# Macroeconomic and Political Uncertainty and Cross Sectional Return Dispersion around the World

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This study provides evidence that the cross sectional return dispersion is able to capture global macroeconomic uncertainty. On average of the 18 countries we tested, return dispersion increases 10% during country specific recessions but global recessions seem more important, raising return dispersion almost 40%. International political crises also raise return dispersion of around 13% on average. We further show that stocks with higher sensitivity to return dispersion result in higher returns. Moreover, we compare return dispersion with implied volatility and find that they capture different types of uncertainties.

**JEL classification:** G12, G15, E60

**Key words:** Return dispersion, business cycles, political risk, economic policy uncertainty, stock returns.

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# 1. Introduction

Macroeconomic uncertainty has a strong impact on aggregate employment, productivity (Bloom, 2009), firms, consumer behaviour (Bloom, 2014), and the stock market (Pastor & Veronesi, 2012). The recent financial crisis of 2008 has made it clear that we lack a proper, simple and easy measure to capture macroeconomic and political uncertainty, let alone that we would be able to capture it in real-time. As a consequence, the number of papers trying to link different volatility measures to uncertainty has been growing (see for instance Cesa-Bianchi, Pesaran, Rebucci (2014) and the papers within). Our goal is a simple one. Can we find a measure that might capture at least some of the general uncertainty and which can also be easily calculated in real time? Preferably one that is simple to measure and simple to understand and that would give investors, financial regulators and other stake holders at least a feel in real time for the level of uncertainty as perceived by financial markets. Of course, stock return volatility itself does not qualify as this measure cannot be observed in real time. Moreover, it suffers from more serious problems. As Diebold and Yamilz (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.[1]

The literature suggests that 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 unemployment (Loungani, Rush, & Tave, 1990), the business cycle (Loungani, Rush, & Tave, 1991), the state of the aggregate economy (Gomes, Kogan, & Zhang, 2003), micro-economic uncertainty (Bloom, 2009) and market volatility (C. T. Stivers, 2003). Apart from this empirical evidence it also intuitively seems a good measure for uncertainty. When there is good (bad) macroeconomic news for 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.

To investigate the usefulness of cross sectional dispersion as a practically useful and simple, real time measure of uncertainty we embark on a comprehensive endeavour using a large set of international data to verify whether return dispersion correlates with a broad set of alternative uncertainty measures (which are hard to measure in real time). More specifically, we link return dispersion at a monthly level to different aspects of uncertainty including (local and international) business cycles, political crises, economic policy uncertainty and general uncertainty measured by

[1] Of course one could extract implied volatilities from option prices but this would make the interpretation much harder to understand.

use of the word 'uncertainty' in the media. We use monthly data as these other measures are often monthly. However, cross sectional dispersion can be measured at much higher frequencies. We look at the international evidence extending the existing literature which focuses on the US market mostly. We construct monthly return dispersion series using the 50 largest market capitalization stocks in 18 different countries. We focus on the fifty largest market capitalization stocks as this makes the measure even simpler and as we show gives similar results to a broader measure including more stocks. Moreover, this enables us to use a long sample starting in 1986 and which can easily be replicated in practise. Last but not least, it is well-known (Lo & MacKinlay, 1990) that small stocks lag stocks of larger firms, hence focusing on the largest fifty stocks prevents delayed trading effects of smaller stocks. In the next step we 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[2]) return dispersion offer higher returns. For the countries where direct implied volatility data are available we compare both measures.

Overall our results suggest that risk dispersion seems to capture different kinds of macroeconomic and political uncertainty well. Further, return dispersion (either measured in changes or levels) is strongly linked to the cross-sectional stock returns in all countries we tested. Stocks with higher sensitivities to return dispersion have higher average returns. We compare our return dispersion measure with implied volatility and find both measures respond differently to our 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, we find no evidence that (levels or changes in) implied volatility correlates with the cross section of stock returns.

