \varepsilon_t$  where BC is the business cycle dummy, Start Crisis is crisis starting in month t, During Crisis is the ongoing crisis in month t and End Crisis is the crisis ending in month t. System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression. I use robust standard errors. Coefficients are in percentage.

	constant	t- value	local BC	t- value	global BC	t- value	start Crisis	t- value	during Crisis	t- value	end Crisis	t- value	Word Count Risk	t- value	Adjusted R2
Australia	10.79	<b>6.62</b>	-0.03	-0.04	5.10	<b>4.85</b>	0.11	1.07	0.03	0.55	0.01	0.16	-0.52	<b>-2.72</b>	0.13
Austria	4.63	<b>3.27</b>	1.95	<b>2.71</b>	4.50	<b>3.54</b>	0.00	0.05	0.00	0.03	0.18	1.18	0.43	<b>2.53</b>	0.20
Belgium	0.92	0.57	0.75	1.61	4.85	<b>4.72</b>	0.15	<b>1.78</b>	0.07	<b>1.67</b>	0.14	1.59	0.61	<b>3.56</b>	0.26
Denmark	1.75	<b>1.75</b>	0.60	1.29	5.89	<b>3.84</b>	0.14	<b>1.66</b>	0.18	<b>4.40</b>	-0.08	-1.27	0.63	<b>5.35</b>	0.27
Finland	8.60	<b>5.59</b>	2.02	<b>2.87</b>	3.99	<b>3.53</b>	0.12	1.40	0.28	<b>5.83</b>	-0.03	-0.37	-0.19	-1.08	0.23
France	3.31	<b>3.29</b>	1.32	<b>3.73</b>	1.95	<b>2.75</b>	0.14	1.46	0.14	<b>3.78</b>	0.05	0.51	0.28	<b>2.30</b>	0.18
Germany	1.18	1.23	0.46	0.47	4.85	<b>5.12</b>	0.17	<b>2.08</b>	0.08	<b>2.61</b>	0.04	0.43	0.63	<b>5.36</b>	0.30
Ireland	5.18	<b>2.77</b>	3.72	<b>4.65</b>	5.29	<b>3.17</b>	0.29	1.52	0.24	<b>3.33</b>	-0.07	-0.59	0.35	1.49	0.22
Italy	4.57	<b>4.38</b>	1.21	<b>2.06</b>	1.13	<b>1.66</b>	-0.01	-0.06	0.09	1.61	0.08	0.80	0.27	<b>1.80</b>	0.03
Japan	3.30	<b>2.47</b>	0.10	0.20	2.80	<b>3.97</b>	0.19	<b>1.86</b>	0.18	<b>3.36</b>	0.04	0.47	0.37	<b>2.47</b>	0.10
Netherlands	1.09	0.82	3.63	<b>3.51</b>	0.87	0.73	0.23	<b>1.91</b>	0.15	<b>3.24</b>	-0.05	-0.42	0.65	<b>3.87</b>	0.22
Norway	8.31	<b>4.71</b>	1.98	<b>2.19</b>	3.57	<b>3.44</b>	0.12	0.80	0.17	<b>2.46</b>	-0.08	-0.73	0.09	0.45	0.08
New Zealand	18.94	<b>10.20</b>	0.01	0.02	3.02	<b>4.10</b>	0.13	0.75	0.17	<b>3.26</b>	-0.17	-1.62	-1.36	<b>-6.28</b>	0.20
Spain	10.68	<b>9.02</b>	1.24	<b>2.17</b>	3.33	<b>3.77</b>	0.31	<b>3.03</b>	0.15	<b>3.33</b>	0.16	1.34	-0.59	<b>-4.26</b>	0.21
Sweden	6.06	<b>6.05</b>	-0.52	-1.56	4.09	<b>6.57</b>	0.22	<b>1.93</b>	0.24	<b>6.38</b>	0.11	1.10	-0.01	-0.04	0.22
Switzerland	1.92	<b>1.75</b>	2.82	<b>1.94</b>	0.69	0.42	0.08	1.12	0.12	<b>2.63</b>	0.14	<b>1.65</b>	0.49	<b>4.00</b>	0.20
UK	1.78	<b>1.91</b>	-0.08	-0.25	4.66	<b>5.15</b>	0.26	<b>3.31</b>	0.14	<b>4.53</b>	-0.13	<b>-2.02</b>	0.49	<b>4.44</b>	0.30
US	-0.11	-0.13	1.11	<b>3.03</b>	3.35	<b>4.17</b>	0.08	1.54	0.18	<b>5.66</b>	0.09	1.19	0.67	<b>6.53</b>	0.36
System	5.08	<b>15.04</b>	0.88	<b>6.19</b>	3.83	<b>18.41</b>	0.16	<b>6.01</b>	0.15	<b>11.72</b>	0.03	1.04	0.19	<b>4.85</b>	
Sur	5.61	<b>8.28</b>	0.41	<b>4.47</b>	4.06	<b>10.25</b>	0.10	<b>1.99</b>	0.16	<b>6.30</b>	0.06	1.28	0.10	1.23	

## Appendix B

I report all results using the changes in return dispersion. I measure the changes in return dispersion as the residuals from an AR(1) process estimated for the levels. I re-estimate the main results by using changes of return dispersion as dependent variables.

### Appendix B 1 Changes in Return Dispersion and Local Business Cycles

This table reports the results of the univariate regressions of  $RD_t = \alpha + \beta_1 BC\_local_t + \varepsilon_t$ , where  $RD_t$  is the change in return dispersion. Local BC is a dummy variable that equals one if the country is in recession and zero otherwise. System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression. I use robust standard errors. Coefficients are in percentage.

	constant	t-value	local BC	t-value	Adjusted R2
Australia	0.04	0.19	0.71	1.07	0.00
Austria	-0.12	-0.59	1.82	<b>2.49</b>	0.03
Belgium	-0.12	-0.74	0.43	0.87	0.00
Denmark	-0.08	-0.42	0.37	0.70	0.00
Finland	-0.04	-0.21	1.75	<b>2.85</b>	0.02
France	-0.19	-1.43	0.71	<b>2.56</b>	0.02
Germany	-0.03	-0.21	1.09	1.01	0.01
Ireland	-0.56	<b>-1.98</b>	2.41	<b>3.32</b>	0.04
Italy	-0.14	-0.70	1.33	<b>2.43</b>	0.01
Japan	0.00	0.03	0.30	0.83	0.00
Netherlands	-0.25	-1.61	1.63	<b>2.14</b>	0.03
Norway	0.06	0.25	1.39	1.62	0.01
New Zealand	0.23	0.97	-0.17	-0.24	0.00
Spain	-0.14	-0.86	1.32	<b>2.01</b>	0.02
Sweden	0.22	1.20	-0.27	-0.81	0.00
Switzerland	-0.15	-1.22	1.71	<b>2.26</b>	0.05
UK	-0.04	-0.26	0.34	0.90	0.00
US	-0.06	-0.54	0.82	<b>1.78</b>	0.02
System	-0.07	-1.57	0.85	<b>7.56</b>	
Sur	0.03	0.39	0.24	<b>2.65</b>	

## Appendix B 2 Changes in Return Dispersion and Global Business Cycles

This table reports the coefficients estimates and t-statistics of the regression in the form of  $RD_t = \alpha + \beta_1 local BC_t + \beta_2 global BC_t + \varepsilon_t$ , where  $RD_t$  is the change in return dispersion at time t,  $local BC_t$  and  $global BC_t$  are the contemporaneous dummy variable for business cycle (1= recession, 0 = expansion) in local country and global respectively. System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression. I use robust standard errors. Coefficients are in percentage.

	constant	t-value	local BC	t-value	global BC	t-value	Adjusted R2
Australia	-0.05	-0.28	0.22	0.41	1.78	<b>1.95</b>	0.02
Austria	-0.23	-1.10	0.90	1.42	2.92	<b>2.82</b>	0.07
Belgium	-0.26	-1.53	-0.02	-0.04	2.90	<b>3.26</b>	0.07
Denmark	-0.27	-1.34	0.00	0.00	3.81	<b>2.65</b>	0.09
Finland	-0.13	-0.71	1.22	<b>1.75</b>	1.85	<b>1.88</b>	0.04
France	-0.21	-1.54	0.55	<b>1.88</b>	0.85	1.39	0.03
Germany	-0.13	-1.05	0.28	0.34	2.02	<b>2.31</b>	0.05
Ireland	-0.64	<b>-2.21</b>	1.69	<b>2.41</b>	2.86	<b>2.52</b>	0.06
Italy	-0.20	-0.93	0.94	<b>1.73</b>	1.06	<b>2.23</b>	0.01
Japan	-0.02	-0.13	0.02	0.05	1.01	<b>1.69</b>	0.00
Netherlands	-0.27	-1.72	1.33	1.55	0.98	0.88	0.04
Norway	-0.05	-0.21	1.10	1.39	1.75	<b>1.87</b>	0.02
New Zealand	0.21	0.82	-0.18	-0.25	0.34	0.47	-0.01
Spain	-0.17	-1.01	0.88	1.33	1.13	1.26	0.03
Sweden	0.13	0.69	-0.50	-1.53	1.82	<b>3.46</b>	0.03
Switzerland	-0.15	-1.22	1.35	0.94	0.69	0.45	0.05
UK	-0.09	-0.61	-0.18	-0.72	2.21	<b>2.36</b>	0.05
US	-0.06	-0.53	0.18	0.47	1.21	1.44	0.03
System	-0.14	<b>-3.05</b>	0.40	<b>3.40</b>	1.85	<b>11.12</b>	
Sur	-0.09	-1.18	0.12	1.31	1.71	<b>6.20</b>	

### Appendix B 3 Changes in Return Dispersion and International Political Crisis

This table provides the results of changes in return dispersion regress on world crisis index with the control of business cycle in each country ( $RD_t = \alpha + \beta_1 local BC_t + \beta_2 global BC_t + \beta_3 Start\_WCI_t + \beta_4 During\_WCI_t + \beta_5 End\_WCI_t + \varepsilon_t$ ).  $RD_t$  is the change in return dispersion at time  $t$ .  $local BC_t$  and  $global BC_t$  are the dummy variables for business cycle (1= recession, 0 = expansion) in local country and global respectively.  $Start\_WCI_t$ ,  $During\_WCI_t$  and  $End\_WCI_t$  are ongoing crisis starting at month  $t$ , during month  $t$  and ending at month  $t$ . System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression. I use robust standard errors. Coefficients are in percentage.

	Constant	t-value	Local BC	t-value	Global BC	t-value	Start WCI	t-value	During WCI	t-value	End WCI	t-value	Adjusted R2
Australia	-0.29	-1.01	0.16	0.28	1.93	<b>2.14</b>	0.12	1.24	0.01	0.16	0.06	0.79	0.02
Austria	-0.31	-0.95	0.83	1.27	2.98	<b>2.85</b>	-0.10	-1.18	-0.01	-0.15	0.22	1.43	0.08
Belgium	-0.40	-1.12	-0.01	-0.02	2.94	<b>3.29</b>	-0.02	-0.24	0.01	0.29	0.09	1.22	0.07
Denmark	-0.61	<b>-2.56</b>	0.02	0.05	3.90	<b>2.75</b>	0.12	1.41	0.08	<b>1.92</b>	-0.18	<b>-2.51</b>	0.10
Finland	-1.00	<b>-2.92</b>	1.05	1.51	2.18	<b>2.22</b>	0.13	<b>1.72</b>	0.16	<b>3.40</b>	-0.08	-1.05	0.08
France	-0.43	<b>-2.59</b>	0.47	1.57	0.97	1.56	0.04	0.53	0.04	1.42	-0.03	-0.48	0.03
Germany	-0.22	-1.08	0.27	0.30	2.07	<b>2.40</b>	0.07	1.04	0.01	0.32	-0.03	-0.53	0.05
Ireland	-1.08	<b>-2.65</b>	1.74	<b>2.48</b>	3.00	<b>2.61</b>	0.19	1.17	0.07	1.08	-0.13	-0.91	0.07
Italy	-0.50	-1.16	0.80	1.46	1.19	<b>2.30</b>	-0.03	-0.32	0.06	1.04	0.04	0.44	0.01
Japan	-0.41	-1.44	-0.02	-0.05	1.18	<b>1.94</b>	0.11	1.01	0.06	1.33	-0.02	-0.26	0.01
Netherlands	-0.38	-1.31	1.30	1.49	1.03	0.94	0.07	0.58	0.04	0.99	-0.15	<b>-1.70</b>	0.04
Norway	-0.59	-1.13	1.02	1.25	1.95	<b>2.03</b>	0.18	1.49	0.09	1.43	-0.10	-0.93	0.02
New Zealand	-0.51	-1.12	-0.10	-0.14	0.59	0.80	0.20	1.40	0.11	<b>1.91</b>	-0.06	-0.55	0.00
Spain	-0.85	<b>-3.76</b>	0.74	1.17	1.53	<b>1.70</b>	0.25	<b>2.07</b>	0.06	1.48	0.12	1.29	0.06
Sweden	-0.71	<b>-2.67</b>	-0.39	-1.24	2.06	<b>3.80</b>	0.11	0.73	0.12	<b>3.50</b>	0.08	1.01	0.06
Switzerland	-0.47	<b>-2.03</b>	1.37	0.95	0.77	0.50	-0.02	-0.27	0.04	1.08	0.11	1.59	0.05
UK	-0.18	-0.82	-0.21	-0.81	2.28	<b>2.48</b>	0.19	<b>3.11</b>	0.02	0.71	-0.21	<b>-3.60</b>	0.10
US	-0.30	-1.69	0.14	0.37	1.30	1.55	-0.02	-0.31	0.05	<b>1.78</b>	0.00	0.04	0.03
System	-0.53	<b>-6.63</b>	0.39	<b>3.28</b>	1.99	<b>11.89</b>	0.09	<b>4.18</b>	0.06	<b>5.45</b>	-0.01	-0.65	
Sur	-0.45	<b>-3.36</b>	0.12	1.30	1.83	<b>6.68</b>	0.07	<b>1.83</b>	0.05	<b>3.00</b>	0.00	0.12	

#### Appendix B 4 Changes in Return Dispersion and Word Count Uncertainty

This table reports the regression of changes in return dispersion on word count uncertainty around the world. I run the regression in the form of  $RD_t = \alpha + \beta_1 local\_BC_t + \beta_2 global\_BC_t + \beta_3 Start\ Crisis_t + \beta_4 During\ Crisis_t + \beta_5 End\ Crisis_t + \beta_6 \ln(word\ count\ uncertainty)_t + \varepsilon_t$  where  $RD_t$  is the change in return dispersion. Local BC and global BC are business cycle dummies, Start Crisis is crisis starting in month t, During Crisis is the ongoing crisis in month t and End Crisis is the crisis ending in month t. Word count uncertainty is the number of Bloomberg reports in every month that contains the word “uncertainty” and take a log of it. System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression. I use robust standard errors. Coefficients are in percentage.

	consta nt	t- value	local BC	t- value	global BC	t- value	start Crisis	t- value	during Crisis	t- value	end Crisis	t- value	Word Count uncertain ty	t- value	Adj R2
Australia	0.95	0.79	0.02	0.03	2.26	<b>2.41</b>	0.10	1.03	0.00	0.03	0.04	0.48	-0.19	-1.07	0.02
Austria	-2.33	<b>-2.13</b>	0.80	1.23	2.55	<b>2.40</b>	-0.06	-0.78	0.00	0.04	0.25	<b>1.68</b>	0.31	<b>1.89</b>	0.09
Belgium	-2.26	<b>-1.69</b>	0.21	0.46	2.46	<b>2.75</b>	0.02	0.19	0.02	0.45	0.12	1.57	0.28	<b>1.67</b>	0.08
Denmark	-3.11	<b>-3.61</b>	0.25	0.59	3.29	<b>2.33</b>	0.16	<b>1.89</b>	0.09	<b>2.19</b>	-0.14	<b>-1.85</b>	0.37	<b>2.92</b>	0.11
Finland	-0.86	-0.64	1.03	1.40	2.22	<b>2.16</b>	0.12	1.60	0.16	<b>3.27</b>	-0.08	-1.00	-0.02	-0.12	0.08
France	-1.38	<b>-1.81</b>	0.51	1.67	0.73	1.11	0.06	0.70	0.05	1.47	-0.01	-0.21	0.14	1.33	0.03
Germany	-2.26	<b>-3.18</b>	0.62	0.68	1.49	<b>1.73</b>	0.10	1.51	0.02	0.60	-0.01	-0.09	0.31	<b>2.88</b>	0.07
Ireland	-1.49	-0.95	1.71	<b>2.38</b>	2.92	<b>2.42</b>	0.20	1.15	0.07	1.08	-0.12	-0.84	0.06	0.27	0.06
Italy	-2.37	<b>-3.30</b>	1.01	<b>1.89</b>	0.68	1.10	0.01	0.08	0.06	1.17	0.07	0.73	0.28	<b>2.12</b>	0.02
Japan	-1.83	<b>-1.94</b>	0.02	0.06	0.83	1.31	0.13	1.24	0.06	1.43	0.00	0.05	0.21	<b>1.66</b>	0.02
NL	-2.63	<b>-2.47</b>	1.25	1.48	0.56	0.47	0.11	0.90	0.05	1.25	-0.11	-1.35	0.34	<b>2.05</b>	0.05
Norway	-1.90	-1.23	0.98	1.20	1.67	<b>1.73</b>	0.20	1.56	0.09	1.48	-0.08	-0.71	0.20	1.01	0.02
NZ	4.15	<b>2.59</b>	0.07	0.10	1.64	<b>2.15</b>	0.11	0.81	0.09	1.63	-0.14	-1.22	-0.71	<b>-3.18</b>	0.05
Spain	0.75	0.86	0.78	1.22	1.86	<b>2.06</b>	0.22	<b>1.84</b>	0.05	1.29	0.09	0.99	-0.24	<b>-1.87</b>	0.07
Sweden	-1.12	-1.52	-0.42	-1.33	1.98	<b>3.41</b>	0.12	0.79	0.12	<b>3.54</b>	0.09	1.07	0.06	0.55	0.06
Switzerla nd	-2.60	<b>-2.59</b>	1.15	0.84	0.48	0.31	0.02	0.28	0.05	1.22	0.14	<b>2.15</b>	0.33	<b>2.42</b>	0.07
UK	-1.80	<b>-2.51</b>	-0.02	-0.07	1.82	<b>1.95</b>	0.22	<b>3.54</b>	0.03	1.00	-0.18	<b>-3.17</b>	0.24	<b>2.33</b>	0.11
US	-1.74	<b>-2.77</b>	0.20	0.55	0.92	1.09	0.01	0.20	0.06	<b>1.95</b>	0.03	0.43	0.22	<b>2.40</b>	0.05
System	-1.36	<b>-5.70</b>	0.41	<b>3.49</b>	1.79	<b>10.20</b>	0.10	<b>4.79</b>	0.06	<b>5.75</b>	0.00	-0.01	0.13	<b>3.71</b>	
Sur	-1.31	<b>-3.24</b>	0.13	1.38	1.66	<b>5.80</b>	0.08	<b>2.13</b>	0.06	<b>3.13</b>	0.02	0.45	0.13	<b>2.27</b>	

## Appendix B 5 Changes in Return Dispersion and Country Risk

This table reports the relation between changes in return dispersion and international country risk. I run the regression in the form of  $RD_t = \alpha + \beta_1 local BC_t + \beta_2 global BC_t + \beta_3 Start\_Crisis_t + \beta_4 During\_Crisis_t + \beta_5 End\_Crisis_t + \beta_6 WordCount_t + \beta_7 Country Risk_t + \varepsilon_t$  where  $RD_t$  is the change in return dispersion.  $BC\_local_t$  and  $BC\_global_t$  are the dummy variables for business cycle (1= recession, 0 = expansion) in local country and global respectively.  $Start\_Crisis_t$ ,  $During\_Crisis_t$  and  $End\_Crisis_t$  are ongoing crisis starting at month t, during month t and ending at month t.  $WordCount_t$  is the log number of the counts of Bloomberg reports in every month that contains the word “uncertainty”.  $Country Risk_t$  is the country-level uncertainty obtained from the International Country Risk Guide (ICRG) composite index. System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression. I use robust standard errors. Coefficients are in percentage.