In our empirical analysis we focus on four aspects of macroeconomic uncertainty. First, we test how return dispersion captures local and global business cycles using the business cycle data from Fushing, Chen, Berge, and Jordà (2010). Our results confirm that in 11 out of 18 countries return dispersion is significantly higher during local business cycles. Once we 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 the global recession raises return dispersion up for almost 40 percent (0.104 versus 0.076 in expansions, assuming no local recession) suggesting that international uncertainty might be more important than local uncertainty. To the best of our knowledge this a new finding.

[2] We measure changes as the residuals from an AR(1) process estimated for the levels.

Second, we test whether return dispersion captures international political instability controlling for business cycle effects. According to the rare disaster risk literature, stock market returns correlate strongly with changes in international crisis risk. Based on the well-known ICB international crisis risk database, Berkman, Jacobsen, and Lee (2011) show that stock market returns go down significantly at the start of perceived international crises. While stock market returns may be lower crisis starts, this does not necessarily hold for risk dispersion as all stocks may go down together. However, ongoing crises may lead to higher uncertainty, hence higher risk dispersion. We test this hypothesis and find that international political uncertainty is an important contributing factor to return dispersion. The evidence for perceived starts of crises is indeed mixed (although significantly positive when we pool the data). However, return dispersion is significantly higher during crises in all but one of the countries we consider. On average, the return dispersion is 13 percent higher during crisis. Our estimates indicate that return dispersion captures international political risk.

Third, we consider uncertainty that relates to fiscal, regulatory and monetary policies which has large impact on employment, productivity and firm level investment (Bloom, 2009). Baker, Bloom, and Davis (2015) construct an economic policy uncertainty index which is computed by counting the number of articles with policy related keywords in the leading newspapers. We use this index as a proxy to test if return dispersion is associated with this type of uncertainty. We show that return dispersion increases during periods with high economic policy in Germany, Italy, Japan and Spain but not in France, UK and US. Economic policy uncertainty has relatively small effect on return dispersion as ten percent increase in uncertainty only raise return dispersion up around 15 basis points on average.

Fourth, we consider whether risk dispersion is related to what may be considered general uncertainty by linking our measure to the frequency with which the words ‘uncertainty’ and ‘risk’ appear in Bloomberg in different months (controlling for the business cycle, international political crises and economic policy uncertainty effects). If we are willing to assume that when uncertainty is higher these words occur more frequently in Bloomberg articles, we can test whether return dispersion also indicates higher uncertainty when measured by this simple word count. Even though this may be a crude test, our results suggest that risk dispersion is also significantly positively related to the frequency of these words being used in Bloomberg. Even after controlling for business cycles international political crises and economic policy uncertainty effects return dispersion is significantly higher in 12 out of 18 countries during the period that “uncertainty” is used frequently.

As return dispersion seems to capture different aspect of international uncertainty we also test if return dispersion is able to explain the cross-section of stock returns. If so, stocks that are more sensitive to return dispersion are expecting to earn higher returns. Jiang (2010) builds a model that includes return dispersion directly in the pricing kernel. Chichernea, Holder, and Petkevich (2014) 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, we find strong positive relation between high sensitive return dispersion stocks and stock returns in 18 countries, regardless whether we look at levels or changes in dispersion. The difference between stocks with the high sensitivity to risk dispersion and the portfolios with low sensitivity to risk dispersion is substantial (around 5% on average a month regardless whether we control for sensitivity to the market or not). This holds in every country we consider. Results are also highly significant with an average t-value for the difference between the high risk dispersion portfolios minus the low risk dispersion portfolios of 15.22, controlling for market risk and 8.67 for the raw returns. These t-values suggest that risk dispersion easily passes the thresholds recently suggested by Harvey, Liu, and Zhu (2014).[3]

Finally, we compare return dispersion with the implied volatility in seven countries for which implied volatility data are available. We choose implied volatility as this measure can also be observed in real time and at any frequency unlike many other risk measures and has been considered in the literature (for instance, Beber and Brandt (2009) and Baker et al. (2015)). Implied volatility alone also captures uncertainty associated with business cycles, international crises and economic policy. However, both measures respond differently to the uncertainty measures we use. Return dispersion responds strongly to our measures of global business cycles and world crisis risk. It does so even if when we control for implied volatility. Implied volatility significantly captures the economic policy uncertainty in all five countries (for which we have economic policy and implied volatility data) but return dispersion does not.