	constant	t- value	local BC	t- value	global BC	t- value	start Crisis	t- value	during Crisis	t- value	end Crisis	t- value	word count uncertainty	t- value	Country Risk	t- value	Adjusted R2
Australia	16.45	<b>1.99</b>	0.17	0.28	1.70	<b>1.94</b>	0.07	0.73	-0.01	-0.27	0.03	0.36	-0.04	-0.21	-0.20	<b>-2.01</b>	0.03
Austria	-8.07	-0.90	0.84	1.28	2.60	<b>2.45</b>	-0.06	-0.74	0.00	0.01	0.25	1.69	0.34	<b>2.00</b>	0.06	0.65	0.08
Belgium	13.78	1.56	-0.02	-0.04	2.11	<b>2.50</b>	0.00	-0.01	-0.02	-0.35	0.11	1.43	0.34	<b>2.26</b>	-0.20	<b>-1.99</b>	0.09
Denmark	3.76	0.59	0.27	0.62	3.18	<b>2.27</b>	0.16	<b>1.92</b>	0.09	<b>2.14</b>	-0.14	<b>-1.85</b>	0.47	<b>2.76</b>	-0.09	-1.07	0.11
Finland	0.44	0.06	1.03	1.40	2.21	<b>2.14</b>	0.13	1.59	0.16	<b>3.18</b>	-0.08	-0.98	0.01	0.03	-0.02	-0.20	0.07
France	-9.42	-1.65	0.45	1.43	0.84	1.28	0.07	0.80	0.04	1.26	-0.01	-0.13	0.19	1.54	0.10	1.51	0.04
Germany	-11.32	-1.42	1.18	1.11	0.96	1.14	0.06	0.59	0.07	<b>2.02</b>	-0.01	-0.07	0.69	<b>3.32</b>	0.07	0.83	0.09
Ireland	6.45	0.90	1.61	<b>2.28</b>	2.64	<b>2.22</b>	0.20	1.16	0.06	0.82	-0.11	-0.81	0.29	1.21	-0.11	-1.24	0.07
Italy	-2.87	-0.60	1.03	<b>1.81</b>	0.68	1.10	0.01	0.07	0.06	1.14	0.07	0.72	0.28	<b>2.11</b>	0.01	0.11	0.01
Japan	-3.71	-0.61	0.04	0.10	0.85	1.32	0.13	1.22	0.07	1.47	0.00	0.07	0.24	1.56	0.02	0.31	0.01
Netherlands	-20.17	<b>-1.95</b>	0.84	1.06	0.59	0.50	0.09	0.75	0.05	1.25	-0.12	-1.42	0.49	<b>2.35</b>	0.19	<b>1.76</b>	0.06
Norway	-3.97	-0.43	0.97	1.19	1.69	<b>1.75</b>	0.20	1.54	0.10	1.61	-0.08	-0.70	0.16	0.62	0.03	0.22	0.02
New Zealand	21.01	<b>1.87</b>	0.25	0.35	1.16	1.50	0.09	0.57	0.07	1.27	-0.14	-1.26	-0.90	-3.31	-0.19	-1.56	0.06
Spain	6.58	0.96	0.70	1.08	1.70	<b>2.04</b>	0.22	1.80	0.04	1.14	0.09	1.00	-0.15	-0.86	-0.08	-0.85	0.07
Sweden	5.36	1.10	-0.45	-1.40	1.98	<b>3.44</b>	0.12	0.80	0.10	<b>2.92</b>	0.09	1.06	0.09	0.83	-0.08	-1.37	0.06
Switzerland	-24.74	<b>-1.83</b>	0.96	0.76	0.73	0.50	0.01	0.11	0.07	1.40	0.13	<b>2.12</b>	0.55	<b>2.37</b>	0.23	<b>1.71</b>	0.09
UK	-8.34	<b>-1.86</b>	-0.10	-0.32	2.00	<b>2.09</b>	0.22	<b>3.63</b>	0.03	1.07	-0.18	<b>-3.22</b>	0.27	<b>2.55</b>	0.08	1.48	0.12
US	-8.24	<b>-2.22</b>	0.27	0.72	0.79	0.91	0.01	0.13	0.04	1.48	0.02	0.41	0.36	<b>2.78</b>	0.07	<b>1.84</b>	0.05
System	-1.39	-1.62	0.42	<b>3.48</b>	1.79	<b>10.14</b>	0.10	<b>4.70</b>	0.06	<b>5.83</b>	0.00	0.03	0.13	<b>3.70</b>	0.00	0.01	
Sur	-1.38	<b>-1.67</b>	0.13	1.39	1.64	<b>5.79</b>	0.08	<b>2.15</b>	0.05	<b>3.11</b>	0.01	0.37	0.14	<b>2.52</b>	0.00	0.02	

## Appendix B 6 Changes in Return Dispersion and Economic Policy Uncertainty

This table reports the results of changes in return dispersion regressions on both local and global economic policy uncertainty. Regressions are in the form of  $RD_t = \alpha + \beta_1 Local BC_t + \beta_2 Global BC_t + \beta_3 Start Crisis_t + \beta_4 During Crisis_t + \beta_5 End Crisis_t + \beta_6 WordCount_t + \beta_7 Country_{Risk}_t + \beta_8 \ln(EPU_{local})_t + \beta_9 \ln(EPU_{global})_t + \varepsilon_t$  where  $RD_t$  is the change in return dispersion. I include two economic policy indexes, one is the country specific index ( $EPU_{local}$ ) and the other is the global index ( $EPU_{global}$ ). System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression. I use robust standard errors. Coefficients are in percentage.

Country	Coefficient	Constant	Local BC	Global BC	Start Crisis	During Crisis	end Crisis	Word Count Uncertainty	Country Risk	ln(Local EPU)	ln(Global EPU)	N	Adjusted R2
Australia	Coeff. (%)	-1.16	1.04	0.95	0.17	-0.08	0.31	0.56	0.00	2.93	-3.60	144	0.13
	t-Stat	-0.08	0.52	1.04	1.09	-1.00	<b>1.94</b>	1.09	0.02	<b>3.41</b>	<b>-2.44</b>		
France	Coeff. (%)	-11.34	0.29	0.26	-0.05	0.10	-0.10	-0.24	0.03	-0.26	2.64	156	0.09
	t-Stat	-0.93	0.38	0.33	-0.25	1.24	-1.18	-0.50	0.25	-0.54	<b>2.52</b>		
Germany	Coeff. (%)	-15.04	1.40	0.54	0.03	0.09	-0.02	0.06	0.06	0.43	1.74	156	0.07
	t-Stat	-1.04	0.63	0.54	0.21	1.58	-0.15	0.16	0.41	0.66	1.41		
Ireland	Coeff. (%)	-9.76	1.37	2.41	0.26	0.04	-0.15	-0.10	-0.01	0.92	1.60	156	0.05
	t-Stat	-0.55	1.52	<b>1.91</b>	0.63	0.37	-0.44	-0.15	-0.11	0.94	0.85		
Italy	Coeff. (%)	-6.09	1.14	0.70	-0.04	0.10	0.07	-0.50	-0.07	2.06	1.21	156	0.02
	t-Stat	-0.63	1.45	1.44	-0.28	0.95	0.33	-1.17	-0.69	<b>2.73</b>	1.30		
Japan	Coeff. (%)	-5.94	0.19	0.80	0.16	0.13	0.00	0.43	0.04	0.99	-1.26	156	0.00
	t-Stat	-0.54	0.30	1.05	1.18	<b>1.77</b>	-0.04	0.69	0.45	1.05	-1.01		
Netherland	Coeff. (%)	10.02	1.71	1.36	-0.18	-0.06	-0.23	-0.99	-0.09	-0.67	1.72	82	0.06
	t-Stat	0.61	0.71	1.11	-1.02	-0.49	-1.57	-1.05	-0.50	-0.55	0.71		
Spain	Coeff. (%)	0.14	1.29	0.95	0.04	0.11	0.13	-0.74	-0.05	-0.28	2.08	108	0.08
	t-Stat	0.01	1.48	0.90	0.13	1.11	0.62	-0.83	-0.27	-0.39	1.28		
Sweden	Coeff. (%)	-2.49	-0.38	1.41	-0.02	0.07	0.13	0.88	-0.16	1.94	0.18	156	0.11
	t-Stat	-0.23	-0.84	<b>2.16</b>	-0.15	1.41	0.94	1.44	-1.64	1.39	0.16		
UK	Coeff. (%)	-12.50	-0.04	1.19	0.16	0.04	-0.24	0.21	0.01	-1.50	3.80	156	0.13
	t-Stat	-1.58	-0.08	1.23	1.25	0.76	<b>-2.32</b>	0.49	0.13	<b>-2.03</b>	<b>2.91</b>		
US	Coeff. (%)	-14.13	0.18	0.45	-0.03	0.08	0.00	-0.10	0.09	1.60	0.18	156	0.04
	t-Stat	<b>-1.91</b>	0.31	0.51	-0.29	1.33	-0.01	-0.23	1.59	0.96	0.13		
System	Coeff. (%)	-8.37	0.43	1.20	0.06	0.09	0.00	-0.14	0.02	0.47	1.25		
	t-Stat	<b>-3.42</b>	<b>1.90</b>	<b>4.48</b>	1.13	<b>4.18</b>	0.08	-0.74	0.76	<b>2.10</b>	<b>3.36</b>		
Sur	Coeff. (%)	-6.24	0.18	1.25	0.06	0.09	0.05	-0.05	0.01	0.20	1.08		
	t-Stat	<b>-2.43</b>	1.06	<b>3.70</b>	0.84	<b>2.96</b>	0.89	-0.18	0.33	1.19	<b>2.44</b>		

## Appendix B 7 Changes in Return Dispersion and Cross Section of Returns

This table reports the four factor alphas of portfolios sorted by their sensitivity to changes in return dispersion. The four factors are market, size, value and momentum factors. I report the monthly value-weighted portfolio returns in panel A and equal-weighted portfolio returns in panel B. The coefficients are in percentage.

<i>Panel A: value weighted portfolio four-factor alphas</i>												
	Low		Group 2		Group 3		Group 4		High		High - Low	
	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value
Australia	-3.77	<b>-10.55</b>	-0.85	<b>-3.80</b>	0.07	0.42	1.04	<b>5.18</b>	1.94	<b>5.88</b>	5.70	<b>11.74</b>
Belgium	-2.56	<b>-5.22</b>	-0.33	-0.97	0.34	1.35	0.20	0.72	2.05	<b>5.31</b>	4.61	<b>7.38</b>
France	-2.65	<b>-7.57</b>	-0.94	<b>-3.94</b>	-0.14	-0.68	0.57	<b>2.57</b>	2.24	<b>7.38</b>	4.90	<b>10.56</b>
Germany	-2.88	<b>-6.31</b>	-0.73	<b>-2.82</b>	-0.10	-0.39	0.59	<b>2.25</b>	1.87	<b>4.75</b>	4.76	<b>7.89</b>
Italy	-2.88	<b>-7.19</b>	-1.01	<b>-3.09</b>	-0.65	<b>-2.08</b>	0.11	0.33	1.80	<b>4.77</b>	4.67	<b>8.50</b>
Japan	-2.89	<b>-10.08</b>	-1.54	<b>-7.69</b>	-0.87	<b>-4.90</b>	0.12	0.65	1.86	<b>7.33</b>	4.75	<b>12.41</b>
Netherland	-3.35	<b>-8.16</b>	-0.80	<b>-2.43</b>	0.03	0.11	0.53	<b>1.74</b>	2.58	<b>6.72</b>	5.93	<b>10.55</b>
Norway	-4.05	<b>-7.44</b>	-1.02	<b>-2.98</b>	-0.15	-0.40	0.52	1.46	2.49	<b>5.05</b>	6.54	<b>8.91</b>
Spain	-3.30	<b>-6.44</b>	-0.76	<b>-2.52</b>	-0.17	-0.59	0.58	1.78	2.24	<b>6.20</b>	5.54	<b>8.84</b>
Sweden	-3.25	<b>-7.18</b>	-0.37	-1.03	0.19	0.55	1.52	<b>4.52</b>	3.46	<b>8.03</b>	6.71	<b>10.74</b>
Switzerland	-2.68	<b>-6.97</b>	-0.33	-1.28	0.08	0.33	0.44	1.35	2.77	<b>7.24</b>	5.45	<b>10.05</b>
UK	-3.22	<b>-9.27</b>	-0.63	<b>-2.80</b>	0.14	0.74	0.66	<b>3.22</b>	2.21	<b>8.89</b>	5.43	<b>12.71</b>
US	-1.94	<b>-11.81</b>	-0.58	<b>-7.06</b>	0.06	0.98	0.52	<b>8.41</b>	1.67	<b>9.31</b>	3.61	<b>14.83</b>
average	-3.03		-0.76		-0.09		0.57		2.25		5.28	
min	-4.05		-1.54		-0.87		0.11		1.67		3.61	
max	-1.94		-0.33		0.34		1.52		3.46		6.71	
median	-2.89		-0.76		0.03		0.53		2.21		5.43	

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(Appendix B7 Continued)

*Panel B: equally weighted portfolio four-factor alphas*

	Low		Group 2		Group 3		Group 4		High		High - Low	
	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value
Australia	-1.54	<b>-3.88</b>	-0.89	<b>-4.15</b>	-0.38	<b>-2.17</b>	-0.15	-0.75	0.28	0.80	1.81	<b>3.46</b>
Belgium	-0.72	<b>-2.44</b>	-0.13	-0.60	-0.01	-0.06	0.22	0.98	1.33	<b>4.26</b>	2.05	<b>4.77</b>
France	-0.76	<b>-2.63</b>	-0.47	<b>-2.28</b>	-0.26	-1.59	-0.09	-0.46	0.72	<b>2.67</b>	1.48	<b>3.75</b>
Germany	-1.04	<b>-3.39</b>	-0.69	<b>-3.56</b>	-0.52	<b>-3.30</b>	-0.59	<b>-3.11</b>	-0.45	-1.51	0.58	1.36
Italy	-1.32	<b>-3.82</b>	-1.24	<b>-4.29</b>	-0.90	<b>-3.61</b>	-0.65	<b>-2.29</b>	0.78	<b>2.10</b>	2.10	<b>4.14</b>
Japan	-1.01	<b>-3.86</b>	-1.15	<b>-6.26</b>	-0.96	<b>-5.94</b>	-0.57	<b>-3.39</b>	0.76	<b>3.15</b>	1.77	<b>4.98</b>
Netherland	-1.04	<b>-3.48</b>	-0.29	-1.39	-0.03	-0.16	-0.08	-0.39	0.92	<b>2.84</b>	1.97	<b>4.45</b>
Norway	-1.94	<b>-3.75</b>	-0.96	<b>-2.51</b>	-0.19	-0.55	0.47	1.36	1.56	<b>3.15</b>	3.50	<b>4.88</b>
Spain	-1.75	<b>-4.71</b>	-0.93	<b>-3.56</b>	-0.50	<b>-2.18</b>	0.12	0.45	1.10	<b>3.31</b>	2.85	<b>5.72</b>
Sweden	-1.11	<b>-2.64</b>	-0.32	-0.97	0.08	0.27	0.39	1.23	1.46	<b>3.18</b>	2.57	<b>4.13</b>
Switzerland	-1.09	<b>-3.54</b>	-0.04	-0.20	-0.01	-0.05	0.10	0.41	1.39	<b>4.59</b>	2.48	<b>5.74</b>
UK	-0.77	<b>-2.54</b>	-0.31	-1.46	-0.20	-1.05	-0.10	-0.48	0.51	1.60	1.28	<b>2.91</b>
US	0.51	<b>2.66</b>	-0.24	<b>-2.27</b>	-0.16	<b>-1.69</b>	-0.04	-0.48	1.02	<b>4.20</b>	0.51	1.63
average	-1.04		-0.59		-0.31		-0.08		0.87		1.92	
min	-1.94		-1.24		-0.96		-0.65		-0.45		0.51	
max	0.51		-0.04		0.08		0.47		1.56		3.50	
median	-1.04		-0.47		-0.20		-0.08		0.92		1.97	

## Appendix B 8 Changes in Implied Volatility and Uncertainties

This table shows the results of implied volatility regressions on uncertainties in G5 countries. Regressions are in the form of  $VIX_t = \alpha + \beta_1 local\ BC_t + \beta_2 global\ BC_t + \beta_3 Start\_WCI_t + \beta_4 During\_WCI_t + \beta_5 End\_WCI_t + \beta_6 WordCount_t + \beta_7 Country\_Risk_t + \beta_8 \ln(local\ EPU)_t + \beta_9 \ln(global\ EPU)_t + \varepsilon_t$ .  $VIX_t$  is the changes in implied volatilities at time t in each country.  $BC\_local_t$  and  $BC\_global_t$  are the dummy variables for business cycle (1= recession, 0 = expansion) in local country and global respectively.  $Start\_WCI_t$ ,  $During\_WCI_t$  and  $End\_WCI_t$  are ongoing crisis starting at month t, during month t and ending at month t.  $WordCount_t$  is the log number of the counts of Bloomberg reports in every month that contains the word “uncertainty”.  $Country\_Risk_t$  represents the ICRG composite risk index for each country. I include two economic policy index, one is the country specific index ( $EPU\_local$ ) and the other is the global index ( $EPU\_global$ ). System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression.

Country	Coefficient	Constant	Local BC	Global BC	Start WCI	during WCI	end WCI	Word Count Uncertainty	Country Risk	ln(Local EPU)	ln(Global EPU)	N	Adjusted R2
France	Coeff. (%)	-39.73	-0.31	0.97	0.62	0.19	-0.28	-0.94	0.32	1.25	3.49	119.00	0.08
	t-Stat	-1.50	-0.16	0.69	1.38	1.00	-0.74	-0.60	0.99	1.04	1.32		
Germany	Coeff. (%)	-29.13	3.31	-1.75	0.03	0.06	-0.17	-0.78	0.12	1.03	4.61	156.00	0.05
	t-Stat	-1.19	0.92	-1.38	0.09	0.49	-0.63	-0.86	0.53	0.77	<b>1.93</b>		
Japan	Coeff. (%)	-18.48	1.74	-0.18	-0.27	-0.05	0.04	-0.45	-0.12	-1.62	8.84	143.00	0.11
	t-Stat	-0.85	1.03	-0.09	-0.98	-0.39	0.18	-0.30	-0.68	-1.12	2.40		
UK	Coeff. (%)	-6.79	-0.59	0.61	0.41	0.00	-0.14	-0.37	-0.12	-1.85	6.25	119.00	0.06
	t-Stat	-0.44	-0.78	0.52	1.03	-0.01	-0.59	-0.26	-0.90	-1.18	<b>2.25</b>		
US	Coeff. (%)	-24.14	-0.38	1.48	0.09	0.01	-0.19	-0.65	0.11	3.54	0.96	156.00	0.04
	t-Stat	-2.07	-0.31	0.87	0.34	0.09	-1.04	-0.87	1.15	1.32	0.31		
System	Coeff. (%)	-22.03	0.58	0.23	0.12	0.03	-0.14	-0.75	0.04	0.27	5.24		
	t-Stat	<b>-3.46</b>	0.96	0.34	0.93	0.49	-1.20	-1.45	0.69	0.41	<b>5.35</b>		
Sur	Coeff. (%)	-11.86	0.19	1.17	-0.07	0.02	-0.09	-0.72	0.01	0.13	3.64		
	t-Stat	<b>-1.90</b>	0.64	1.20	-0.37	0.31	-0.54	-1.17	0.28	0.34	<b>3.08</b>		

## Appendix B 9 Changes in Implied Volatility and Cross Section of Returns

This table shows the factor alphas for the portfolios sorted by implied volatility loadings. I run the time-series regression using individual stock return regress on market return and changes in implied volatility:  $R_{i,t} = \alpha_i + \beta_{i,RMRF}RMRF_t + \beta_{i,vix}VIX_t + \varepsilon_{i,t}$ , where  $RMRF_t$  is the market return and  $VIX_t$  is the change in implied volatility. Then I sort all stocks into quintile portfolios based on their loadings on  $VIX_t$ . “Low” and “High” represent the portfolios that contains stocks that are most and least sensitive to implied volatility loadings. The results for the four factor alphas are in percentage.

<i>Panel A: value weighted portfolio four-factor alphas</i>												
	Low		Group 2		Group 3		Group 4		High		High - Low	
	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value
Australia	-2.75	<b>-3.64</b>	-0.60	-1.63	-0.62	<b>-1.81</b>	-0.27	-0.64	-0.86	-1.44	1.89	<b>1.95</b>
France	-0.18	-0.46	-0.37	-1.15	-0.34	-1.22	-0.35	-1.27	-0.55	-1.27	-0.37	-0.64
Germany	-0.43	-0.78	-0.03	-0.10	-0.12	-0.45	-0.34	-1.11	-1.05	<b>-2.09</b>	-0.63	-0.84
Japan	-0.50	-1.60	-0.84	<b>-3.53</b>	-0.93	<b>-3.88</b>	-0.57	<b>-2.28</b>	-0.24	-0.68	0.26	0.56
Netherland	-1.21	<b>-1.83</b>	-0.06	-0.14	-0.27	-0.77	0.19	0.39	-1.23	<b>-1.90</b>	-0.03	-0.03
Sweden	-0.49	-0.90	-0.08	-0.20	0.31	0.85	0.28	0.65	-0.91	-1.53	-0.42	-0.52
Switzerland	0.06	0.17	-0.14	-0.54	-0.01	-0.05	0.06	0.18	-0.12	-0.23	-0.18	-0.28
UK	-1.14	<b>-2.59</b>	-0.33	-1.21	0.02	0.10	0.04	0.18	-0.40	-1.04	0.75	1.29
US	-0.12	-0.75	0.08	0.84	0.08	1.05	0.00	-0.03	-0.04	-0.40	0.08	0.41
average	-0.75		-0.26		-0.21		-0.11		-0.60		0.15	
min	-2.75		-0.84		-0.93		-0.57		-1.23		-0.63	
max	0.06		0.08		0.31		0.28		-0.04		1.89	
median	-0.49		-0.14		-0.12		0.00		-0.55		-0.03	

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*Panel B: equally weighted portfolio four-factor alphas*

	Low		Group 2		Group 3		Group 4		High		High - Low	
	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value
Australia	-2.39	<b>-4.00</b>	-2.40	<b>-5.55</b>	-1.75	<b>-4.86</b>	-1.73	<b>-4.37</b>	-0.91	-1.40	1.48	<b>1.67</b>
France	-0.46	-1.14	-0.69	<b>-2.72</b>	-0.59	<b>-2.55</b>	-0.63	<b>-2.64</b>	0.08	0.19	0.53	0.95
Germany	-1.30	<b>-3.39</b>	-0.81	<b>-3.70</b>	-0.65	<b>-3.79</b>	-0.66	<b>-3.03</b>	-0.59	-1.63	0.71	1.35
Japan	-0.27	-0.91	-1.00	<b>-4.77</b>	-0.98	<b>-4.99</b>	-0.80	<b>-3.64</b>	0.21	0.64	0.47	1.09
Netherland	-1.03	<b>-2.40</b>	-0.60	-1.80	-0.25	-0.96	-0.68	<b>-2.29</b>	-1.01	<b>-1.95</b>	0.02	0.03
Sweden	-1.50	<b>-3.70</b>	-0.98	<b>-3.23</b>	-0.32	-1.05	-0.60	-1.85	-0.45	-0.99	1.05	<b>1.72</b>
Switzerland	-0.42	-1.33	-0.14	-0.69	-0.09	-0.53	0.09	0.44	0.07	0.21	-0.28	1.04
UK	-1.21	<b>-3.96</b>	-0.75	<b>-3.64</b>	-0.57	<b>-3.10</b>	-0.51	<b>-2.68</b>	-2.68	-1.64	0.71	1.65
US	0.14	0.88	-0.06	-0.64	-0.05	-0.71	-0.03	-0.34	0.24	<b>2.27</b>	0.10	0.53
average	-0.94		-0.83		-0.58		-0.62		-0.56		0.53	
min	-2.39		-2.40		-1.75		-1.73		-2.68		-0.28	
max	0.14		-0.06		-0.05		0.09		0.24		1.48	
median	-1.03		-0.75		-0.57		-0.63		-0.45		0.53	

## Appendix C

This appendix contains the robustness results of return dispersion made by market index constituents. For Australia, Finland, France, Germany, Japan, Switzerland and the US, I construct return dispersion series using all constituents of their major market indices.

### Appendix C 1 Local Business Cycle

This table shows the results of the regressions estimated in Table 3-2 using return dispersion made by market index constituents as the dependent variable. Local BC is a dummy variable that equals one if the country is in recession and zero otherwise. System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression. I use robust standard errors. Coefficients are in percentage.

	constant	t-value	local BC	t-value	Adjusted R2
Australia	10.97	<b>53.96</b>	2.33	<b>1.77</b>	0.03
Finland	8.78	<b>25.21</b>	1.80	<b>1.81</b>	0.01
France	6.25	<b>32.34</b>	1.89	<b>4.94</b>	0.10
Germany	6.45	<b>34.54</b>	2.16	1.41	0.03
Japan	7.58	<b>42.91</b>	1.60	<b>3.80</b>	0.06
Switzerland	6.27	<b>34.92</b>	2.30	<b>4.12</b>	0.09
US	8.30	<b>49.30</b>	3.78	<b>7.01</b>	0.23
System			1.72	<b>7.44</b>	
Sur			0.86	<b>5.60</b>	

## Appendix C 2 Local and Global Business Cycles

This table shows the results of regressions estimated in Table 3-3 using return dispersion made by market index constituents as dependent variable. Local BC and global BC are dummy variables that equal one if the country and global are in recession respectively, and zero otherwise. System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression. I use robust standard errors. Coefficients are in percentage.

	constant	t-value	local BC	t-value	global BC	t-value	Adjusted R2
Australia	10.60	<b>56.52</b>	0.16	0.16	6.32	<b>5.77</b>	0.25
Finland	8.46	<b>25.12</b>	0.06	0.06	5.57	<b>4.29</b>	0.09
France	6.20	<b>33.36</b>	1.28	<b>3.12</b>	2.68	<b>3.83</b>	0.16
Germany	6.15	<b>32.08</b>	0.24	0.24	4.93	<b>5.64</b>	0.18
Japan	7.50	<b>43.29</b>	0.97	<b>2.10</b>	2.33	<b>4.20</b>	0.11
Switzerland	6.27	<b>34.85</b>	1.17	1.36	2.17	<b>2.12</b>	0.11
US	8.30	<b>49.20</b>	2.06	<b>3.60</b>	3.22	<b>3.65</b>	0.27
System			0.24	0.96	4.38	<b>13.54</b>	
Sur			0.38	<b>2.46</b>	3.64	<b>8.30</b>	

### Appendix C 3 Business Cycles and International Political Crisis

This table shows the results of regressions estimated in Table 3-5 using return dispersion made by market index constituents as the dependent variable.  $local\ BC_t$  and  $global\ BC_t$  are the dummy variables for business cycle (1= recession, 0 = expansion) in local country and global respectively.  $Start\_WCI_t$ ,  $During\_WCI_t$  and  $End\_WCI_t$  are ongoing crisis starting at month t, during month t and ending at month t. System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression. I use robust standard errors. Coefficients are in percentage.

	Con	t-value	Local BC	t-value	Global BC	t-value	Start WCI	t-value	During WCI	t-value	End WCI	t-value	Adjusted R2
Australia	11.40	<b>37.25</b>	0.04	0.04	6.17	<b>5.78</b>	0.08	0.62	-0.13	<b>-3.38</b>	-0.18	<b>-1.98</b>	0.27
Finland	7.17	<b>9.19</b>	-0.25	-0.24	6.04	<b>4.53</b>	0.09	0.48	0.24	<b>2.61</b>	-0.02	-0.15	0.11
France	5.46	<b>24.50</b>	0.89	<b>2.02</b>	3.17	<b>4.43</b>	0.12	0.89	0.14	<b>3.16</b>	0.00	0.04	0.18
Germany	5.92	<b>20.54</b>	0.23	0.20	5.01	<b>5.88</b>	0.08	0.55	0.04	0.99	-0.05	-0.33	0.17
Japan	7.34	<b>30.38</b>	0.98	<b>2.11</b>	2.37	<b>4.24</b>	0.04	0.52	0.05	1.30	-0.17	<b>-2.09</b>	0.12
Switzerland	5.41	<b>21.01</b>	1.21	1.42	2.41	<b>2.36</b>	0.19	1.55	0.11	<b>2.69</b>	0.11	1.14	0.14
US	7.16	<b>38.07</b>	1.90	<b>3.71</b>	3.67	<b>4.32</b>	-0.01	-0.15	0.22	<b>6.15</b>	0.05	0.47	0.35
System	7.15	<b>47.25</b>	0.14	0.58	4.61	<b>14.18</b>	0.10	<b>2.29</b>	0.10	<b>4.93</b>	-0.03	-0.68	
Sur	7.36	<b>35.90</b>	0.37	<b>2.37</b>	3.82	<b>8.80</b>	0.09	<b>1.77</b>	0.09	<b>3.38</b>	0.01	0.17	

#### Appendix C 4 Business Cycles, International Political Crisis and Word Count Uncertainty

This table reports the results of regressions estimated in Table 3-6 using return dispersion made by market index constituents as the dependent variable. Local BC and global BC are business cycle dummies, Start Crisis is crisis starting in month t, During Crisis is the ongoing crisis in month t and End Crisis is the crisis ending in month t. Word count uncertainty is the number of Bloomberg reports in every month that contains the word “uncertainty” and take a log of it. System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression. I use robust standard errors. Coefficients are in percentage.

	constant	t- value	local BC	t- value	global BC	t- value	start Crisis	t- value	during Crisis	t- value	end Crisis	t- value	Word Count Uncertainty	t- value	Adjusted R2
Australia	9.45	<b>7.70</b>	0.24	0.24	5.73	<b>5.33</b>	0.10	0.83	-0.12	<b>-3.14</b>	-0.17	<b>-1.79</b>	0.28	1.61	0.28
Finland	5.02	1.24	0.15	0.12	5.49	<b>3.70</b>	0.11	0.55	0.25	<b>2.48</b>	0.00	-0.01	0.32	0.63	0.11
France	0.74	0.75	0.93	<b>2.33</b>	2.25	<b>3.06</b>	0.18	1.38	0.16	<b>3.66</b>	0.05	0.38	0.70	<b>5.06</b>	0.26
Germany	-1.97	-1.65	1.93	<b>1.77</b>	2.91	<b>3.83</b>	0.14	1.10	0.07	<b>1.89</b>	-0.02	-0.16	1.17	<b>6.75</b>	0.31
Japan	3.37	<b>3.60</b>	1.27	<b>2.84</b>	1.46	<b>2.47</b>	0.08	0.95	0.07	<b>1.73</b>	-0.14	<b>-1.83</b>	0.58	<b>4.51</b>	0.18
Switzerland	1.28	1.21	0.96	1.28	1.85	<b>1.87</b>	0.23	<b>2.10</b>	0.13	<b>3.13</b>	0.15	1.58	0.61	<b>4.01</b>	0.19
US	2.15	<b>2.74</b>	2.31	<b>4.98</b>	2.35	<b>2.73</b>	0.04	0.64	0.24	<b>7.37</b>	0.09	1.01	0.74	<b>6.34</b>	0.42
System	3.74	<b>8.00</b>	0.33	1.35	3.79	<b>11.24</b>	0.15	<b>3.30</b>	0.11	<b>5.52</b>	0.01	0.35	0.51	<b>7.69</b>	
Sur	5.11	<b>8.62</b>	0.40	<b>2.60</b>	3.47	<b>7.95</b>	0.13	<b>2.45</b>	0.10	<b>3.87</b>	0.05	0.89	0.33	<b>3.92</b>	

### Appendix C 5 Business Cycles, International Political Crisis, Word Count Uncertainty and Country Risk

This table reports the results of regressions estimated in Table 3-7 using return dispersion made by market index constituents as the dependent variable. Local BC and global BC are business cycle dummies, Start Crisis is crisis starting in month t, During Crisis is the ongoing crisis in month t and End Crisis is the crisis ending in month t. Word count uncertainty is the number of Bloomberg reports in every month that contains the word “uncertainty” and take a log of it. Country Risk is the International Country Risk Guide (ICRG) composite index. System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression. I use robust standard errors. Coefficients are in percentage.

	constant	t- value	local BC	t- value	global BC	t- value	start Crisis	t- value	during Crisis	t- value	end Crisis	t- value	word count uncertainty	t- value	Country Risk	t- value	Adj R2
Australia	76.08	<b>9.01</b>	0.52	0.67	3.68	<b>4.13</b>	-0.03	-0.36	-0.18	<b>-4.66</b>	-0.17	<b>-1.95</b>	0.69	<b>4.34</b>	-0.85	<b>-8.01</b>	0.43
Finland	-7.78	-0.84	0.03	0.02	5.68	<b>3.74</b>	0.11	0.53	0.27	<b>2.92</b>	-0.01	-0.04	-0.04	-0.06	0.18	1.30	0.11
France	-23.81	<b>-3.16</b>	0.70	<b>1.69</b>	2.55	<b>3.28</b>	0.19	1.58	0.13	<b>3.10</b>	0.05	0.47	0.91	<b>5.48</b>	0.29	<b>3.46</b>	0.30
Germany	-14.68	-1.77	3.06	<b>2.71</b>	1.97	<b>2.73</b>	0.14	1.07	0.17	<b>4.05</b>	-0.03	-0.22	1.88	<b>7.88</b>	0.09	0.90	0.37
Japan	14.56	<b>2.56</b>	1.23	<b>2.74</b>	1.29	<b>2.20</b>	0.06	0.63	0.04	1.03	-0.15	<b>-1.97</b>	0.44	<b>3.02</b>	-0.12	<b>-1.97</b>	0.19
Switzerland	-17.78	<b>-1.85</b>	0.77	1.14	2.13	<b>2.27</b>	0.23	<b>2.17</b>	0.14	<b>3.51</b>	0.14	1.59	0.76	<b>4.22</b>	0.20	<b>2.05</b>	0.20
US	-9.78	<b>-2.09</b>	2.44	<b>5.42</b>	2.08	<b>2.34</b>	0.04	0.63	0.20	<b>6.33</b>	0.09	0.93	1.00	<b>6.74</b>	0.13	<b>2.57</b>	0.44
System	10.95	<b>6.20</b>	0.25	1.02	3.83	<b>11.33</b>	0.15	<b>3.20</b>	0.11	<b>5.16</b>	0.01	0.34	0.44	<b>6.39</b>	-0.08	<b>-4.12</b>	
Sur	8.89	<b>7.23</b>	0.37	<b>2.21</b>	3.47	<b>7.89</b>	0.14	<b>2.64</b>	0.11	<b>4.17</b>	0.04	0.75	0.32	<b>3.94</b>	-0.04	<b>-3.63</b>	

### Appendix C 6 Business Cycles, International Political Crisis, Word Count Uncertainty, Country Risk and Economic Policy Uncertainty

This table reports the results of regressions estimated in Table 3-8 using return dispersion made by market index constituents as the dependent variable. Local BC and global BC are business cycle dummies, Start Crisis is crisis starting in month t, During Crisis is the ongoing crisis in month t and End Crisis is the crisis ending in month t. Word count uncertainty is the number of Bloomberg reports in every month that contains the word “uncertainty” and take a log of it. Country Risk is the International Country Risk Guide (ICRG) composite index. I include two economic policy index, one is the country specific index (*EPU\_local*) and the other is the global index (*EPU\_global*). System shows the results of pooled OLS and Sur shows the results of seemingly unrelated regression. I use robust standard errors. Coefficients are in percentage.

	Constant	Local BC	Global BC	Start WCI	during WCI	end WCI	Word Count Uncertainty	Country Risk	ln(Local EPU)	ln(Global EPU)	Adjusted R2
<i>Australia</i>											
Coeff. (%)	28.54	1.85	2.20	0.04	-0.19	-0.22	0.46	-0.42	2.57	0.78	0.51
t-Statistic	<b>1.77</b>	1.01	<b>2.24</b>	0.35	<b>-3.12</b>	<b>-2.23</b>	0.80	<b>-2.19</b>	<b>3.44</b>	0.57	
<i>France</i>											
Coeff. (%)	-31.74	0.11	1.53	0.10	0.27	-0.03	0.20	0.19	-0.38	5.23	0.45
t-Statistic	<b>-2.36</b>	0.13	<b>2.01</b>	0.60	<b>3.39</b>	-0.16	0.38	1.40	-0.79	<b>5.01</b>	
<i>Germany</i>											
Coeff. (%)	-18.88	3.84	0.59	-0.02	0.20	-0.08	-0.07	-0.04	0.46	6.19	0.47
t-Statistic	-1.52	<b>2.10</b>	0.85	-0.15	<b>3.43</b>	-0.41	-0.18	-0.33	0.69	<b>5.26</b>	
<i>Japan</i>											
Coeff. (%)	-2.73	0.82	1.07	-0.03	0.18	-0.15	-0.46	0.00	1.45	1.71	0.26
t-Statistic	-0.32	1.48	<b>1.78</b>	-0.29	<b>3.41</b>	<b>-1.77</b>	-1.07	-0.02	<b>2.08</b>	<b>1.92</b>	
<i>US</i>											
Coeff. (%)	-36.46	1.30	1.61	-0.05	0.30	0.09	0.74	0.24	4.30	0.22	0.55
t-Statistic	<b>-6.09</b>	<b>2.41</b>	<b>1.86</b>	-0.58	<b>5.60</b>	0.69	<b>1.70</b>	<b>4.10</b>	<b>2.26</b>	0.13	
System											
Coeff. (%)	-17.97	0.32	2.24	0.02	0.20	-0.08	0.22	0.04	-0.27	4.98	
t-Statistic	<b>-4.75</b>	0.91	<b>5.58</b>	0.23	<b>6.38</b>	-1.15	0.82	1.24	-0.83	<b>9.10</b>	
Sur											
Coeff. (%)	-18.94	0.92	1.87	0.02	0.20	-0.08	0.13	0.08	0.42	3.93	
t-Statistic	<b>-5.63</b>	<b>3.59</b>	<b>4.23</b>	0.18	<b>5.30</b>	-1.09	0.42	<b>3.50</b>	<b>1.82</b>	<b>6.79</b>	



## Chapter 4 The Performance of Asset Allocation

### Strategies Across Datasets and Over Time

#### 4.1 Introduction

Asset allocation determines the investment outcomes by identifying investable assets and assigning appropriate weights for them in the portfolio. Markowitz (1952) derives a theoretically (ex-post) optimal asset allocation strategy, which produces the mean variance portfolio with maximum return in excess of the risk-free rate per unit of risk. However, when the true parameters are unknown and are estimated using historical parameters (ex-ante), the mean variance weighting rule generates unsatisfactory reward to variability ratios. Its poor performance in reality leads to the focus on alternative asset allocation methods, especially the naïve diversification rule that assigns weights equally to each asset, which is easy to implement and hard to outperform.<sup>18</sup> Recently, risk-based approaches that determine the weighting of each asset based only on assets' risk characteristics become attractive, as they are expected to sufficiently improve portfolio mean-variance efficiency by increasing the accuracy during the weighting process. How do different asset

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<sup>18</sup> For instance, Jobson and Korkie (1980), Duchin and Levy (2009) and DeMiguel, Garlappi, and Uppal (2009) show that neither the Markowitz rule, nor its extensions, are able to consistently outperform the equal weighting method. Jacobs, Müller, and Weber (2014) extend this conclusion to international and asset class diversification. Plyakha, Uppal, and Vilkov (2012) illustrate that the equally weighted portfolio substantially outperforms the value- and price-weighted portfolios.

allocation strategies influence the portfolio performance? Is there a strategy that could consistently produce the highest risk-adjusted returns across any assets and over time? What is the impact of these portfolio construction rules on portfolios' risk exposures?

This chapter addresses these questions by constructing portfolios using seven popular asset allocation strategies and evaluating their ex-ante performance: (i) with regards to different measurements; (ii) across investment universes (countries, industries, stocks only, and a more general portfolio of assets that mixes bonds with stocks); (iii) with respect to changes in risk exposures; and (iv) over time. In terms of risk-adjusted returns, the results show that there are no significant differences between portfolio construction methods for country- and industry-based portfolios. For individual stock and multi-asset class portfolios, the differences between strategies are large, but none of the strategies are able to remain superior over time. These results are robust to changes in the estimation window, using different rebalancing periods and adjusting the transaction costs. In terms of the risk factor loadings associated with these asset allocation strategies, this chapter identifies that the implementation of the mean variance approach leads to fluctuating exposures in size, value and momentum factors for all four datasets. It is riskier than all the other strategies in the sense of risk exposure shifting.

How far are these strategies from mean variance efficient? By comparing them with the ex-post optimal portfolio, I discover that none of the strategies are close to efficient irrespective of any dataset. In fact, for the portfolios made up using country indices, industries and stocks, the highest Sharpe ratios

generated from the current construction methods are approximately two-thirds of the corresponding optimal Sharpe ratios. For the multi-asset case, strategy-constructed portfolios are even further from the optimal portfolio.

This study selects seven asset allocation approaches for several reasons. Firstly, as DeMiguel, Garlappi, and Uppal (2009) show that none of the extensions of the Markowitz models are able to consistently outperform the naïve diversification rule, I only use the classic mean variance rule as a representative for all Markowitz-based models. Secondly, this chapter focuses on several risk-based methods, as they are relatively new and their performance in the previous literature is inconsistent. In other words, different research supports different methods and a systematic comparison is required. A well-known risk-based method is the minimum variance method, which determines the weighting of each asset in order to minimise the portfolio's total risk. Moreover, I apply two naïve risk parity strategies; one of them assigns weights based on the assets' inverse volatility, and the other assigns weights based on the assets' inverse variance. I also use the equal risk contribution approach developed by Qian (2006). The method aims to assign weights in order to equalise each asset's risk contribution by using their full covariance matrix.<sup>19</sup> Additionally, I include the maximum diversification approach proposed by Choueifaty and Coignard (2008). In this method the proportion of each asset is designed to maximise an overall portfolio diversification ratio, which is the weighted average volatility divided by the portfolio volatility. Lastly,

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<sup>19</sup> The equal risk contribution approach sometimes refers to the real risk parity in other studies. By using the full assets' covariance matrix, Qian (2006) assigns Weights to equalise their risk contribution, hence also taking correlations between assets into account.

as a benchmark I use the equally weighted portfolio (also known as the naïve 1/N diversification) following DeMiguel, Garlappi, and Uppal (2009) because it is extensively used in both academic and real world applications.<sup>20</sup> Thus, I compare the performance of the other portfolio construction methods against this equally weighted benchmark.