We feel this paper makes the following contributions to the existing literature. First, we provide international evidence in 18 countries (as opposed to US only) that cross sectional risk dispersion correlates strongly with (new) measures of general, macro and political proxies of uncertainty. It is important to focus on the international evidence particularly for macroeconomic and international political uncertainty as the United States might be a special case as it is the world the largest economy and a military superpower which has only rarely seen battle in its own territory. Hence,

[3] 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.

earlier results for the US may not necessarily be representative internationally. Second, we link return dispersion to all sorts of proxies of macroeconomic and political uncertainty that have not been considered before. Our 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, we also extent the US evidence cross sectional evidence and find that cross sectional return dispersion (both levels and changes) correlate with the cross section of returns internationally whereas implied volatility (both levels and changes) does not. And fourth, and maybe most importantly we feel our international evidence indicates that cross sectional return dispersion (based on even a limited number of 50 stocks) may for each country be a simple and real time proxy to gauge uncertainty.

Our results are consistent with previous findings in the literature. The US evidence suggests that during local recessions when uncertainty seems higher, also return dispersion tends to be higher than during local expansions (Loungani et al., 1990). We add international evidence on the relation between the local and the international business cycle and return dispersion in individual countries. Return dispersion is also internationally linked to the cross section of stock returns. Chichernea et al. (2014) for the US illustrate that return dispersion largely explains the excess returns to accrual and investment hedge portfolios in US stock market. Jiang (2010) considers US return dispersion as a priced factor and find it captures differences in the cross sectional returns better than other well-known factors like momentum, size and value. Our international evidence supports this finding. There are a number of studies which compare return dispersion to conventional volatility measures. For instance, Cesa-Bianchi, Pesaran, and Rebucci (2014) find that their results for global dispersion measures are highly correlated with their realized volatility measure. C. T. Stivers (2003) provides evidence that return dispersion is positively linked to future market-level volatility in US. However, little evidence consists whether return dispersion and implied volatility are related to the proxies we use for macroeconomic and political uncertainties.

## 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, 2010) finds that risk 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.

## 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 an economy. For instance, economic policy uncertainty affects stock prices (Pastor & Veronesi, 2012), economic activities (Baker, Bloom, & Davis, 2013), consumption and investment expenditures (Alexopoulos & Cohen, 2009). 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 is an essential factor in driving business cycles.

Therefore, it is important to measure the 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 has no or little direct effect on real GDP. They suggest that volatility might be more a result rather than a cause of economic uncertainty.

A relatively new measure of economic policy uncertainty (EPU) is developed by Baker et al. (2013). They count the frequency of articles that refer to economy uncertainty and use it to build a news-based EPU index. Baker et al. (2013) test their EPU index and find that it captures policy related economic uncertainty well over time. Other studies propose other proxies of EPU. 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 (2014) 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) measures economic uncertainty by the conditional volatility of dividend growth. Last but not least, Jurado, Ludvigson, and Ng (2013) suggest several indicators of uncertainty including volatility of market returns (both implied and realized), cross sectional dispersion of firm profits, returns, productivity and subjective (survey-based) forecast, and the appearance of uncertainty-related key words in news publications.

## 2.2 Return dispersion

In the literature there is an increasing focus on the cross sectional return dispersion as a measure of uncertainty. Theoretically, William G 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 & 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, William Gary Christie and Huang (1994) and 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. Bali and Zhou (2014) find that price uncertainty explains the cross-sectional variations in stock returns. 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.