I construct long only portfolios, as short sales often lead to extreme weightings and are hard to implement in practice.<sup>21</sup> In the baseline study, I assume investors determine the proportions for each asset according to the past five years' performance of these assets. I use an estimation window of 60 months. Portfolios are rebalanced monthly by rolling the estimation window one month forward.

This chapter uses two measures to evaluate the risk-adjusted returns of asset allocation methods. Firstly, I compare the Sharpe ratios between strategy made portfolios and their statistical significance. The results demonstrate that the differences between strategy performances are negligible for country- and industry-based portfolios, but relatively large for stock- and multi-asset portfolios. I report a summary of the highest Sharpe ratio, the lowest Sharpe ratio and the p-value of the difference in Table 4-1. To be precise, all of the strategies result in similar Sharpe ratios, especially if I invest

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<sup>20</sup> The equally weighted portfolio is widely used in empirical asset pricing. In practice, equal weighting is the common way for investors to allocate their assets. Even in defined contribution pension plans, Benartzi and Thaler (2001) and Huberman and Jiang (2006) indicate that some investors divide contribution evenly across the funds.

<sup>21</sup> Short-selling often leads to extreme values in assets' Weighting, which cause serious estimation errors. Jagannathan and Ma (2003) find that short sales constraints improve portfolio performance by decreasing estimation error. Also, Huij, Lansdorp, Blitz, and Van Vliet (2014) indicate that short-selling may face practical issues, such as benchmark restriction and implementation costs.

in industries where the highest Sharpe ratio of 0.54 (for the minimum variance portfolio) is not much higher than the lowest Sharpe ratio of 0.46 (for the mean variance portfolio). The full sample period Sharpe ratio difference is 0.11 for country diversification and 0.08 for industries. For the stock portfolio, the Sharpe ratios of the equal risk contribution (0.59) and maximum diversification (0.63) portfolios are statistically higher than for the equally weighted portfolio (0.54) at the 5% level. In the multi-asset case, the differences in outcomes are even larger. The minimum variance and maximum diversification portfolios underperform the others with Sharpe ratios of 0.04 and 0.07, respectively, compared with a Sharpe ratio for the equally weighting portfolio of 0.31.

Secondly, I use alphas from the usual asset pricing models as another measure. I regress the different portfolios on risk factors stated in the usual asset pricing models. The alphas obtained from these regressions are the adjusted returns against the specific risk factors. For the country indices I use Jensen's alpha, the Fama and French (1993) three factor alpha and the Carhart (1997) four factor alpha. For the other three datasets I also consider the Fama and French (2014) five factor alpha. I find that all the portfolio construction methods produce statistically indistinguishable alphas with the equally weighting approach for every asset pricing model tested. Those results hold for country indices, industry indices and individual stocks, but not for multi-asset classes. For instance, Table 4-1 shows that, for the industry-based portfolios, the highest Carhart alpha of 0.10 is slightly and insignificantly higher than the lowest one of 0.02. In contrast, for the multi-asset class case, the minimum variance, the equal risk contribution and the maximum diversification

approaches produce significantly less negative alphas than the naïve 1/N rule with respect to all four different alphas I consider.

In order to compare the risk exposures associated with the strategies, this study uses market, size, value and momentum factor exposures as the measurements. These are the betas in the Carhart (1997) four factor model. I apply the rolling window analysis with an estimation window of five-years to obtain a series of betas over time. I then compute the average and the standard deviation of those betas. By identifying the risk exposures, investors are able to understand what drives the performance of each allocation approach. Also, the higher the standard deviation of betas, the more risk exposures fluctuate, which might by itself be a deterrent to a strategy being used as it may imply risk shifting over time.

The results show that strategy risk loadings are dependent on the assets invested in and the mean variance weighting method has the most fluctuation in risk loadings. To be precise, the mean variance rule is associated with highly shifting risk towards all factors in almost all datasets. For instance, for the country indices, the standard deviations of the size and value betas for the mean variance portfolio are 0.14 and 0.33, compared with those of the equal-weighted portfolio, which are 0.10 and 0.14, respectively. For the industries, both the mean variance and minimum variance approaches have relatively higher variation in all four factor loadings. As shown in Table 4-1, the highest standard deviation of the momentum beta is generated by the mean variance portfolio of 0.18, followed by the one in the minimum variance portfolio of 0.12, which are both much higher than that of the equal-weighted

portfolio of 0.04. For the individual stocks, the performance of the equally weighted portfolio is driven by a small-cap effect, as its size beta is high at 0.75. All the strategies result in relatively similar variation in betas. For the multi-asset class dataset, again the mean variance rule is the only strategy, with highly shifting risk towards all factors.

I further compare the ex-ante strategies made portfolios with the real (ex-post) optimal portfolio. For all four datasets, the Sharpe ratios of the optimal portfolios are exceedingly higher than any of the strategies, and are all significant (p-values less than 5%). For country indices, the highest Sharpe ratio generated from the equally weighted portfolio is 0.4, compared with the optimal Sharpe ratio of 0.6. For the multi-asset case, the smallest Sharpe ratio produced by the minimum variance portfolio of 0.04 is even less than one-tenth of the optimal Sharpe ratio of 0.58.

Table 4-1 An Overview of the Differences Between Asset Allocation Strategies

This table shows the highest figures and the lowest figures of the strategy made portfolios with respect to each criterion. The Sharpe ratios are calculated during the full sample (August 1931 to April 2013), contraction and expansion periods. I use a bootstrap approach established by Ledoit and Wolf (2008) to test the statistical differences between strategies' Sharpe ratios. For each asset allocation strategy, I run the rolling sample regression (with an estimation window of five-years) to obtain a series of risk loadings. Then I calculate the average and the standard deviation of the risk loadings for each strategy.

	country indices		industries		stocks		multi-assets	
	High	Low	High	Low	High	Low	High	Low
<b>Sharpe ratio</b>								
full period	0.40	0.29	0.54	0.46	0.63	0.44	0.31	0.04
p-value (high-low)	(0.15)		(0.32)		(0.01)		(0.05)	
during recession	-0.47	-0.70	-0.16	-0.31	0.05	-0.18	0.03	-0.60
p-value (high-low)	(0.26)		(0.18)		(0.30)		(0.07)	
during expansion	0.68	0.53	0.83	0.77	0.84	0.60	0.61	0.05
p-value (high-low)	(0.22)		(0.41)		(0.01)		(0.00)	
<b>Alphas (%)</b>								
Jensen's alpha	0.00	-0.20	0.18	0.09	0.82	0.26	-0.01	-0.10
p-value(high-low)	(0.23)		(0.97)		(0.06)		(0.60)	
3 factor alpha	0.08	-0.19	0.18	0.05	0.66	0.22	0.08	-0.09
p-value(high-low)	(0.23)		(0.63)		(0.06)		(0.60)	
Carhart alpha	0.15	-0.18	0.10	0.02	0.71	0.13	-0.03	-0.10
p-value(high-low)	(0.23)		(0.97)		(0.12)		(0.59)	
5 factor alpha	-	-	0.11	-0.02	0.58	0.12	0.05	-0.11
p-value(high-low)	-		(0.62)		(0.06)		(0.60)	
<b>Average risk loadings every five-year (%)</b>								
$\beta_{mkt}$	0.93	0.81	0.96	0.78	0.86	0.76	0.42	0.03
$\beta_{smb}$	0.04	-0.20	0.00	-0.20	0.75	0.22	-0.03	-0.10
$\beta_{hml}$	0.08	-0.13	0.26	-0.05	0.30	0.04	-0.01	-0.06
$\beta_{umd}$	0.04	0.01	0.23	-0.04	0.13	-0.23	0.09	0.02
<b>Standard deviation (SD) of risk loadings (%)</b>								
SD( $\beta_{mkt}$ )	0.20	0.06	0.12	0.03	0.20	0.14	0.27	0.04
SD( $\beta_{smb}$ )	0.15	0.09	0.22	0.05	0.31	0.22	0.13	0.03
SD( $\beta_{hml}$ )	0.33	0.13	0.29	0.11	0.30	0.16	0.15	0.04
SD( $\beta_{umd}$ )	0.16	0.08	0.18	0.04	0.26	0.13	0.10	0.03

As the performance of asset allocation strategies may vary over time, this study explores whether one strategy could dominate the others during certain periods. For the country- and industry-based portfolios, none of the strategies perform significantly differently from the naïve diversification rule, whether we separate returns during contractions from returns during expansions, or we plot the variation of performance of the different strategies over time. For the stocks and multi-asset classes, the differences between strategies are large, but the superiority is inconsistent. For example, during the expansion period, the risk-based approaches generally show better performance than the equal weighting method in the stock dataset. However, during the same period, the risk-based strategies are substantially inferior to the equal weighting rule for multi-asset classes. Additionally, when I rank the strategies over non overlapping ten-year periods, the results show that no single method stays in the first place for more than two periods. This holds for all four datasets.

Motivated by the increasing interest in risk-based strategies, this study aims to provide a guideline for both practitioners and academics. On the one hand, companies start to promote risk parity funds following the instructions on the Wall Street Journal that “risk parity funds held up relatively well during the financial crisis” (Eleanor, 2010). There seems to be a tendency to move from the cornerstone mean variance approach to the new wave of risk-based approaches. The evaluation of allocation methods is essential for both the fund managers and private investors as they are looking forward to reversing their failure during the crisis. On the other hand, to identify a superior strategy is expected to address the inefficiency in commonly used benchmarks. Most of

the commonly used market benchmarks are value-weighted, which is suggested to be substantially inefficient than the equal weight market benchmark (Plyakha, Uppal, and Vilkov, 2014). Seeking a better construction method that could improve the benchmark mean-variance efficiency is crucial for investors who track it, and academics who use it to measure the systematic risk.

To conclude, this study contributes to the literature in several ways. Firstly, this chapter demonstrates that the asset allocation strategies do not have a strong impact on portfolio performance if we invest in country and industry indices. Investors can just use simple naïve diversification, as sophisticated methods do not improve the outcomes. Secondly, this chapter reveals how the performance of asset allocation techniques depend on datasets and the time periods under consideration. Previous studies never reach consensus on which portfolio construction method is the best. I illustrate that any superiority is relative. Moreover, to the best of my knowledge, this chapter is the first to demonstrate the variation of risk exposures associated with each strategy over time. This is interesting, as we are able to understand not only which risk factors lead to the performance of the construction methods, but also how stable those factors are. I identify that the implementation of the mean variance rule leads to highly fluctuating risk shifting, which is undesirable for investors. Last but not least, I document that all the strategies tested in this study are far from optimal. New available methods do not seem to improve investment outcomes markedly or consistently. There is still a long way to go in improving the portfolio mean variance efficiency.

## **4.2 Description of asset allocation strategies**

This study focuses on several well-known asset allocation strategies including equal weighting, mean variance, naïve risk parity, minimum variance, equal risk contribution and maximum diversification. For each one, I present the theoretical background and illustrate the basic characteristics. I also present a short discussion of the previous studies of strategy comparison in the last part of this section.

### **4.2.1 Equal weighting**

The equal weighting approach (also called the 1/N portfolio strategy, or naïve diversification) assigns weights equally to each asset without incorporating any information from the asset. It is acknowledged as the simplest method and is widely used in both empirical finance (for instance, Jensen, Black, and Scholes, 1972; Fama and MacBeth, 1973) and in practice (documented by Benartzi and Thaler, 2001) for a long time. Previous studies tend to compare different portfolio construction methods with the equal weighting strategy, and most of them favour the latter. For example, Plyakha et al. (2014) discover that the equal-weighted portfolio outperforms the value- and price-weighted portfolios in terms of returns, the four-factor alpha and the Sharpe ratio. Jacobs et al. (2014) suggest simple heuristic allocation approaches (including the naïve 1/N rule) to private investors, as simple methods perform indifferently from the optimisation methods.

To take this a step further, many studies analyse the characteristics of the naïve diversification that attribute to the superiority of equal-weighted portfolio. For instance, Plyakha et al. (2012) firstly find that the returns of the equal-

weighted portfolio relative to the value- and price-weighted portfolios are monotonically decreasing with size and price, but monotonically increasing with idiosyncratic volatility. Secondly, Plyakha et al. (2012) use the Carhart four-factor model to explore the relations between the outperformance of the equal-weighted portfolio and factor exposures. Their results show that 42% of the returns of the equal-weighted portfolio in excess of the value-weighted portfolio come from the differences in alphas and the remaining 58% comes from the systematic components. Compared with the value- and price-weighted portfolios, the equal-weighted portfolio bears more risk exposure to market, size and value factors and more negative exposure to the momentum factor. Thirdly, the frequently rebalancing is another reason for the higher alphas produced by equal-weighted portfolios compared with value- and price-weighted portfolios. If the rebalancing frequency decreases from one month to twelve months, there will be no difference in alpha between all three strategies. Similarly, Hsu, Chow, Kalesnik, and Little (2011) review several investment strategies and discover the outperformance of an equal-weighted portfolio over a value-weighted index, owing to market, value and size factors. Moreover, in the out-of-sample analysis, Brown, Hwang, and In (2013) indicate that the inconsistent outperformance of the naïve 1/N rule over the optimal diversification is due to the compensation for the increased tail risk in the naïve diversification.

#### **4.2.2 Mean variance weighting**

Markowitz (1952) derived the famous mean variance weighting method, which is the optimal rule theoretically. It determines weightings to each asset

in order to maximise the total portfolio's Sharpe ratio, as shown in equation (4.1). However, this Markowitz rule performs poorly in the out-of-sample test. Many empirical studies suggest that the failure of the ex-ante mean-variance weighted portfolio is due to the large errors produced in estimating the returns and covariance matrix (see for instance, Chopra and Ziemba, 1993; Michaud, 1989). Thus, in practice, mean-variance weighting can sometimes also be regarded as *error maximising*, rather than *Sharpe ratio maximising*. A vast body of literature deals with the estimation error in order to improve the performance of the Markowitz model. A practical suggestion is to use "shrinkage estimators", which basically means that each asset mean should be "shrunk" toward a common value for predicting expected returns (Jobson and Korkie, 1980; Jorion, 1985; Stein, 1956). Recently, Pástor (2000) and Pástor and Stambaugh (2000) propose using an asset pricing model to form a prior. Ledoit and Wolf (2003) concentrate on reducing the estimation error in the covariance matrix. Kan and Zhou (2007) suggest diversifying across markets and estimation risk. Also, Chopra (1993) and Jagannathan and Ma (2003) illustrate the performance improvement by imposing short selling constraints.

$$\{w\}^p \text{Sharpe Ratio}_{max} = \frac{r_p}{\sigma_p} \quad (4.1)$$

DeMiguel, Garlappi, and Uppal (2009) evaluate the out-of-sample performance of 14 Markowitz based mean variance models and their extensions using eight datasets. They also use industries and country indices

to construct portfolios, which is similar to the datasets used in this study<sup>22</sup>. They find that none of the 14 mean variance extensions are able to perform consistently better than equal Weighting in terms of the Sharpe ratio, certainty-equivalent return, or turnover for all data sets. On the other hand, Kirby and Ostdiek (2012) claim that the 14 mean variance extensions used by DeMiguel, Garlappi, and Uppal (2009) could outperform the naïve 1/N model if the mean variance rules are targeting the conditional expected returns of the naïve diversification. In another out-of-sample study, Kritzman, Page, and Turkington (2010) show that optimised portfolios often outperform the naïve 1/N portfolio when the estimations of the expected returns are reliant on long-term samples.

#### **4.2.3 Naïve risk parity**

The naïve risk parity approach only considers the volatility or variance of each asset and ignores the correlation between assets (equation 4.2). A portfolio is said to be in “parity” when weights are proportional to the inverse volatility of assets (Clarke, De Silva, and Thorley, 2013). This study considers both risk parity based on variance and risk parity based on volatility as they have been used separately in the literature and in practice. The original risk parity method is proposed by Qian (2005) based on variance, however, there are advocates for weighting on volatilities (e.g. Martellini, 2008; Choueifaty and Coignard, 2008). Moreover, Ang (2012) runs a horserace between several strategies and he distinguishes those two strategies. He forms portfolios using

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<sup>22</sup>DeMiguel, Garlappi, and Uppal (2009) use ten industries and the US equity market indices as one dataset. In contrast, our study only uses the ten industry portfolios. Also, DeMiguel, Garlappi, and Uppal (2009) include eight MSCI country indices and the World Index in one dataset. However, this study chooses five widely used country indices (S&P 500, NIKKEI 225, FTSE 225, DAX and CAC) in one dataset.

US government bond, US corporate bonds, US stocks and international stocks during 1978 to 2011. He finds that portfolio made of risk parity (variance) results in Sharpe ratio of 0.59 while portfolio made of risk parity volatility results in Sharpe ratio of 0.65. Thus, those two methods do not always have similar performance. Furthermore, Hallerbach (2013) points out that risk parity techniques are popularly used in recent practice. For instance, the S&P Low Volatility Index uses weighting based on inverse volatility while the MSCI Risk Weighted Indices weights stocks based on inverse variance.

$$W_i = \frac{\frac{1}{\text{variance}(i)}}{\sum_j \frac{1}{\text{variance}(j)}} \quad \text{or,} \quad W_i = \frac{\frac{1}{\sigma(i)}}{\sum_j \frac{1}{\sigma(j)}} \quad (4.2)$$

#### 4.2.4 Minimum variance weighting

Minimum variance weighting is also a Markowitz-based optimisation method. As shown in equation (4.3), the weighting for each asset is allocated in order to minimise the portfolio total risk and  $\Omega$  is the covariance matrix. Thus, the minimum variance technique often assigns larger weights to assets with low volatility and low correlations in the portfolio. It ensures that each asset has the same marginal risk contribution to the portfolio. Since Blitz and Van Vliet (2007) provide empirical evidence that lower volatility stocks earn higher risk-adjusted returns, the minimum variance portfolio is expected to benefit from the low volatility anomaly.

$$\{w\}^p \sigma_{min} = w^T \Omega w \quad (4.3)$$

Several previous studies report the superiority of the minimum variance strategy especially in back-testing. For instance, Clarke, De Silva, and Thorley

(2006) illustrate that the minimum variance portfolio generates higher returns and lower risk compared with the value-weighted portfolio. Additionally, Hallerbach (2013) finds that the minimum variance portfolio is the closest to the optimal portfolio and dominates all other portfolios they test (including equal-weighted, maximum diversification and risk parity, among others).

#### 4.2.5 Equal risk contribution

Qian (2006) improves the naïve risk parity approach by also considering the correlation between assets when equalising assets' risk. I call this new method equal risk contribution. Hallerbach (2013) points out that the weight of each asset multiplied with its marginal contribution to the portfolio is equal. In other words, the beta of each asset multiplied by its weight is the same as shown in equation (4.4). Thus, the weight of an asset is the inversed proportion of its beta. The asset with larger volatility, or higher correlation with other assets, will be assigned a smaller weight. Compared with the mean variance rule, Merton (1980) suggests that the only required input for equal risk contribution is the covariance matrix, which can be estimated more accurately than expected returns using historical data.

$$w_i \frac{\partial \sigma_p}{\partial w_i} = w_j \frac{\partial \sigma_p}{\partial w_j} w_i \beta_{ip} = w_j \beta_{jp} \quad (4.4)$$

$$w_i \sim \frac{1}{\beta_{ip}} \quad (4.5)$$

#### 4.2.6 Maximum diversification

Choueifaty and Coignard (2008) first document a diversification ratio to measure how diversified a portfolio is. Consider a portfolio  $P$  with asset  $X_1, X_2, \dots, X_N$ , where each has a weighting of  $W_{p1}, W_{p2}, \dots, W_{pN}$  ( $\sum_{i=1}^N W_{pi} = 1$ ). The covariance matrix is denoted as  $V$  and the vector of asset volatilities is  $\Sigma$ .

$$P = [W_{p1} \quad W_{p2} \quad \dots \quad W_{pN}], \quad \Sigma = \begin{bmatrix} \sigma_1 \\ \sigma_2 \\ \dots \\ \sigma_N \end{bmatrix} \quad (4.6)$$

The diversification ratio  $D(P)$  is the weighted average volatility divided by portfolio total volatility:

$$D(P) = \frac{P' \Sigma}{\sqrt{P' V P}} \quad (4.7)$$

The weights of the maximum diversification portfolio are obtained by maximising the diversification ratio:

$$\max \frac{P' \Sigma}{\sqrt{P' V P}} \quad (4.8)$$

Choueifaty and Coignard (2008) point out that if each asset has the same volatility, the maximum diversification is the same as the minimum-variance portfolio. They also find that the changes in data frequency or the estimation period have little effect on the performance of the maximum diversification strategy. Hallerbach (2013) shows the maximum diversification portfolio is the same as the optimal portfolio if each asset's excess return is proportional to its volatility.