### 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 risk 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 risk 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.

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. (2014) 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 risk dispersion.

### 2.4 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. Risk dispersion seems to be a better risk factor than time-series volatility (Gorman et al., 2010) and the book-to-market factor (Jiang, 2010). C. T. Stivers (2003) and Connolly and Stivers (2006) show that return dispersion conveys information about future volatility and C. T. 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. Bali, Cakici, and Levy (2008) use the difference between the variance of non-diversified portfolios and the variance of the fully diversified portfolios as the average idiosyncratic volatility. They further decompose total risk into firm, industry and market variance. Additionally, de Silva, Sapra, and Thorley (2001) indicate that return dispersion is a function of stocks' cross-sectional variation and their sensitivity to market changes and the general level of idiosyncratic volatility.

## 3. Data

We obtain our return data from Compustat Global for all countries except for the US where we 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:

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

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 $t$.

We prefer long series and preferably many countries but need to restrict our attention to countries for which we can find reliable business cycle data and can create long enough dispersion series. We use the international business cycle data derived by Fushing et al. (2010). An advantage is that their methodology also allows for the creation of a global business cycle so we can test whether the source of uncertainty may be global or local. We create the longest series possible and as we want to compare results between countries we can create dispersion series starting from January 1986. Therefore, the data time period for all the countries starts from January 1986 to March 2014 except for US, where we use data from January 1926 to December 2013.

If we apply all these criteria we can measure 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 we can create long series based on the constituents of the main indices in those countries and we use these as a robustness test in our analysis (We report those results in the Appendix). Our set to check robustness of our results for market indices consists of 7 countries: Australia, Finland, France, Germany, Japan, Switzerland and the United States. For these countries we can create time series of at least 300 return dispersion observations based on the constituents of the main indices in these countries. We consider returns at a monthly frequency as these tend to be less noisy than high frequency data and many of our other variables are only available at monthly frequency but return dispersion can of course be measured at much higher frequencies.

Table 1 contains basic statistics and panel A shows the characteristics for our return dispersion series. The mean values of return dispersion series range from 0.06 to 0.11 and the median values are a bit lower from 0.05 to 0.09. The US market has the lowest mean and median return dispersion., all the distributions show positive skewness and are leptokurtic. We reject the null hypothesis that return dispersion series follow normal distribution for all countries. Panel B reports the main characteristics of the market returns for each country. All the countries have mean returns close to zero.

*Please insert Table 1 around here*

# 4. Return dispersion and macro economy

To whether return dispersion is linked to macroeconomic uncertainty, we use the US market as an example. We plot the monthly return dispersion of the US largest 50 stocks from January 1985 to December 2013 in Figure 1. The line graph clearly show that return dispersion is higher during periods of macroeconomic news shocks. The US return dispersion spikes during major events such as the Russian Crisis, 9/11, Lehman brother bankruptcy and the following crisis of 2008.

*Please insert Figure 1 around here*

## 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), we create dummy variables for both the country specific local business cycle and the global business cycle (1= recession, 0 = expansion). We first regress our return dispersion series on the country specific business cycle variable alone as shown in equation (2):

$$RD_t = \alpha + \beta_1 BC\_local_t + \varepsilon_t \qquad (2)$$

where $BC\_local_t$ is the dummy variable for local business cycle (1= recession, 0 = expansion). Then we include the global business cycle $BC\_global_t$ as well in our second regression (equation 3):

$$RD_t = \alpha + \beta_1 BC\_local_t + \beta_2 BC\_global_t + \varepsilon_t \qquad (3)$$

For both regressions, the data end in September 2009 because the business cycle data end in that month. We report these results in Table 2 and 3. When we consider 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 eleven out of our eighteen countries return dispersion is significantly higher during recessions (New Zealand is significant but with the opposite sign). However, many countries do not show as strong an effect as in the US where return dispersion is on average fifty percent higher (0.09 versus 0.06 in non-recessions, mostly expansions). For instance, return dispersion in Ireland and Switzerland is 40 percent higher during recessions. However, return dispersion in Australia and Japan is only 10 percent higher. On average we find that for other countries the difference is around 20 percent (0.093 versus 0.077).

*Please insert Table 2 around here*

However, things change quite dramatically once we also allow return dispersion to fluctuate with the global business cycle as well. We report the results for both local and global business cycles in Table 3. The local business cycle is still significant in 7 out of 18 countries but the size of the effect halved 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 13 out of 18 countries. The size of the effect is substantial. On average a global recession seems to raise the return dispersion with almost 40% (0.104 versus 0.076 in expansions, assuming no local recession) and the effect of return dispersion is 10 percent higher on average in a local recession (0.084 versus 0.076 in expansions assuming no global recession). Interestingly, these results also hold for the US. Return dispersion in the US seems to depend more on global economic conditions than economic conditions in the US. In fact, once we control for global recessions, the US is one of the countries where local effects become insignificant. 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 0.02 for New Zealand to 0.70 for the US ) but the higher return dispersion is associated with global dummy rather than the local dummy in almost all regressions. We find a similar result if we pool the data and estimate it either as a SUR regression or as a system. The local business cycle is significant but the global factor seems to weigh more heavily.

*Please insert Table 3 around here.*

### 4.2 International political crisis

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 recent empirical evidence by Berkman et al. (2011) suggest that the changes in likelihood of international political crises has a strong impact on stock market returns. Stock market returns go down significantly at the start of perceived international crises based on the well-known ICB international crisis risk database. We expect that return dispersion might be higher when new perceived crises start, during crises and lower 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.

We now test this hypothesis using the international crises variables introduced by Berkman et al. (2011). In line with their approach, we use the variables that denote the number of crisis starting in a month (start), ongoing crises in a month (during) and a variable indicating the number of crises ending (end). We 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. This may be a better proxy for actual perceived crisis risk. Table 4 presents the descriptive statistics of the world crises variables and world crises index (WCI). The data range from January 1986 to December 2013 as the crises data end in that month. The number of ongoing crisis is 1.44 a month on average. The means of the world crisis index start, during and end are 1.08, 5.06 and 1.11.

*Please insert Table 4 around here*

We control the effect of both local and global business cycle and add three variables to equation (3) The first variable measures the WCI of crises starting in that month, ($Start_t$) the second one the WCI for ongoing crises during month t ($During_t$) and the last variable the WCI of crises ending in month t ($End_t$).

$$RD_t = \alpha + \beta_1 BC\_local_t + \beta_2 BC\_global_t + \beta_3 Start_t + \beta_4 During_t + \beta_5 End_t + \varepsilon_t \quad (4)$$

Table 5 shows the estimation results for international political crises. Return dispersion is higher during times of crises. In all but one country the effect is significant. The crisis index has a mean of 5.05 per month. This means that on average during international political crises return dispersion is around 13 percent higher. There also seems to be a start of a crisis effect although less strong (significant in five out of the 18 countries). If we pool the data in a system, the overall effect also indicates significance. Crises starts add another 1.5 percent to return dispersion. The end of crises does not seem to add significantly to return dispersion.

*Please insert Table 5 around here*

### 4.3 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, we 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.[4] Baker et al. (2013) first establish their index in the US and evaluate its impact on 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 EPU index in eleven countries. We employ the EPU index in seven countries (France, Germany, Italy, Japan, Spain, UK and US) which overlap with our sample of countries. 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)). We obtain the data 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 compare to that of 32.82 in the US. We extend our previous regression to include (the log of) economic policy ($EPU_t$) (equation 5).