In the back-testing, Choueifaty and Coignard (2008) use daily data from the S&P 500 Index during December 1990 to February 2008, and find that the maximum diversification portfolio has the highest excess return and Sharpe ratio among value-weighted, minimum-variance and equally weighted portfolios. However, in the sub-periods testing, the superiority of maximum diversification does not hold in the first sub-period (1992-2000), where it performs the worst among all four strategies. Furthermore, Choueifaty and Coignard (2008) find that the maximum diversification portfolio has the highest, and a statistically significant, Fama-French three factor alpha of 3.1%. Again, the result does not hold during the period of 1992 to 2000.

#### **4.2.7 Strategy performance comparison**

Each portfolio construction strategy has its merits. The previous literature never reaches a consensus regarding which is the best. Even in the ex-post testing, the performance of allocation approaches differs across studies; not to mention their performance in the ex-ante evaluations, each study has its own insights. None of the approaches is able to consistently outperform the others. To better illustrate, I list several representative studies that are recently published.

For the historical performance analysis, Clarke et al. (2013) construct portfolios using the largest 1,000 common stocks in the CRSP database at the end of each month from 1968 to 2012. They find that the minimum variance portfolio results in the highest Sharpe ratio and lowest market beta compared with the others (equal risk contribution, maximum diversification and minimum variance, market-capitalisation weighting and equal weighting). In another

study, Hallerbach (2013) also evaluates those asset allocation policies listed above, but using 4 asset classes; equities, aggregate treasuries, corporate investment grade, and corporate high yield. Hallerbach (2013) indicates that the minimum variance portfolio performs best with a Sharpe ratio of 1.11, which is quite close to the optimal portfolio, with the maximum Sharpe ratio being 1.19.

In contrast, the studies on the out-of-sample strategy performance produce quite different results. Similar to this study regarding the datasets used, Jacobs et al. (2014) conduct ex-ante analysis on the international stock market and different asset classes. The portfolio construction methods compared by Jacobs et al. (2014) are similar to those used by DeMiguel, Garlappi, and Uppal (2009), which include the mean-variance based methods as well as simple heuristic approaches. Both studies indicate that none of the Markowitz rules are able to significantly outperform the naïve diversification. By taking a further look into the results shown by Jacobs et al. (2014), it is clear that there is no difference between asset allocation strategies for international equity indices.<sup>23</sup>

In another ex-ante performance analysis, Ang (2012) runs a horse race between several portfolio formation techniques. Ang (2012) also uses multi-asset classes, which include the US government bond (Barcap US Treasury), US corporate bonds (Barcap US Credit), US stocks (S&P 500) and international stocks (MSCI EAFE). He constructs ex-ante portfolio returns

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<sup>23</sup> As shown in Jacobs et al. (2014) Table 3, the p-values for the Sharpe ratios are almost all insignificant, which indicates that all the models they tested result in statistically the same Sharpe ratio using the GDP-Weighting method.

based on assets' previous five-year performance. Ang (2012) aims to illustrate that the investment outcomes will alter as various portfolio construction methods are applied and, because short selling is allowed, the Sharpe ratios produced by different strategies do have large differences. Ang (2012) shows that the naïve risk parity portfolios, equally weighted portfolio and minimum variance portfolio strategies are outperformed. In contrast, the mean variance portfolio results in an extremely low Sharpe ratio.

Moreover, Chaves, Hsu, Li, and Shakernia (2011) compare the ex-ante performance of portfolios formed by the US treasury, US bond, Global bond, US equities, international equities, emerging market equities, commodities and real estate. They estimate the covariance matrix based on assets' previous five-year returns and they use the shrinkage technique rather than simple covariance. All techniques are rebalanced annually and a short selling constraint is applied. In the full sample period (January 1980 to June 2010), optimisation approaches (mean variance and minimum variance weighting) tend to underperform simple methods (60/40, equal weighting and equal risk contribution). In the sub-period analysis, no one strategy can consistently outperform the others. Chaves et al. (2011) show that the performance of all approaches is highly time dependent. For example, the Sharpe ratio of the first 60/40 equity/bond portfolio is very high, at 0.99, in the 1990s, but is only 0.04 during the 2000s. On the contrary, the minimum variance portfolio produces a negative Sharpe ratio of -0.02 in the 1980s, but a high Sharpe ratio of 0.49 in the 2000s.

Furthermore, the strategy performance is dependent on the asset classes included in the portfolio. In a similar article regarding the characteristics of the equal risk contribution portfolio, Maillard, Roncalli, and TeïLetche (2010) find totally different results from those of Chaves et al. (2011). Maillard et al. (2010) show that the minimum variance portfolio beats both the equal weighted and equal risk contribution portfolios, in terms of risk, return and Sharpe ratio. The major difference between the studies conducted by Chaves et al. (2011) and Maillard et al. (2010) is that Maillard et al. (2010) use a historical simulation on agricultural commodities during the period of January 1979 to March 2008 to construct the portfolios.

All in all, the previous literature shows mixed evidence on the performance of the asset allocation strategies. It is hard to say whether one strategy is better than the others. Previous studies lack a comprehensive comparison on the portfolio construction methods. This study fills this gap by covering different levels of datasets and analysing performance over time.

### **4.3 Data and methodology**

This study includes four datasets as representatives of different levels of diversification. I incorporate five country indices with regards to the raising trend of global diversification. I consider industry level investment and include ten US industries. Then I choose individual stocks as the third dataset to take into account the perspective of equity investors. Lastly, I choose four asset classes since investors tend to include fixed income assets for risk diversification. All four datasets contain monthly data from August 1926 to April

2013. For each dataset, I employ the rolling-sample approach to construct portfolios according to asset allocation rules.

#### **4.3.1 Description of datasets**

For global diversification, I select the five most commonly used international equity indices, which are the S&P 500 composite price index, Nikkei 225 composite index, UK FTSE all-share index, CAC all-tradable index and CDAX composite index. Returns are obtained from the Global Financial Data database. I compute monthly excess returns for each index by using index returns minus the corresponding country T-bill index returns.

In the second dataset, I use the monthly return of ten value-weighted industry portfolios obtained from Kenneth French's website. These ten industries are consumer nondurables (Nodur), consumer durables (Durbl), manufacturing (Manuf), energy (Enrgy), high technologies (Hitec), telephone and television transmission (Telcm), wholesale and retail shops (Shops), healthcare (Hlth), utilities (Utils), and others (Other). I calculate the excess return of each industry portfolio over the one-month Treasury bill rate.

In the third dataset, I dig into the individual stock level. I consider private investors who normally hold only a few stocks in their portfolios. I generate ten stock portfolios by randomly selecting ten stocks from the Centre for Research in Security Prices (CRSP) all stock universe. The process involves randomly selecting ten stocks that contain full returns for the previous 60 months, calculating the weightings using those 60 returns, computing the out-of-sample return for the next period according to those weightings, and rebalancing it

every month until the end of the data period. In total, I have 981 months during the testing period, which means that I have conducted the random selection 981 times.

Lastly, in the fourth dataset I incorporate bonds with equities as fixed-income assets are one of the main asset classes in the investment field. This multi-asset class dataset contains the US government bond (US ten-year government bond total return index), US corporate bond (Moody's Corporate AAA yield), US equity (S&P 500) and world equity (Global Financial Data world composites stock index). These four indices are obtained from the Global Financial Data database.

Table 4-2 demonstrates the returns, volatilities, Sharpe ratios and correlations for each asset in the four data sets. Country indices have slightly lower volatility, but much smaller returns on average compared with industries. Thus, the average Sharpe ratio of the country indices is lower than that of the industries. Ten industries are the closest integrated assets among all of the datasets. The highest correlation of 0.91 comes from Manufacturing industry and Other industry. The average return of the individual stocks is a bit higher than that of the industries, but is associated with much larger volatility. Therefore, the average Sharpe ratio of a ten-stock dataset (0.29) is lower than that of the industry dataset (0.41). The stocks have less correlation with each other compared with industries and countries. The multi-asset class dataset is a special case, as the corporate bond is negatively correlated with all the other three assets. The corporate bond has correlations of -0.73 with the government bond, -0.17 with US equity and -0.2 with world equity. The

corporate bond has an extremely low excess return of -3.37 and, thus, a low Sharpe ratio of -0.35. This particular feature of the four-asset class dataset leads to its distinct outcomes when compared with the other three datasets.

Table 4-2 Descriptive Statistics for Four Datasets

This table shows the excess returns, volatilities, Sharpe ratios and correlations of each asset within four datasets. All data are monthly from August 1926 to April 2013. Five country indices returns are taken from Global Financial Data. Ten industry portfolios are obtained from the Kenneth French website. Ten stocks are randomly selected every month from CRSP all stocks. Multi-asset classes are obtained from Global Financial Data.

Panel A: G5 country indices													
Countries	Excess Return	Volatility	Sharpe Ratio	Correlation Matrix									
				US	Japan	UK	Germany	France					
US	7.74	19.32	0.40	1.00									
Japan	5.65	22.59	0.25	0.16	1.00								
UK	1.68	16.67	0.10	0.40	0.22	1.00							
Germany	3.94	21.80	0.18	0.32	0.13	0.30	1.00						
France	4.29	21.58	0.20	0.33	0.18	0.39	0.31	1.00					

Panel B: Ten industry portfolios														
Industries	Excess Return	Volatility	Sharpe Ratio	Correlation Matrix										
				Nodur	Durbl	Manuf	Enrgy	Hitec	Telcm	Shops	Hlth	Utils	Other	
Nodur	8.37	16.16	0.52	1.00										
Durbl	9.48	27.10	0.35	0.75	1.00									
Manuf	8.68	22.08	0.39	0.85	0.87	1.00								
Enrgy	9.26	20.87	0.44	0.62	0.61	0.73	1.00							
Hitec	9.46	25.61	0.37	0.74	0.78	0.86	0.62	1.00						
Telcm	6.85	16.07	0.43	0.68	0.63	0.69	0.51	0.68	1.00					
Shops	8.64	20.53	0.42	0.87	0.80	0.85	0.59	0.79	0.68	1.00				
Hlth	9.49	19.62	0.48	0.80	0.64	0.76	0.57	0.72	0.61	0.75	1.00			
Utils	7.16	19.37	0.37	0.71	0.62	0.70	0.62	0.63	0.64	0.66	0.63	1.00		
Other	7.31	22.63	0.32	0.85	0.81	0.91	0.70	0.80	0.70	0.83	0.74	0.73	1.00	

(Continued on next page)

(Table 4-2 Continued)

Panel C: Random selected ten stocks													
Stocks	Excess Return	Volatility	Sharpe Ratio	Correlation Matrix									
				1	2	3	4	5	6	7	8	9	10
1	12.61	46.97	0.27	1.00									
2	11.15	46.62	0.24	0.20	1.00								
3	10.88	44.22	0.25	0.21	0.24	1.00							
4	13.31	43.71	0.30	0.16	0.22	0.24	1.00						
5	20.25	53.47	0.38	0.15	0.31	0.24	0.19	1.00					
6	9.47	44.68	0.21	0.20	0.29	0.26	0.26	0.24	1.00				
7	9.18	44.02	0.21	0.22	0.25	0.25	0.23	0.22	0.27	1.00			
8	22.68	63.11	0.36	0.21	0.18	0.21	0.17	0.21	0.29	0.13	1.00		
9	19.23	45.94	0.42	0.19	0.35	0.28	0.21	0.27	0.24	0.26	0.15	1.00	
10	14.05	50.08	0.28	0.22	0.28	0.21	0.14	0.24	0.26	0.21	0.22	0.23	1.00

Panel D: Four asset classes							
Assets	Excess Return	Volatility	Sharpe Ratio	Correlation Matrix			
				govt bond	corp bond	us equity	world equity
govt bond	1.92	6.47	0.30	1.00			
corp bond	-3.37	9.72	-0.35	-0.73	1.00		
us equity	7.84	19.30	0.41	0.07	-0.17	1.00	
world equity	2.13	13.40	0.16	0.09	-0.20	0.76	1.00

### **4.3.2 Out-of-sample portfolio construction**

For each dataset, I generate out-of-sample expected returns for strategy-based portfolios in order to evaluate and compare their performance in Section 4.4. I adopt the rolling sample analysis, which contains the process of computing the weighting matrix based on a certain estimation window and rolling it down one month forward until the end of the observation. To be precise, the first step is to analyse the assets' characteristics (return, variance, covariance, etc.) within the estimation window. In the baseline study, I choose an estimation window of 60 months ( $M=60$ ) based on the assumption that investors construct portfolios according to assets' previous five-year performance. I also analyse the situation when the estimation window is three years ( $M=36$ ) and ten years ( $M=120$ ). The strategy performance does not exhibit significant change when the estimation window changes. Based on the parameters obtained within the estimation window, the second step is to decide on the weighting matrix for the following month (the first observation starts at time  $t=M+1$ ) according to each asset allocation rule. I apply a short sale constraint when applying allocation methods, so the sum of the weights equals to one. I then use the weights multiplied by each asset return at time  $t=M+1$  in order to obtain the out-of-sample portfolio return. The final step is to roll down the process by removing the first return and adding the next month return into the estimation window. Thus, the portfolios are rebalanced monthly.

## 4.4 Strategy performance evaluation

In this section, I report the ex-ante performance of seven asset allocation strategies with regard to three measurement categories; Sharpe ratios (Table 4-3), risk-adjusted returns (Table 4-4), and risk factor loadings (Table 4-5). I then compare their performance with the ex-post optimal portfolio (Table 4-6). In each table, I report the results for the four datasets in separate panels.

### 4.4.1 Sharpe ratios

Within each dataset, I construct seven portfolios using each asset allocation strategy. I calculate the portfolios' out-of-sample returns over the full sample period, August 1931 to April 2013. Table 4-3 provides the annualised risk and return characteristics of the portfolios. I compare the economic and statistical differences in the portfolios' Sharpe ratios. I use the equally weighted portfolios as benchmarks in each dataset and compute the p-values of the differences between each strategy and the equally weighted portfolio. I adopt the circular block bootstrap method developed by Ledoit and Wolf (2008), which improves the validity of the time series sample hypothesis test in previous studies (Jobson and Korkie, 1981; Memmel, 2003). The null hypothesis I test is that the strategy Sharpe ratio has no statistical difference to the Sharpe ratio of the equally weighted portfolio,

$H_0: \mu_i/\sigma_i = \mu_{EW}/\sigma_{EW}$  where  $i$  stands for each strategy. Following DeMiguel, Garlappi, Nogales, and Uppal (2009), I employ a block size  $b=5$  and bootstrap re-samples  $B=1000$  when computing the p-value for the null hypothesis.

Panel A of Table 4-3 shows the performance of the strategy constructed portfolios using five country indices. The equally-weighted portfolio (EW) gets the highest excess return (5.25%), lowest volatility (13.22%) and highest Sharpe ratio (0.4) among all seven portfolios. However, the Sharpe ratio of the best strategy, equal weighting (0.4), is not significantly different from the worst strategy, which is mean variance (0.29), with a p-value of 0.16. The Sharpe ratios of the other six strategies are even closer.

For industry-based portfolios, the asset allocation strategies also perform indistinguishably from each other. Panel B shows that the differences in Sharpe ratios produced by strategies are quite small in economic terms. The minimum variance strategy (Min V) performs the best, with a Sharpe ratio of 0.54. This is only 0.08 higher than the lowest Sharpe ratio in the mean variance method (Mean V). They (minimum variance and mean variance approaches) both lack statistical difference from the naïve diversification rule (EW). Although the equal risk contribution approach (ERC) produces statistically higher Sharpe ratio than the naïve 1/N rule, the difference is only 0.01.

In panel C, I report the characteristics of the stock-based portfolios. The equal risk contribution method (ERC) and the maximum diversification method (MD) perform better than the other strategies, with Sharpe ratios of 0.63 and 0.59, respectively. They both perform significantly better than the equal weighting method, which has a Sharpe ratio of 0.54. In particular, the maximum diversification portfolio produces a higher return (15.7%) and lower risk (24.79%) than the equally weighted portfolio.

Panel D reveals the performance of portfolios made by the four asset classes. Three risk-based approaches, minimum variance, equal risk contribution and maximum diversification generate extremely low annual excess returns of 0.12%, 0.47% and 0.18%, respectively. The reason for this is that they allocate large weights to low volatility assets (the corporate bond), which has a negative average return. Therefore, the Sharpe ratio of the minimum variance (0.04) and maximum diversification (0.07) is significantly different from that of naïve diversification (0.31).

It is worth mentioning that none of the equally weighted portfolios is significantly different from either the mean variance or risk parity portfolios for all of the datasets I test. Although the Sharpe ratios of the mean variance rule are less than for all of the other methods in every dataset except the four assets class, none of them is statistically different from the naïve diversification. The result indicates that the choice of naïve diversification, mean variance, or risk parity strategies does not have a strong impact on the investment outcomes irrespective of the assets invested in. Also, if investors allocate funds on highly correlated assets, such as countries and industries, all the asset allocation strategies tested here will perform indifferently.

Table 4-3 Out-of-sample Performance of Strategy Constructed Portfolios

This table reports the out-of-sample performance of each strategy constructed portfolio from August 1931 to April 2013. The excess returns and volatility are in percentages. All the parameters are annualised. The p-value is the probability that each strategy is the same as the equal-weighting (EW) strategy. P-values are calculated using Oliver Ledoit and Wolf (2008) method. Mean V denotes the mean variance approach; RP Var, the risk parity based on variance; RP Vol, the risk parity based on volatility; Min V, the minimum variance; ERC, the equal risk contribution; and MD, the maximum diversification.

Strategy	Excess Return	Volatility	Sharpe Ratio	P-value
Panel A: G5 country indices				
EW	5.25	13.22	0.40	-
Mean V	4.33	14.93	0.29	0.16
RP Var	4.98	15.28	0.33	0.10
RP Vol	5.09	14.25	0.36	0.15
Min V	5.16	15.33	0.34	0.29
ERC	5.03	14.09	0.36	0.13
MD	5.02	13.85	0.36	0.29
Panel B: Ten industry portfolios				
EW	8.69	17.90	0.49	-
Mean V	8.33	18.05	0.46	0.67
RP Var	8.35	16.39	0.51	0.22
RP Vol	8.54	17.13	0.50	0.20
Min V	7.42	13.85	0.54	0.37
ERC	8.51	16.96	0.50	0.08
MD	8.28	15.78	0.52	0.19
Panel C: Random selected ten stocks				
EW	14.28	26.61	0.54	-
Mean V	10.70	24.19	0.44	0.25
RP Var	12.44	21.23	0.59	0.26
RP Vol	13.25	23.17	0.57	0.12
Min V	11.41	20.32	0.56	0.74
ERC	13.71	23.08	0.59	0.03
MD	15.70	24.79	0.63	0.03
Panel D: Four asset classes				
EW	2.29	7.45	0.31	-
Mean V	2.55	8.85	0.29	0.85
RP Var	1.19	3.89	0.31	0.99
RP Vol	1.48	4.72	0.31	0.91
Min V	0.12	2.56	0.04	0.05
ERC	0.47	2.86	0.16	0.15
MD	0.18	2.63	0.07	0.05

#### 4.4.2 Alphas from factor models

In this section, I evaluate the risk-adjusted performance of asset allocation strategies by regressing strategy made portfolios on the risk factors that are stated in several commonly used asset pricing models. The alphas generated from the models are the returns that a portfolio produces in excess of what should be earned based on the risk taken. Within the dataset, if one strategy makes the portfolio produce a larger alpha than the others, this particular strategy is shown to be superior in terms of the risk-adjusted return. For comparison, I also compute the p-values to explore whether the alphas generated from the strategies are significantly different from the alphas produced by equal weighting.

I consider alphas from the four usual asset pricing models. The first one is the Jensen's alpha from the Single Index Model (Jensen et al., 1972; Lintner, 1965; Sharpe, 1964), which links portfolio returns with the market risk (RMRF), as shown in equation (4.9). The second model is the widely used Fama and French (1993) three factor model that includes market risk, size (SMB) and value (HML) factors as explanatory variables (equation 4.10). The third one is the Carhart (1997) four factor model, which aims to capture the momentum effect. As shown in equation (4.11), the four factor model adds a momentum factor (UMD) to the existing three factor model. Additionally, I include the recently developed Fama and French (2014) five factor model in our tests. Equation 4.12 illustrates that Fama and French (2014) introduce profitability (RMW) and investment (CMA) factors into their original three factor model (equation 4.10) as based on the valuation theory; the expected return is

positively correlated with the firm's profitability and negatively correlated with the firm's investment.

$$R_{it} - R_{Ft} = \alpha_i + \beta_{mkt}RMRF_t + e_{it} \quad (4.9)$$

$$R_{it} - R_{Ft} = \alpha_i + \beta_{mkt}RMRF_t + \beta_{smb}SMB_t + \beta_{hml}HML_t + e_{it} \quad (4.10)$$

$$R_{it} - R_{Ft} = \alpha_i + \beta_{mkt}RMRF_t + \beta_{smb}SMB_t + \beta_{hml}HML_t + \beta_{umd}UMD_t + e_{it} \quad (4.11)$$

$$R_{it} - R_{Ft} = \alpha_i + \beta_{mkt}RMRF_t + \beta_{smb}SMB_t + \beta_{hml}HML_t + \beta_{rmw}RMW_t + \beta_{cma}CMA_t + e_{it} \quad (4.12)$$

Table 4-4 demonstrates the alphas from all four asset pricing models. In panel A, the dependent variables are the portfolios constructed using five country indices. I use the global factors from the Kenneth French website for the period from November 1990 to April 2013. As the profitability and investment factors are not available on international data, I only run the CAPM, three factor model and the Carhart four factor model.<sup>24</sup> The results show that all the strategies generate negative alphas for all three models except for the mean variance rule, which produces a positive three factor alpha of 0.08 and a Carhart alpha of 0.15. Those negative alphas indicate that the strategy makes portfolios underperform the world index in general. Also, no strategy

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<sup>24</sup> The global factors on the Kenneth French website include 23 countries. As G5 countries are in the leading position and are included in these 23 countries, I use global factors in this study. The momentum factor is denoted as WML in the global factor, while it is denoted as Mom in the US factor.

performs statistically differently from the naïve diversification on a risk-adjusted basis.

For portfolios constructed using industries, stocks and asset classes, I regress them on US factors, which are available from the Kenneth French website from July 1963 to April 2013. Panel B reports the alphas for the industry dataset. The mean variance approach bears high momentum exposure, as it generates a Carhart alpha of 0.02 compared with its five-factor alpha of 0.11. Except for the mean variance approach, the minimum variance strategy performs the best with a CAPM alpha of 0.18, a three-factor alpha of 0.09, a Carhart alpha of 0.10 and a five factor alpha of 0.06, which are all higher than those of the other strategies. These results on alphas are in line with the previous test using the Sharpe ratio, where the minimum variance approach produces the highest Sharpe ratio in the industry dataset. On the other hand, the investment and profitability factors has added an explanatory power to the variation of portfolio returns as the five factor model alphas are much smaller than three factor alphas for all of the strategies except the mean variance rule. The equal weighting, risk parity and equal risk contribution approaches even result in negative five factor alphas, while the other alphas they produce are positive.

For the stock-based portfolios shown in panel C, all the alphas are positive and much higher than the alphas in the other datasets. The maximum diversification portfolio generates the three highest alphas, with a CAPM alpha of 0.82, a three factor alpha of 0.66 and a five factor alpha of 0.58. This is also in line with the previous section that finds that maximum diversification obtains

the highest Sharpe ratio among all strategies in the stock dataset. Moreover, none of the strategies are statistically different to the equally weighted portfolio for all four models I test.

In panel D of Table 4-4 I report the alphas for the multi-asset class portfolios. Including bonds in the portfolio greatly reduces the risk-adjusted returns. Almost all of the alphas in the multi-asset portfolios are negative, except for the mean variance portfolio, which produces a three-factor alpha of 0.08 and a five factor alpha of 0.05. These positive alphas are, however, not statistically significantly different from the negative alphas produced by the equally weighted portfolios. However, the three risk-based portfolios; the minimum variance, the equal risk contribution, and the maximum diversification portfolios; result in statistically smaller negative alphas (with p-values less than 10%) compared with the alphas in the equally weighted portfolio.

Table 4-4 Alphas from Asset Pricing Models

This table compares the alphas generated by strategy made portfolios regressed on the risk factors, as stated in asset pricing models. For the country indices dataset, I test CAPM, the Fama-French three factor model and the Carhart four factor model. I use global factors on the Kenneth French website from November 1990 to April 2013. For the remaining three datasets I also use the Fama-French five factor model. I obtain the US factors on the Kenneth French website from July 1963 to April 2013. The p-value is tested for the hypothesis that the intercept from each regression is the same as the intercept generated from equal weighting.

Portfolios	CAPM $\alpha$	P- value	FF three Factor $\alpha$	P- value	Carhart four Factor $\alpha$	P- value	FF five Factor $\alpha$	P- value
Panel A: G5 country indices (Nov 1990 - Apr 2013)								
EW	-0.20	1.00	-0.19	1.00	-0.18	1.00		
Mean V	0.00	0.23	0.08	0.23	0.15	0.23		
RP Var	-0.14	0.74	-0.13	0.74	-0.11	0.74		
RP Vol	-0.16	0.86	-0.16	0.86	-0.15	0.86		
Min V	-0.06	0.51	-0.05	0.51	-0.04	0.51		
ERC	-0.17	0.91	-0.17	0.91	-0.16	0.91		
MD	-0.15	0.77	-0.15	0.78	-0.15	0.78		
Panel B: Ten industry portfolios (Jul 1963 - Apr 2013)								
EW	0.11	1.00	0.05	1.00	0.08	1.00	-0.02	1.00
Mean V	0.09	0.63	0.18	0.63	0.02	0.63	0.11	0.62
RP Var	0.14	0.96	0.07	0.95	0.09	0.95	-0.01	0.95
RP Vol	0.13	0.95	0.06	0.94	0.08	0.94	-0.02	0.94
Min V	0.18	0.57	0.09	0.54	0.10	0.54	0.06	0.54
ERC	0.13	0.97	0.07	0.97	0.08	0.97	-0.01	0.97
MD	0.12	0.48	0.07	0.45	0.08	0.45	0.05	0.44
Panel C: Random selected ten stocks (Jul 1963 - Apr 2013)								
EW	0.62	1.00	0.45	1.00	0.71	1.00	0.47	1.00
Mean V	0.26	0.13	0.22	0.12	0.13	0.12	0.12	0.12
RP Var	0.55	0.56	0.35	0.53	0.46	0.53	0.21	0.53
RP Vol	0.57	0.74	0.38	0.72	0.54	0.71	0.29	0.72
Min V	0.52	0.39	0.35	0.37	0.38	0.36	0.23	0.37
ERC	0.63	0.86	0.44	0.86	0.57	0.85	0.37	0.86
MD	0.82	0.72	0.66	0.71	0.70	0.71	0.58	0.71
Panel D: Four asset classes (Jul 1963 - Apr 2013)								
EW	-0.10	1.00	-0.09	1.00	-0.10	1.00	-0.11	1.00
Mean V	-0.01	0.60	0.08	0.60	-0.03	0.59	0.05	0.60
RP Var	-0.03	0.61	-0.01	0.60	-0.03	0.60	-0.05	0.60
RP Vol	-0.07	0.68	-0.05	0.67	-0.06	0.67	-0.08	0.66
Min V	-0.06	0.04	-0.04	0.04	-0.06	0.04	-0.08	0.04
ERC	-0.07	0.06	-0.04	0.06	-0.06	0.06	-0.09	0.06
MD	-0.07	0.04	-0.05	0.03	-0.06	0.03	-0.09	0.03

#### 4.4.3 Risk factor loadings

In this section, I further evaluate the risk exposures associated with each asset allocation strategy. As illustrated in equation (4.11), I regress strategy-made portfolios on the Carhart four factors; market ( $\beta_{mkt}$ ), size ( $\beta_{smb}$ ), value ( $\beta_{hml}$ ), and momentum ( $\beta_{umd}$ ). The betas ( $\beta_{mkt}$ ,  $\beta_{smb}$ ,  $\beta_{hml}$ ,  $\beta_{umd}$ ) of each risk factor in the regression are the corresponding risk loadings. I aim to compare the risk loadings in order to understand what drives the performance of each asset allocation strategy and how stable the risk shifting is. I employ the rolling sample regression in order to explore the variation of risk exposures in every five-year period. At each time  $t$ , I get the betas by using the data from time  $t-60$  to  $t$ . I then compute the average and the standard deviation of these time series betas.

Panel A of Table 4-5 reports the factor loadings for the portfolio construction methods in country diversification. All of the strategies bear negative exposures to small-cap countries except for the maximum diversification approach, which has a positive size beta of 0.04. Also, all of the methods are positively related to the value effect except for the mean variance rule, which has a negative value factor loading of -0.13. Among all the strategies, the mean variance rule is associated with larger risk shifting with respect to all four factors. For instance, the standard deviations of the market and value betas generated from the mean variance approach are more than twice those generated from the other strategies.

For the industry diversification shown in panel B, the results are similar to the country-based portfolios. Again, the mean variance approach has the

highest variation with respect to all the risk factors. The standard deviations of the market, size and momentum risk loadings in the mean variance portfolio are more than four times those for the equally weighted portfolio. Moreover, it seems that the performance of mean variance is driven by the momentum effect, as a relatively high momentum beta of 0.23 is obtained in the mean variance portfolio, while the other techniques have momentum betas of approximately zero.

The risk loadings for strategies in the individual stock dataset are shown in panel C. The equal weighting method is associated with high small-cap stocks exposure, with a size beta of 0.75 as well as a relatively large negative momentum risk loading of -0.23. The mean variance rule is positively related to the momentum factor, while the other strategies are negatively related. The naïve diversification rule and the mean variance method lead to slightly higher fluctuations in risk exposures. The variation in betas for the other techniques is similar.

Panel D reveals the risk exposures for portfolios made up of multi-asset classes. The four risk factors provide little explanation for the variation in the portfolios, as all the risk loadings are quite small. The mean variance approach still implies higher risk shifting for all the factors. The standard deviations of all the factor loadings generated by the mean variance rule are approximately three times those produced in the other strategies.

Table 4-5 Risk Factor Loadings of the Carhart Four Factor Model

This table reveals the strategies' risk loadings for the market ( $\beta_{mkt}$ ), size ( $\beta_{smb}$ ), value ( $\beta_{hml}$ ) and momentum ( $\beta_{umd}$ ) factors. I run a five-year regression on the four factors from the beginning of the portfolio returns, keep the five-year estimation window and rolling one month forward until the end of the observation. This table reports the average and standard deviation of the betas. EW demotes the equal weighting; Mean V, the mean variance rule; RP Var, the risk parity based on variance; RP Vol, the risk parity based on volatility; Min V, the minimum variance; ERC, the equal risk contribution; and MD, the maximum diversification.

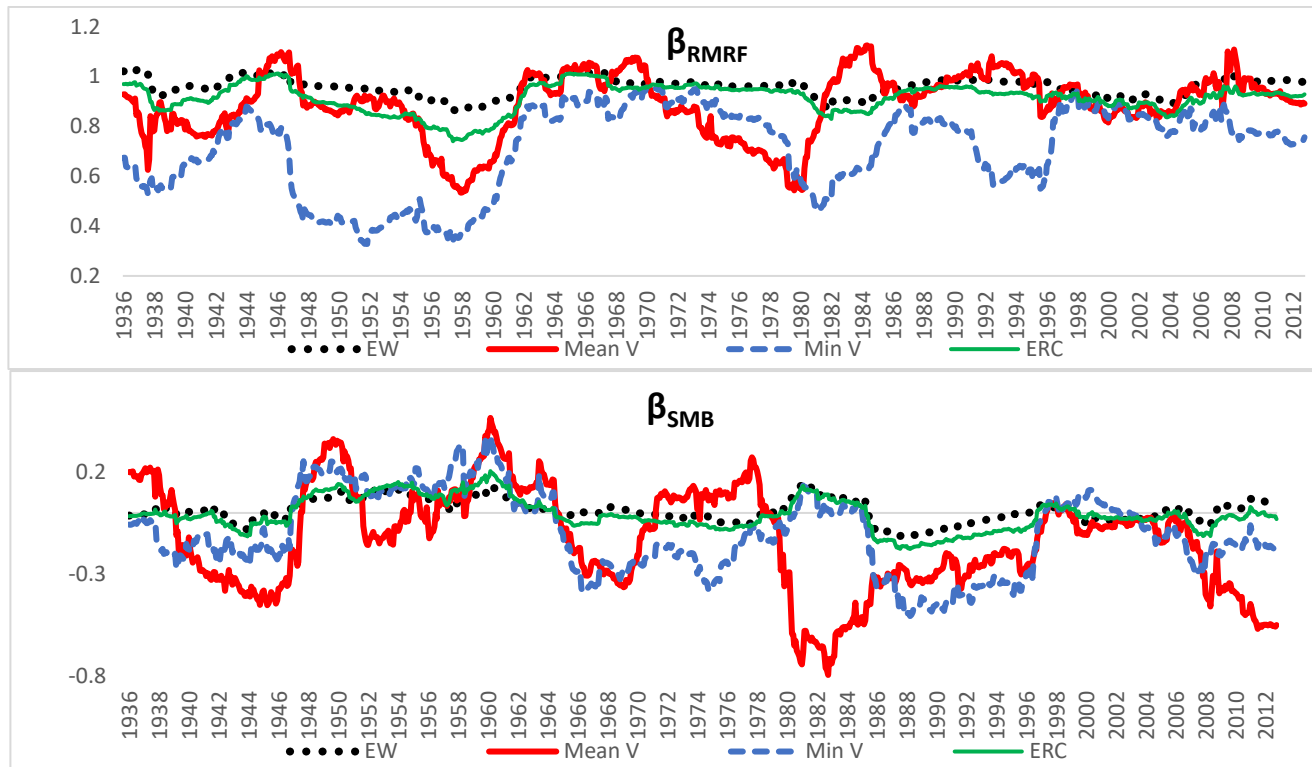
Portfolios	$\beta_{mkt}$	SD( $\beta_{mkt}$ )	$\beta_{umd}$	SD( $\beta_{umd}$ )	$\beta_{smb}$	SD( $\beta_{smb}$ )	$\beta_{hml}$	SD( $\beta_{hml}$ )
Panel A: G5 country indices (Nov 1990 - Apr 2013)								
EW	0.90	0.09	-0.07	0.10	0.08	0.14	0.03	0.09
Mean V	0.93	0.20	-0.20	0.14	-0.13	0.33	0.04	0.16
RP Var	0.86	0.11	-0.10	0.09	0.07	0.16	0.04	0.12
RP Vol	0.88	0.10	-0.08	0.10	0.08	0.15	0.04	0.11
Min V	0.81	0.10	-0.12	0.11	0.03	0.23	0.03	0.10
ERC	0.88	0.09	-0.07	0.10	0.07	0.14	0.03	0.10
MD	0.88	0.06	0.04	0.15	0.02	0.13	0.01	0.08
Panel B: Ten industry portfolios (Jul 1963 - Apr 2013)								
EW	0.96	0.03	0.00	0.05	0.06	0.11	-0.04	0.04
Mean V	0.90	0.12	-0.20	0.22	-0.05	0.29	0.23	0.18
RP Var	0.91	0.04	-0.04	0.07	0.12	0.13	-0.03	0.06
RP Vol	0.93	0.03	-0.02	0.06	0.09	0.12	-0.03	0.05
Min V	0.78	0.12	-0.17	0.17	0.26	0.20	0.00	0.12
ERC	0.92	0.03	-0.04	0.06	0.10	0.12	-0.03	0.05
MD	0.87	0.07	-0.12	0.12	0.15	0.15	-0.02	0.07
Panel C: Random selected ten stocks (Jul 1963 - Apr 2013)								
EW	0.86	0.20	0.75	0.31	0.18	0.30	-0.23	0.26
Mean V	0.76	0.16	0.29	0.25	0.04	0.30	0.13	0.26
RP Var	0.83	0.14	0.39	0.22	0.27	0.18	-0.15	0.13
RP Vol	0.86	0.15	0.56	0.27	0.25	0.16	-0.17	0.15
Min V	0.77	0.15	0.22	0.23	0.30	0.22	-0.10	0.20
ERC	0.84	0.14	0.52	0.23	0.27	0.16	-0.15	0.15
MD	0.80	0.15	0.46	0.24	0.28	0.18	-0.10	0.24
Panel D: Four asset classes (Jul 1963 - Apr 2013)								
EW	0.42	0.04	-0.07	0.04	-0.01	0.04	0.02	0.03
Mean V	0.37	0.27	-0.10	0.13	-0.01	0.15	0.09	0.10
RP Var	0.23	0.09	-0.07	0.05	-0.03	0.05	0.02	0.03
RP Vol	0.32	0.06	-0.07	0.04	-0.02	0.04	0.02	0.03
Min V	0.03	0.04	-0.03	0.04	-0.06	0.06	0.02	0.03
ERC	0.10	0.04	-0.03	0.03	-0.06	0.06	0.02	0.03
MD	0.04	0.05	-0.03	0.03	-0.06	0.06	0.02	0.03

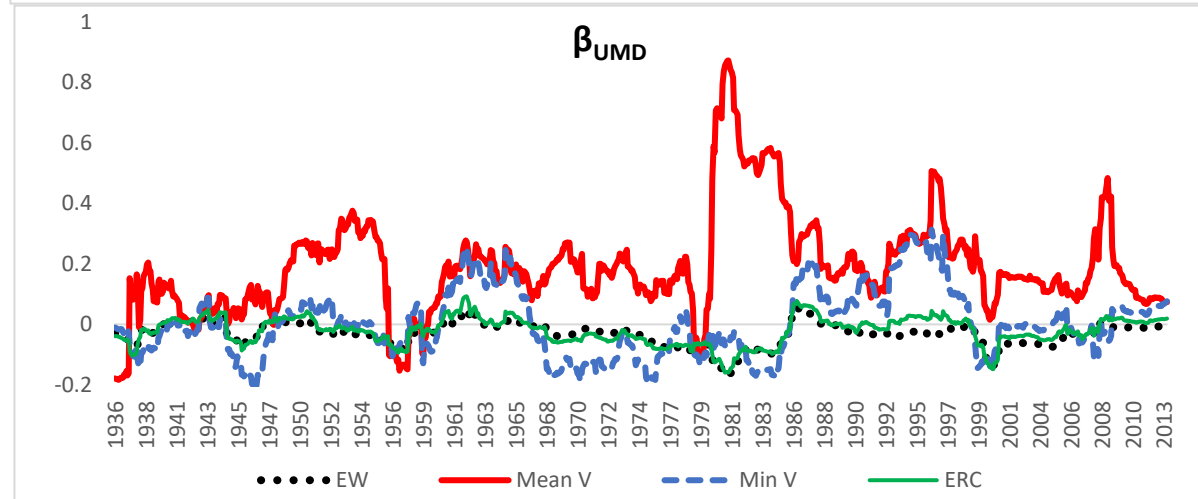
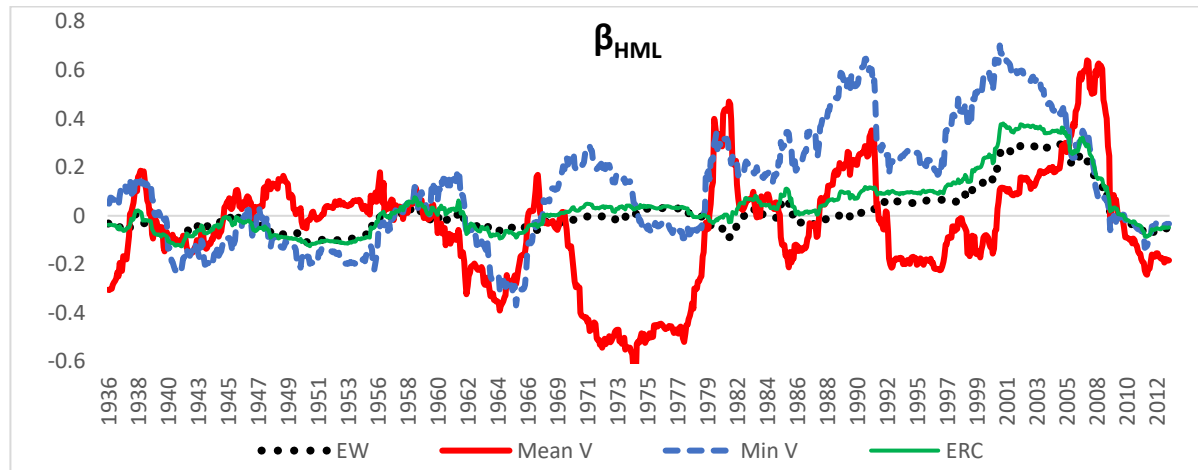
To better demonstrate the risk exposures associated with the portfolio construction methods over time, I plot the risk loadings for every five-year period in Figure 4-1. I use portfolios made by industries as an illustration. The plots for the other three datasets are similar. The four factors are calculated using rolling sample regression with an estimation window of five-years. Figure 4-1 only plots the risk exposures associated with the equal-weighted, mean variance weighted, minimum variance weighted and equal risk contribution portfolios. The risk variations within the other three methods are similar to that of the equal risk contribution technique.

The equal weighting and equal risk contribution strategies lead to relatively stable risk exposures with regards to market, size, value and momentum factors. The market betas of these two strategies are approximately one over time. In contrast, the minimum variance method produces smaller market betas and more fluctuation. Moreover, the naïve diversification and equal risk contribution methods result in size, value and momentum risk loadings of around zero over time. However, the mean variance and minimum variance portfolios imply risk shifting throughout the study period in regard to these three factors. For the momentum factor in particular, it is obvious that the performance of the mean variance portfolio is driven by the momentum factor since the risk loadings are relatively large throughout time.