[4] Baker et al. (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.

$$RD_t = \alpha + \beta_1 BC\_global_t + \beta_2 Start_t + \beta_3 During_t + \beta_4 End_t + \beta_5 \ln(EPU_t) + \varepsilon_t \quad (5)$$

Table 6 shows the results. Return dispersion is statistically higher during higher economic policy uncertainty in Germany, Italy, Japan and Spain but not in France, the UK and the US. Also, the effect is economically small. For instance, 10 percent increase in economic policy uncertainty will raise return dispersion around 17 basis points in Germany and 19 basis points in Italy.

*Please insert Table 6 around here.*

## 4.4 Uncertainty around the world

In order to cover even more general uncertainty, we consider another proxy. This has the advantage that we can use it for all 18 countries. We assume that the word 'risk' and 'uncertainty' will occur more frequently in months with higher perceived risk and uncertainty in general. If so, then we are able to conduct a simple test on whether return dispersion captures more general uncertainty. We count the number of Bloomberg reports in every month that contains these two words and add in turn one of these two variables to our regressions. In both cases we take the log as the number of news articles seems to have grown exponentially over time. We use this word count uncertainty as an explanatory variable with the control variable of business cycles and world crisis index as below:

$$RD_t = \alpha + \beta_1 BC\_local_t + \beta_2 BC\_global_t + \beta_3 Start_t + \beta_4 During_t + \beta_5 End_t + \beta_6 WordCount_t + \varepsilon_t \quad (6)$$

In Table 7 we report our results for the word 'Uncertainty' (as results are similar for the word "risk" we report those in the Appendix). 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. The explanatory power measured by the $R^2$ almost doubles to over 43%. Maybe not surprising because Bloomberg originate from the US. In many other countries we find a positive significant effect as well, with the exception of Australia, New Zealand and Spain where, the word count for uncertainty seems significantly negative. Overall the effect is however significantly positive. The uncertainty effect is significant in 15 out of 18 countries (12 of them are positive).

*Please insert Table 7 around here*

## 4.5 Economic forecast dispersion in the US

For the US we are also able to incorporate economic forecast uncertainty in our analysis (although only at a quarterly frequency). Diether, Malloy, and Scherbina (2002) find that the analyst earning forecast dispersion is positively associated with stock market uncertainty. We employ several economic forecast variables as proxies of uncertainty. We use the survey of professional forecasters provided by the Federal Reserve Bank of Philadelphia. We examine how macroeconomic uncertainty correlates with return dispersion. We use a univariate regression and regress return dispersion on each of the economic forecast dispersion measure as follows:

$$RD_t = \alpha + \beta_1 z_t + \varepsilon_t \tag{7}$$

where $RD_t$ is the quarterly return dispersion which is computed using the average of the three monthly RDs within corresponding quarter. $z_t$ is an economic forecast variable at time t. The contemporaneous economic forecast variables that we consider include:

- Nominal GDP (GDP);
- 3-month Treasury bill rate (TBL);
- unemployment rate (UNE);
- industrial production growth (IPD);
- corporate profits (CPF);
- real GDP growth (GDPG);
- real consumption growth (CSM);
- real non-residential investment growth(NRI);
- real residential investment growth (RSI);
- real federal government spending growth (FGS);
- real state and local government spending growth (LGS);
- Consumer Price Index (CPI, the CPI uses a fixed basket of goods with weightings that do not change over time);
- personal consumption expenditure (PCE, The Chain Price Index for Personal Consumption Expenditures uses a chain index, which takes consumers' changing consumption due to prices into account);

- term spread (TSP, difference between the government bond yield and Treasure bill rate);
- AAA ranked government bond yield (TBY);
- real t-bill pgdp (PGDP);
- real t-bill cpi (RTB,CPI);
- long-term CPI (LTCPI).