Figure 4-1 Strategy Made Portfolio Risk Exposures Over Time

This figure illustrates the time varying risk exposures associated with the industry portfolios constructed according to different asset allocation strategies. The strategies shown here are equal weighting (EW), mean variance weighting (Mean V), minimum variance weighting (Min V) and equal risk contribution (ERC). I evaluate the risk loadings with respect to the market ( $\beta_{RMRF}$ ), size ( $\beta_{SMB}$ ), value ( $\beta_{HML}$ ) and momentum ( $\beta_{UMD}$ ) factors.





#### 4.4.4 How far are they from the real optimal?

Since all of the asset allocation strategies I test are indistinguishable from each other most of the time, it is worth asking; are they all approaching optimal? If not, how far are they from ex-post mean variance efficient? In order to answer these questions, I apply the in sample (ex-post) mean variance method to construct the real optimal portfolio for comparison purposes. In the out-of-sample testing, I use an estimation window of 60 months ( $M=60$ ) and calculate the return at time  $t$  by evaluating the assets' characteristics from time  $t-M$  to  $t-1$ . For the in-sample optimal portfolio construction, I assume that the investors have perfect foresight so that they know the returns at time  $t$ . Therefore, I get the ex-post optimal return at time  $t$  by evaluating the assets' characteristics from time  $t-M+1$  to  $t$  (and the estimation window is still 60 months). Figure 4-2 illustrates the process of ex-ante and ex-post portfolio construction. For the return at the same month, there is only one month return difference between these two portfolios during the estimation process. The ex-ante portfolio uses return at month  $t-M$ , while the ex-post portfolio uses the return at time  $t$ .

## Figure 4-2 Portfolio Returns Construction

Figure 4-2a illustrates the process of the ex-ante portfolio return construction. I estimate the assets' return and risk characteristics during month  $t-M$  to  $t-1$  in order to determine the weighting matrix. Then I calculate the return at time  $t$  by using the weighting matrix multiplied by the return matrix of assets at time  $t$ . The portfolio returns are obtained by rolling the window one month down.

### Figure 4-2a. Ex-ante portfolio returns construction

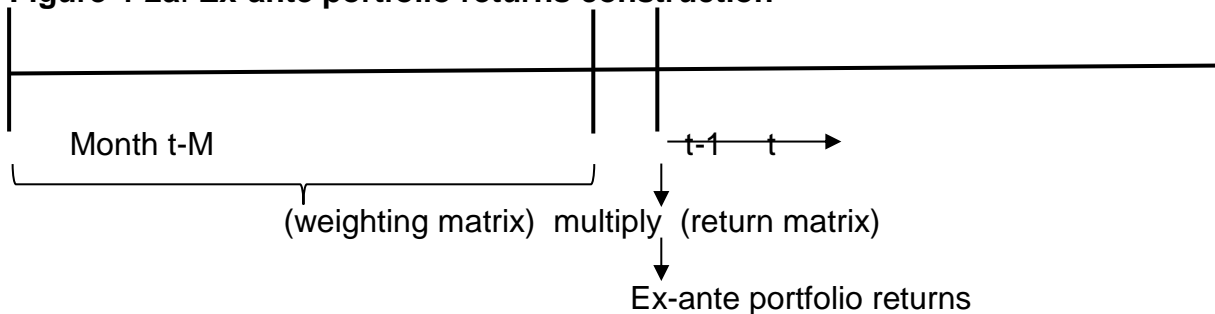


Figure 4-2b illustrates the process of the ex-post optimal portfolio return construction. I assume that investors already know the return at time  $t$ . I first estimate the assets' characteristics during month  $t-M+1$  to  $t$  in order to determine the optimal weighting matrix using the mean variance method. Then I calculate the return at time  $t$  by using the weighting matrix multiplied by the return matrix of assets at time  $t$ . I get the optimal portfolio returns by rolling the window one month forward.

### Figure 4-2b. Ex-post portfolio returns construction

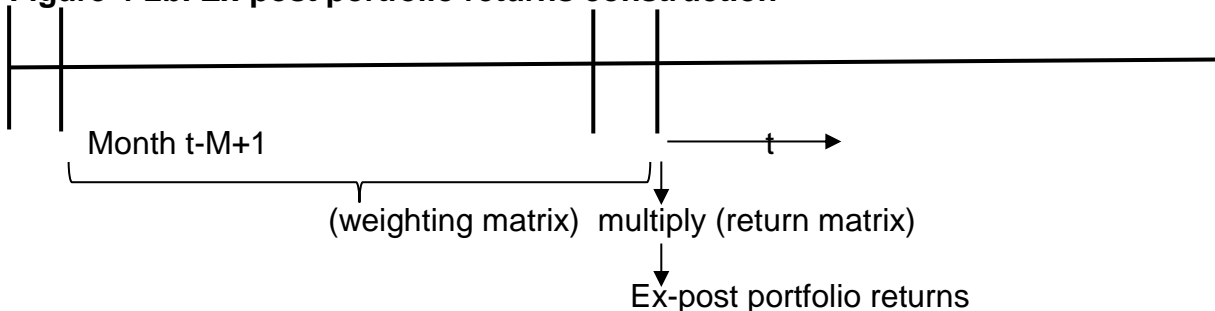


Table 4-6 compares the performance of strategy made portfolios with the optimal one. The p-value is the probability that the strategy is optimal. For all the data sets, the Sharpe ratios for the optimal portfolios are exceedingly higher than for any of the strategies and are all significant at the 5% level. For portfolios made using country indices, the ten industries and individual stocks, the highest Sharpe ratios generated by the strategies are approximately two-

thirds of the corresponding optimal Sharpe ratios. The difference is even larger for portfolios made using the four asset classes. The optimal portfolio has a Sharpe ratio of 0.58, while the highest Sharpe ratio generated by the strategies (equal weighting and risk parity) is around half (0.31) that and the lowest one generated by the minimum variance rule is less than one-tenth that, at only 0.04.

In particular, the out-of-sample mean variance portfolio shares the same methodology with the in sample optimal portfolio, but results in extremely inferior performance to the latter portfolio. By observing the difference between them I gain a sense of the magnitude of estimation errors in practice. For instance, the out-of-sample mean variance Sharpe ratio (0.29) is only half of the optimal Sharpe ratio (0.6) for the country indices portfolio (panel A of Table 4-6).

Although the choice among the current strategies does not significantly affect portfolio performance, asset allocation methods still have a strong impact on investment, as I illustrate how the performance would be better if optimal construction could be approached. After all the new methods proposed in the literature, the portfolios are still far from optimal. In other words, the estimation errors are still large in both the traditional and risk-based strategies.

Table 4-6 Performance of Ex-ante Strategy-based Portfolios Compared with the Ex-post Optimal Portfolio

This table reports the performance of each strategy constructed portfolio compared with the in-sample optimal portfolio. The p-value is the probability that each strategy made portfolio is the same as the in-sample optimal portfolio. All the parameters are annualised; the excess return and volatility are expressed in percentages.

Rules	Excess Return	Volatility	Sharpe Ratio	P-value
<b>Panel A: G5 country indices</b>				
Optimal (in sample)	9.29	15.60	0.60	-
EW	5.25	13.22	0.40	0.003
Mean V	4.33	14.93	0.29	0.001
RP Var	4.98	15.28	0.33	0.002
RP Vol	5.09	14.25	0.36	0.001
Min V	5.16	15.33	0.34	0.004
ERC	5.03	14.09	0.36	0.001
MD	5.02	13.85	0.36	0.003
<b>Panel B: Ten industry portfolios</b>				
Optimal (in sample)	14.23	18.56	0.77	-
EW	8.69	17.90	0.49	0.001
Mean V	8.33	18.05	0.46	0.001
RP Var	8.35	16.39	0.51	0.001
RP Vol	8.54	17.13	0.50	0.001
Min V	7.42	13.85	0.54	0.006
ERC	8.51	16.96	0.50	0.001
MD	8.28	15.78	0.52	0.001
<b>Panel C: Random selected ten stocks</b>				
Optimal (in sample)	22.68	23.43	0.97	-
EW	14.28	26.61	0.54	0.001
Mean V	10.70	24.19	0.44	0.001
RP Var	12.44	21.23	0.59	0.001
RP Vol	13.25	23.17	0.57	0.001
Min V	11.41	20.32	0.56	0.001
ERC	13.71	23.08	0.59	0.001
MD	15.70	24.79	0.63	0.001
<b>Panel D: Four asset classes</b>				
Optimal (in sample)	5.06	8.69	0.58	-
EW	2.29	7.45	0.31	0.013
Mean V	2.55	8.85	0.29	0.001
RP Var	1.19	3.89	0.31	0.049
RP Vol	1.48	4.72	0.31	0.035
Min V	0.12	2.56	0.04	0.002
ERC	0.47	2.86	0.16	0.006
MD	0.18	2.63	0.07	0.002

## 4.5 Strategy performance over time

This chapter illustrates the performance of asset allocation strategies across different datasets in Section 4.4 above. None of the strategies examined is able to significantly outperform the others in all four datasets. In this section, I examine their performance over time. The objective is to check the consistency of strategy performance over different time periods.

### 4.5.1 Business cycle

Firstly, this study analyses strategy performance during different states within business cycles. According to the separation date from the National Bureau of Economic Research (NBER), I obtain 14 business cycles in total from August 1931 to June 2009 (where the NBER dates end). I separate the ex-ante strategy returns during recession from the returns during expansion.

In Table 4-7, I report the annualised average excess returns, volatilities and Sharpe ratios of each of the strategies in both periods. For the country and industry portfolios, the differences between strategies are still small irrespective of the economic status. Panel A shows that none of the strategies are significantly different from the naïve diversification rule when investing in country indices. For the industry dataset exhibits in panel B, although during contraction the Sharpe ratios of the risk parity (-0.29) and equal risk contribution (-0.28) portfolios are statistically significantly higher than that of the equally weighted portfolio (-0.31), the magnitude is negligible.

For the equity portfolio, asset allocation methods perform differently during expansion but not during periods of contraction. Panel C shows that even

though the equally weighted portfolio obtains the lowest Sharpe ratio during contraction, it is not statistically different to the other portfolios. However, when in the bull market, the Sharpe ratios of the equal risk contribution (0.84) and risk parity based on volatility (0.81) strategies are statistically higher than those of the naïve diversification rule (0.76).

Panel D of Table 4-7 shows that the performance of strategies produce even larger differences in the multi-asset class dataset. During the recession period, the minimum variance method obtains the only positive Sharpe ratio of 0.03, which is substantially higher than the other strategies. Also, the risk parity strategy based on variance produces a Sharpe ratio of -0.12, which is significantly higher than the equal weighting rule (-0.6). However, during expansion, the strategy performances completely change. The naïve diversification rule becomes the best one and it significantly outperforms the minimum variance, equal risk contribution and maximum diversification rules at the 1% level. In this case, the minimum variance portfolio generates an extremely low Sharpe ratio of 0.05 which is even less than the 10% Sharpe ratio generated by the equally weighted portfolio.

Table 4-7 Asset Allocation Strategy Performance over Business Cycle

This table reports the annualised strategy performance metrics during contraction and expansion. I separate all the contraction and expansion returns according to the NBER business cycle reference dates during the period from August 1931 to June 2009. The return and volatility are in percentages. The p-value is the probability that the strategy is the same as the equal-weighting (EW). P-values are calculated using the Ledoit and Wolf (2008) method. The mean V denotes the mean variance approach; RP Var, the risk parity based on variance; RP Vol, the risk parity based on volatility; Min V, the minimum variance; ERC, the equal risk contribution; and MD, the maximum diversification.

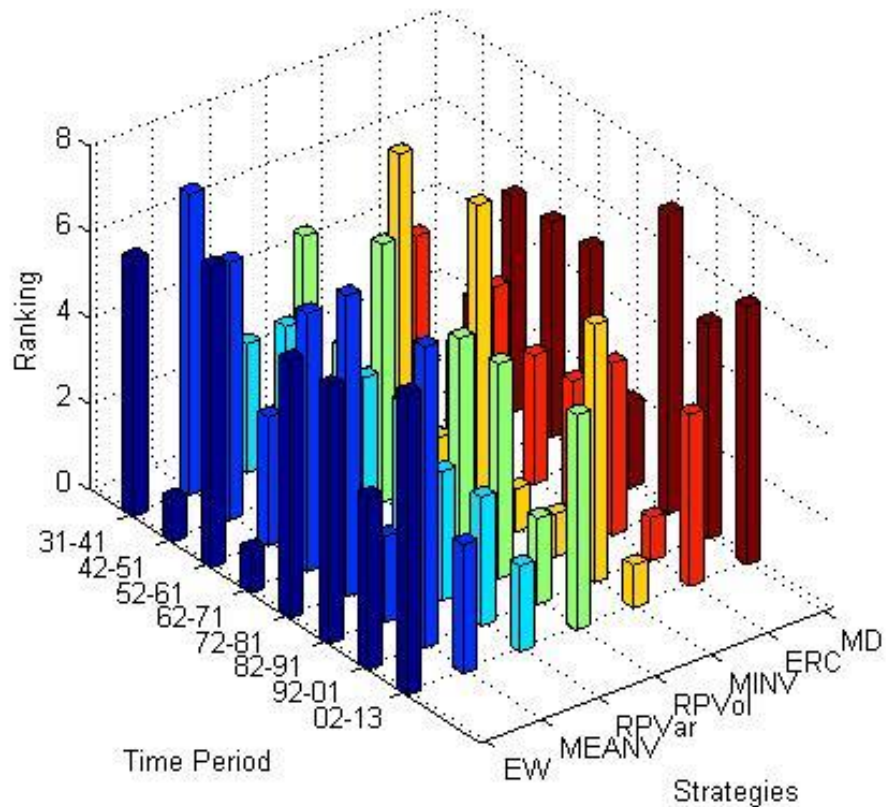
Rules	Contraction				Expansion			
	Excess Return	Volatility	Sharpe Ratio	P-value	Excess Return	Volatility	Sharpe Ratio	P-value
Panel A: G5 country indices								
EW	-8.81	18.66	-0.47	-	7.98	11.73	0.68	-
Mean V	-14.51	20.84	-0.70	0.26	7.98	13.25	0.60	0.40
RP Var	-9.93	16.38	-0.61	0.23	7.87	14.92	0.53	0.22
RP Vol	-9.49	17.10	-0.55	0.27	7.91	13.49	0.59	0.26
Min V	-9.41	16.13	-0.58	0.42	7.99	15.05	0.53	0.27
ERC	-9.09	17.24	-0.53	0.44	7.77	13.26	0.59	0.20
MD	-8.52	18.13	-0.47	0.99	7.64	12.73	0.60	0.12
Panel B: Ten industry portfolios								
EW	-8.68	27.71	-0.31	-	12.16	15.03	0.81	-
Mean V	-8.21	28.11	-0.29	0.81	11.63	15.12	0.77	0.58
RP Var	-6.81	25.58	-0.27	0.10	11.37	13.71	0.83	0.34
RP Vol	-7.68	26.65	-0.29	0.09	11.77	14.34	0.82	0.27
Min V	-3.30	20.93	-0.16	0.18	9.56	11.87	0.81	0.96
ERC	-7.44	26.41	-0.28	0.07	11.69	14.19	0.82	0.15
MD	-5.60	23.77	-0.24	0.30	11.05	13.53	0.82	0.81
Panel C: Random selected ten stocks								
EW	-6.47	35.90	-0.18	-	18.42	24.19	0.76	-
Mean V	-3.45	30.92	-0.11	0.78	13.52	22.55	0.60	0.07
RP Var	-2.96	30.06	-0.10	0.37	15.50	18.89	0.82	0.27
RP Vol	-5.07	32.20	-0.16	0.62	16.91	20.78	0.81	0.09
Min V	1.42	27.38	0.05	0.30	13.40	18.56	0.72	0.61
ERC	-3.93	32.37	-0.12	0.34	17.22	20.62	0.84	0.03
MD	0.82	34.99	0.02	0.17	18.67	22.13	0.84	0.13
Panel D: Four asset classes								
EW	-6.35	10.52	-0.60	-	4.01	6.56	0.61	-
Mean V	-6.09	10.68	-0.57	0.92	4.27	8.36	0.51	0.38
RP Var	-0.63	5.45	-0.12	0.10	1.56	3.50	0.45	0.10
RP Vol	-2.95	6.33	-0.47	0.47	2.37	4.29	0.55	0.24
Min V	0.11	3.51	0.03	0.07	0.12	2.32	0.05	0.001
ERC	-1.28	3.84	-0.33	0.35	0.82	2.62	0.31	0.003
MD	-0.38	3.64	-0.10	0.15	0.29	2.38	0.12	0.001

#### 4.5.2 Performance over time

In this section, I test the consistency of strategy performance. I compute the Sharpe ratio for each strategy made portfolio during every non-overlapping 10-year period and rank them from 1 (the highest) to 7 (the lowest). The rankings exhibit that none of the strategies stay in the 1<sup>st</sup> place for more than two periods for all four datasets. In other words, none of the portfolio construction methods consistently outperform the others over time. The performance of the strategies is highly dependent on the time period tested. To illustrate, I show the bar chart of the rankings for the industry dataset in Figure 4-3. The inconsistency of strategy performance is the same for the other three datasets. The bars shown in Figure 4-3 are the rankings for strategies every ten years. It is apparent that the rankings changes dramatically over time. For instance, the yellow bars show the ranking for the minimum variance approach, which holds the 1<sup>st</sup> place during the most recent period (2002 to 2013). However, in the previous period (1992 to 2001), it ranks 6<sup>th</sup> among all seven methods.

Figure 4-3 Strategy Ranking Every Ten Years in the Industry Dataset

This figure exhibits the ranking of strategies' Sharpe ratios for the industry dataset. I calculate the Sharpe ratios of strategies during every non-overlapping ten-year period from August 1931 to April 2013. A ranking equalling one indicates the highest Sharpe ratio and a ranking of seven is the lowest.



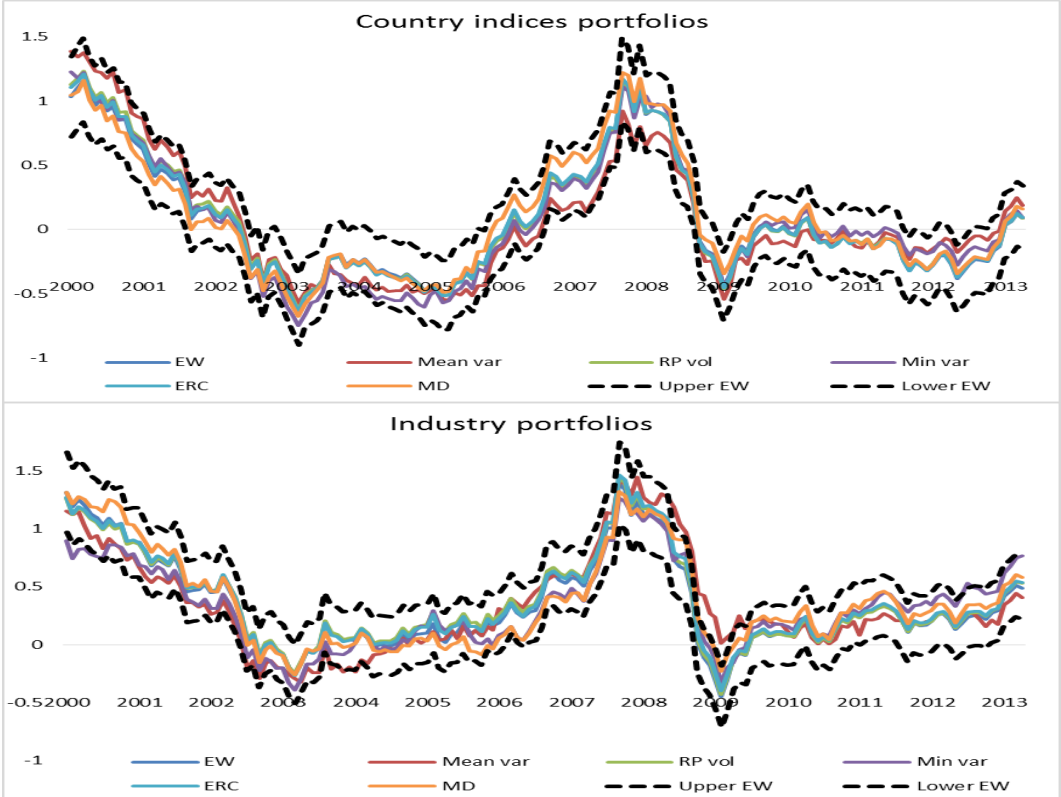
Furthermore, I narrow the observation by exploring the rolling variation of strategy performance in every five-year period. I adopt the rolling window analysis; every month I calculate the strategy Sharpe ratio during the previous five years. I plot the rolling Sharpe ratios over time (in Figure 4-4) in order to discover whether there is one strategy that can dominate the others during certain periods. I calculate the 95% confidence interval of the equally weighted portfolio's Sharpe ratio over time as a benchmark and plot the results in dotted

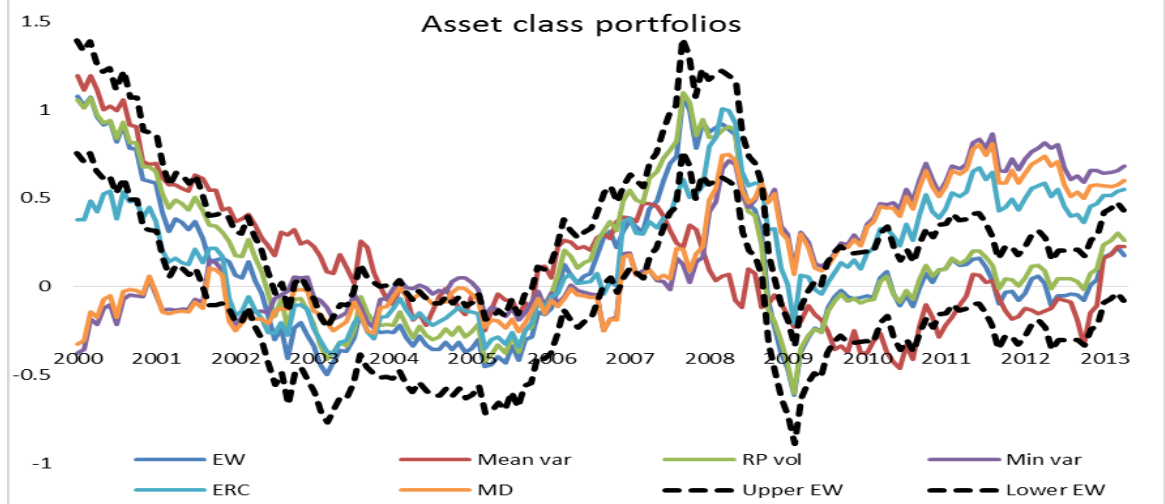
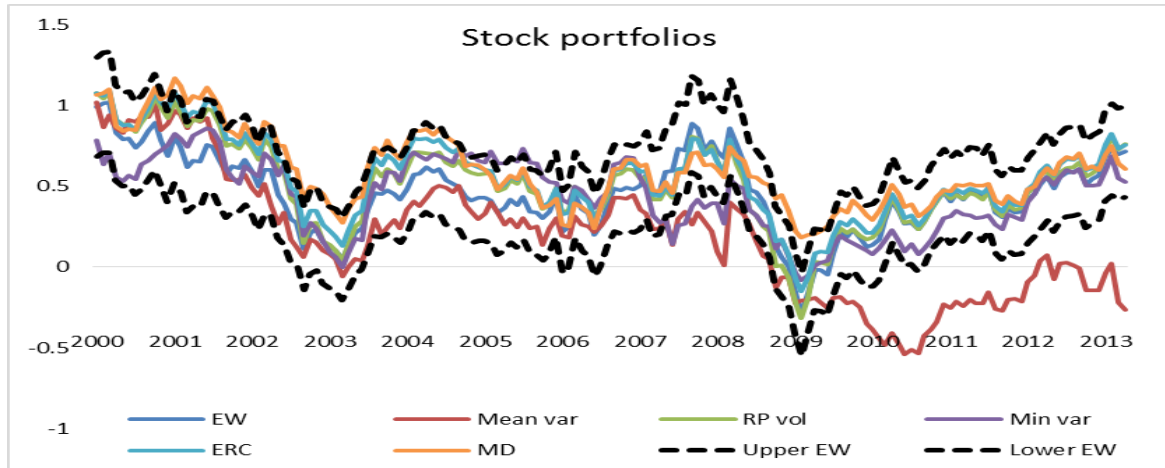
lines, as shown in Figure 4-4. If the line of any strategy's Sharpe ratios is outside the dotted lines this means that they have significantly outperform the naïve diversification rule. To clearly illustrate this, I only report the strategy performance after the year 2000.

For the country indices and industries datasets, almost all the Sharpe ratios produced by strategies are located within the 95% confidence interval of the equal weighting. None of them is distinguishable from the naïve diversification. These results also hold for the whole period (Aug 1931 to Apr 2013). For the stocks and multi-asset classes, the strategy superiority and inferiority over the naïve diversification rule does not persist. For instance, three risk-based approaches (the minimum variance, equal risk contribution and maximum diversification methods) significantly outperform the others after the 2008 financial crisis. Their superiority can explain the rise in the risk-based methods after the financial crisis. However, if we look at the full sample period, these three approaches show significantly lower Sharpe ratios most of the time.

Figure 4-4 Five-year Rolling Window on Sharpe Ratios

This figure demonstrates the performance of asset allocation strategies over time after the year 2000. I plot the Sharpe ratios of each strategy in a rolling sample analysis with a five-year estimation window. The black dotted lines are the upper and lower 95% confidence interval of the equal weighting method (EW). The solid lines are the rolling Sharpe ratios for mean variance (Mean var), risk parity based on volatility (RP vol), minimum variance (Min var), equal risk contribution (ERC) and maximum diversification (MD).





## **4.6 Implications for investors**

I conduct a comprehensive comparison on a range of commonly used asset allocation strategies and I find that no strategy could consistently outperform the others. This study has several practical implications for investors. First, if portfolios are made up with well-diversified and highly correlated indices such as country indices or industry indices, the techniques of constructing portfolio do not really have any influence on portfolio performance. In this case, investors could simply assign equal weights to the indices they invested in without utilizing any sophisticated or newly invented strategies.

Second, the mean variance optimized portfolio does not result in better performance with its added complexity. Besides, I caution investors to pay attention to the risk shifting of mean-variance strategy. Third, for investors holding different types of assets with low correlations, using the minimum variance method would protect their portfolios during bear market. The minimum variance method would assign more weights on assets with lower risk and thus, reduces the likelihood of extreme loss. However, when the market is functioning well, using risk-based strategies will be catastrophic as they limit the upper gains. Overall, the choice of asset allocation strategies highly depends on the assets within the portfolio and market timing.

## **4.7 Other robustness checks**

In this section, I undertake several sensitivity tests to check the robustness of the main results. I use different estimation periods when determining the weighting matrix, adjust the return after taking into account the transaction

costs, employ other rebalancing frequencies and apply other performance measures. The main results do not vary largely in these tests. With respect to all the robustness checks, the asset allocation strategies still perform indifferently in country- and industry-based portfolios, while there are relatively large differences in the stock- and multi-asset class portfolios.

#### **4.7.1 Estimation period**

In the baseline study, I estimate assets' characteristics within the previous five-year period ( $M=60$ ) in order to determine the weights for each asset. I also apply the estimation windows of three-years ( $M=36$ ) and ten-years ( $M=120$ ). Generally speaking, the implementation of a ten-year estimation window produces the highest Sharpe ratio for all the strategies across all four datasets. However, using different estimation periods does not influence the performance differences between strategies. The results are available from the author.

#### **4.7.2 Transaction costs**

In the baseline study, I do not consider the transaction costs as it is difficult to determine the value for different asset types. In this section, I test whether the strategies will perform differently net of costs, assuming the transaction cost is 50 basis points per transaction, as used in Balduzzi and Lynch (1999) and DeMiguel, Garlappi, and Uppal (2009). I first calculate the turnover, which is the average of the sum of assets' weight changes during each rebalance, as shown in equation (4.15).  $M$  is the estimation window used to obtain parameters for determining asset weights. The portfolio returns start from time  $t = M+1$  to  $T$ .  $\widehat{w}_{i,n,t+1}$  is the weight of asset  $n$  at time  $t+1$  under strategy  $i$ . I

calculate the absolute changes in asset weightings, sum them for N asset and compute their average across the whole time period T:

$$Turnover = \frac{1}{T} \sum_{t=M+1}^T \sum_{n=1}^N (|\widehat{w}_{l,n,t+1} - \widehat{w}_{l,n,t}|) \quad (4.15)$$

The results in Table 4-8 show that the equally weighted portfolios produce the smallest turnovers followed by the risk parity (volatility) and equal risk contribution portfolios. In contrast, the mean variance portfolios result in the largest turnovers. These results hold for all four datasets we test. For instance, compared to the equally weighted portfolios, the turnovers of the mean variance portfolios are over ten times higher under the industry dataset and five times higher under the multi-asset dataset. In general, the naïve diversification rule, the risk parity approach and the equal risk contribution method produce the smallest turnovers. The turnovers for the stock-based portfolios are much higher than for the other three datasets.

In order to calculate the portfolio returns net of costs, I use the returns minus the bid and ask spread at each rebalance month. Then I use the returns after transaction costs to compute the annualised average return, volatility and Sharpe ratio for each strategy. For country-based portfolios, only the mean variance method shows significant worse results than the others due to the large costs incurred. For the industries, none of the strategies show significant differences. However, in the stock-based portfolios, all of the strategies are inferior to the equal weighting rule, as their returns have been largely negated by the large costs. For instance, before transaction costs, the annualised average return of the maximum diversification portfolio, at 15.7%, is higher

than that of the equally weighted portfolio of 14.28%. The return for the maximum diversification portfolio becomes 9.65% after deducting a huge turnover of 1195%, while the return of the equally weighted portfolio is 13.88% net of costs. For the multi-asset class portfolios, the differences between strategies are similar before costs and after costs.

#### **4.7.3 Rebalance frequency**

Using semi-annual rebalancing instead of monthly rebalancing does not change the result substantially. In fact, the performance of strategies becomes even closer with semi-annual rebalancing. The Sharpe ratio of all the strategies increases and the differences between them decrease. Even in the multi-asset class portfolio, there is no difference between all of the strategies. The Sharpe ratio of the minimum variance strategy is the same with the naïve diversification rule with semi-annual rebalancing, while it is only one-tenth of the naïve diversification with the monthly rebalancing.

Table 4-8 Asset Allocation Strategy Performance Net of Transaction Costs

This table reports the annualized strategy performance metrics net of transaction costs (50 basis points per transaction). The turnover of each strategy is calculated as the average of the sum of assets' weight changes during each rebalance. The portfolio net of costs returns is computed by using excess returns minus bid and ask spread at each rebalance month. Then I report the average net returns, standard deviations and Sharpe ratios. The p-value is the probability that each strategy performs no different from the equally weighted methods.

Rules	Excess Return	Volatility	Sharpe Ratio	P-value	Turnover
Panel A: G5 country indices					
EW	5.07	13.22	0.38	-	35.12
Mean V	3.48	14.95	0.23	0.04	168.58
RP Var	4.77	15.28	0.31	0.10	41.47
RP Vol	4.90	14.25	0.34	0.18	36.69
Min V	4.80	15.34	0.31	0.18	73.75
ERC	4.83	14.09	0.34	0.14	39.18
MD	4.66	13.86	0.34	0.16	71.90
Panel B: Ten industry portfolios					
EW	8.56	17.90	0.48	-	26.44
Mean V	6.87	18.03	0.38	0.11	295.32
RP Var	8.18	16.40	0.50	0.15	34.37
RP Vol	8.40	17.13	0.49	0.09	28.62
Min V	6.95	13.84	0.50	0.64	97.17
ERC	8.36	16.96	0.49	0.07	30.42
MD	7.78	15.79	0.49	0.65	95.29
Panel C: Random selected ten stocks					
EW	13.88	26.61	0.52	-	85.43
Mean V	1.78	24.21	0.07	0.00	1778.04
RP Var	7.43	21.25	0.35	0.00	1003.72
RP Vol	10.58	23.19	0.46	0.01	538.13
Min V	2.65	20.34	0.13	0.00	1741.59
ERC	10.86	23.10	0.47	0.03	570.36
MD	9.65	24.80	0.39	0.01	1195.53
Panel D: Four asset classes					
EW	2.16	7.45	0.29	-	25.80
Mean V	1.66	8.97	0.18	0.33	185.94
RP Var	1.04	3.90	0.27	0.81	29.28
RP Vol	1.34	4.73	0.28	0.92	26.69
Min V	-0.04	2.56	-0.01	0.03	28.93
ERC	0.34	2.87	0.12	0.06	26.03
MD	0.01	2.63	0.00	0.02	32.66

## 4.8 Conclusion

This study explores how the methods of allocating assets influence the portfolio return and risk characteristics. I comprehensively evaluate the ex-ante performance of seven asset allocation strategies; the equal weighting, mean variance, risk parity based on variance, risk parity based on volatility, minimum variance, equal risk contribution, and maximum diversification strategies. I compare the economical and statistical differences between strategies across four datasets and over time.

The results show that, firstly, the differences between strategy risk-adjusted returns are indistinguishable for country- and industry-based portfolios, but large for equity and multi-asset class portfolios. If investors invest purely in country and industry indices, the method of allocating assets does not matter within any reasonable time period. However, for equity and asset class portfolios, no strategy can consistently outperform the others for more than 20 years. Secondly, in terms of risk exposures, the implementation of the mean variance rule generates highly fluctuating market, size, value and momentum risk factor loadings. Thirdly, all the strategies we test here are far from mean-variance optimal. Those newly innovated strategies do not exhibit strong impacts on investment outcomes.

This study indicates that there is a desire for improving the performance of portfolio construction strategies, as performance in the past does not guarantee performance in the future. It seems that the innovation of new construction approaches can be focused on other aspects instead of just assets' characteristics. Moreover, the performance of strategies varies when I

utilize different datasets to construct portfolios, my conjecture is that correlations between assets played a role in the performance. Further tests are left for future studies. Also, checking the performance of practical indices that apply these strategies can be conducted. This research is also likely to add value in the area of other investable assets, such as derivatives, commodities and hedge funds.



## Chapter 5 Conclusion

This thesis investigates influential factors, characteristics, and trading behaviour affecting international financial markets. It contains three empirical studies that seek to enhance our understanding of financial markets by unfolding the relationships between them and informal institutions; the goal is also to understand the relationship between financial markets and macroeconomics.

The first study aims to discover if corruption culture is a determinant of short-termism in the banking sector and whether it contributed to the 2007 financial crisis. To accomplish this objective, I construct a comprehensive measure for short-termism in the banking sector by combining earnings management, tail risk-taking, and short-term debt taking which are signals for short-termism. I find that banks are more myopic if they are headquartered in countries with higher levels of corruption. This finding is robust to the use of an instrumental variable. Aside from that, European economic policy uncertainty serves to amplify the effect of corruption on myopia. As an alternative, I test if corruption culture imported through foreign shareholders is also a contributing factor for short-termism after controlling for domestic corruption. I find that having a larger percentage of shares held by institutions domiciled in countries with higher levels of corruption is associated with more short-termism for banks with lower-than-average domestic corruption level. Nevertheless, having larger percentages of shares held by institutions

domiciled in less corrupt countries does not reduce the level of short-termism for banks that already have a higher than average level of domestic corruption.

This first study contributes to the literature by capturing bank myopia in every possible aspect. Previous literature has normally focused upon one aspect per study (e.g., Beatty, Ke, and Petroni, 2002; Kanagaretnam, Lim, and Lobo, 2011; Doyle, Jennings, and Soliman, 2013; Chen, Cheng, Lo, and Wang, 2015), and this may have caused the omission of some pieces of evidence related to short-termism. More importantly, this study unveils how corruption culture could influence bank myopia. This finding contributes to the studies that link corruption to corporate behaviour (e.g., DeBacker, Heim, and Tran, 2015; Liu, 2016; Smith, 2016; Huang and Yuan, 2016).

It is essential to monitor bank behaviour as bad functioning would trigger critical market fluctuation. This study has implications for bank regulators and policy makers. They should keep an eye on not only banks headquartered in corrupt countries but also banks with foreign shareholders from countries with higher levels of corruption. The findings in this study echo the Federal Reserve Bank of New York speech (2018) that called for attention to be paid to a healthy banking culture.

This study has a few limitations. First, the measure of myopia could be enhanced if I include managerial compensation as another dimension to capture the incentives for banks to be myopic. Shareholders employ bonus to align their interests with managers towards long-term. Previous literature suggests that compensation practices have strong influence on bank stability

(Bai and Elyasiani, 2013), risk-taking decisions during mergers and acquisition (Hagendorff and Vallascas, 2011), and default risk (Vallascas and Hagendorff, 2013). Unfortunately, executive compensation information for European banks is largely insufficient. The commonly used compensation database, namely Execucomp, only provides information for banks listed on the S&P 1500. Additionally, Boardex provides board information but again data is limited. In total, I only obtain compensation details for 67 European banks. Thus, I could neither incorporate compensation related variables into the myopia index nor include them as control variables due to data limitation.

Second, this chapter focuses only on how myopic behaviour is influenced by corruption from both domestic society and foreign shareholders. However, it is well recognized that bank governance is likely to be a determinant of bank behaviour and decision-making through overseeing, monitoring, and structuring compensation (Srivastav and Hagendorff, 2016). Previous studies in the banking literature have shown that boards play an essential role in risk-taking decisions (e.g., Beltratti and Stulz, 2012; Kirkpatrick, 2009; Pathan, 2009; Walker, 2009), constraining earnings management (Cornett, McNutt, and Tehranian, 2009), and performance (Adams and Mehran, 2012; Aebi et al. 2012). If I am able to include bank governance variables as control variables, I would include board size and board independence. The problem is that data on board characteristics for European banks is very limited. Therefore, despite my attempts to control for a number of accounting and ownership variables, I cannot rule out the possible omitted variable bias. However, after I use the instrumental variable to mitigate potential endogeneity issue, the effect of

domestic corruption on myopia doubled. Thus, I believe that if I am able to control for corporate governance variables, the effect of corruption on myopia would be even stronger.

Third, I could not maintain a causal relationship between foreign shareholders, from countries that have higher levels of corruption, and bank short-termism. Although the estimation model has controlled for many firm-level and country fixed effects as indicated by the literature, I still cannot rule out the possible reverse causality issue for this part of results.

Future research may build on this study in several ways. More research is needed to analyse the determinant on bank short-termism. For instance, one may look at the effect of other cultural dimensions (such as masculinity or harmony) on bank short-termism. Another interesting idea worth exploring is the effect of corruption through culture heritage on a firm's decision-making.

The second study proposes a measure of uncertainty, which is the cross-sectional standard deviation of stocks, namely, return dispersion. I present that return dispersion has a significant association with business cycles, political crises, country risk, media uncertainty, and economic policy uncertainty. Stocks that are more sensitive to return dispersion are found to result in higher returns. Moreover, I compare return dispersion with implied volatility and find that return dispersion is good at capturing political crises while implied volatility does a good job in capturing economic policy uncertainty.

This study contributes to the literature by linking return dispersion with all sorts of macroeconomic and political shocks that have not been considered

before. I focus on the international market which is vital as the interaction effect between markets is strong. For instance, Ehrmann, Fratzscher, and Rigobon (2011) show the transmission from US market shocks to Euro area financial markets. This study also has implications for investors to better track a market's status and enhance their trading performance especially during market fluctuations. Investors could easily obtain real-time stock price data and compute return dispersion to monitor the market. They could also include stocks that are more sensitive to return dispersion in their portfolio, as we find a positive relationship exists between the sensitivity to return dispersion and stock returns.

Nevertheless, there are some limitations in this study. One such limitation is that return dispersion contains both market average variance and correlations between stocks. This study does not distinguish which of these two aspects is related to uncertainty. Additionally, while this study covers 18 countries, they are all developed countries. More research is needed in order to explore the emerging markets for future research. It would also be interesting for future studies to link the cross-sectional stock variation with firm-level uncertainties.

Finally, in the third study, I evaluate the out-of-sample performance of commonly used asset allocation strategies including equal weighting, mean-variance weighting, risk parity weighting, minimum variance weighting, equal risk contribution weighting, and maximum diversification weighting. I comprehensively assess their performance according to different datasets and time periods, and in terms of risk-adjusted returns. I find no statistically

significant differences between those strategies if investors construct their portfolios using market indices or industry indices. Interestingly, large differences do exist between strategies if portfolios are constructed using equities or multi-assets, however, none of the strategies were found to be able to consistently out-perform the others over time. Overall, all the strategies are far from ex-post optimal.

This study contributes to the literature by showing that commonly used asset allocation strategies do not have a significant impact on investment outcomes. I illustrate these results in several datasets and have used a long time period to ensure the results are robust. A key limitation is that I impose a short-sell constraint in this study as short-selling would largely alter portfolio investment outcomes which causes serious estimation errors.

There are several directions for future studies on the basis of this chapter. First, one may include other assets such as commodities, derivatives, and cryptocurrencies in portfolios to test the performance of those strategies. This chapter does not conduct those tests due to data limitation. Second, it seems that the performance of asset allocation strategies is depending on the correlations between assets within portfolio. When assets are highly correlated, such as when investing in country or industry indices, strategies would have little influence on portfolio performance. However, when correlations between assets are relatively low, such as when investing in various types of assets, different strategies would produce different results. One could conduct a simulation on generated returns, volatilities, and correlations to analyse the sensitivity of strategy performance to correlations. Alternatively, one could sort

a bunch of stocks into different portfolios based on their correlations. Then compare the difference in asset allocation strategies' performance between those portfolios. Overall, this study demonstrates that all strategies are far from ex-post optimal. This study leaves room for the development of new portfolio construction strategies.

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