Table 8 reports the results of univariate regression for each macro variable. We use both the return dispersion of the largest 50 stocks in CRSP dataset and the return dispersion of all the stocks on S&P500. In panel A and B we use the economic forecast for current quarter (at time t). Among those variables, the forecast dispersion of PCE, NRI,TSP and TBY are significantly and positively related to return dispersion. The dispersion of PCE forecast for current quarter accounts for more than one third of the variation in return dispersion. The dispersion of NRI is able to explain almost 7 percent changes in cross sectional return dispersion in the US.

In panel C and D we use the economic forecast dispersion for the next quarter (t+1) as independent variable. The dependent variables are return dispersion made by the largest 50 market capitalization stocks in CRSP (Panel C) and return dispersion made by all constitutes in S&P 500 (Panel D). The dispersion of GDP, CSM, NRI, PCE, TSP and TBY forecast for next quarter have explanatory power for the variation in return dispersion. The forecast dispersion for PCE is able to capture 65% changes in return dispersion. The explanatory power for the other variables rarely changes whether we use the forecast for current or next quarter.

*Please insert Table 8 around here*

## 5. Risk dispersion and the cross section of returns

As return dispersion is shown to be a risk measure, one can easily relate it to returns. We 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. We 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). We provide evidence for 13 international stock markets, Australia, Belgium, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, the UK and the US.[5] Our sample period starts from January 1986 to March 2014. We exclude very small firms. For each market in each year, we consider the 90% largest common stocks based on the market capitalization at the end of the previous year.[6] We 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, we run a time-series regression. Specifically, we regress the daily stock return on the mean return of the largest 50 stocks (as a proxy for the market-wide movement) and the return dispersion of the largest 50 stocks:

$$R_{i,t} = \alpha_i + \beta_{i,RMRF} RMRF_t + \beta_{i,RD} RD_t + \varepsilon_{i,t} \tag{8}$$

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 risk dispersion measures.

In the second step we form quintile portfolios based on this estimated coefficient $\beta_{i,RD}$. For each market for each month, we 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 we calculate monthly returns for these portfolios. For each market for each month for each portfolio, we 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 our last step we consider whether stocks with higher sensitivities to return dispersion have higher average returns. We present two sets of results, one is the average monthly raw portfolio

[5] 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.

[6] We only focus on stocks that are traded in the domestic currency, which usually accounts for more than 90% of all stocks.

returns and the other is the CAPM 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). For each portfolio, we regress the monthly return of the portfolio ($R_{p,m}$) on the average monthly return of the largest 50 stock ($RMRF_m$).

Table 9 and table 10 report our results. Stock returns are positively related to their sensitivity with respect to return dispersion. The returns increase monotonically as their sensitivities increase, regardless whether we consider raw returns (table 9) or CAPM alphas (table 10). For all the markets, the average monthly raw returns and CAPM alphas of the portfolios with the smallest return dispersion sensitivities (Group 1) are negative. 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 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 this differences indicate that the differences are highly significant. On average we 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.[7]

*Please insert Table 9 around here*

*Please insert Table 10 around here*

[7] In order to test whether these results are not caused by construction, we conduct the Monte Carlo simulation. We 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, we take the full sample market index to estimate market index sample mean and standard deviation. Use those characteristics of the original market index, we generate simulated market return series. We use the randomly generated market index as the return of the market portfolio. Second, we 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 we generate individual stock return series using simulated market return series and the estimations from CAPM model. Third, we use the randomly generated market index as the return of the market portfolio. We construct return dispersion from the randomly generated stock returns of all individual stocks. Forth, we cumulate the daily returns to get the monthly data. We calculate the return dispersion using all individual stocks. Finally we sort equal-weighted quintile portfolios every month based on stocks' exposure to return dispersion as what we 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 we observe in the real data. These results are available on request from the authors.

# 6. Return dispersion and implied volatility

Implied volatility of 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 associated with high implied volatility. Also, C. T. Stivers (2003) finds that the dispersion in firm returns provide incremental information about US market-level future volatility during period 1927 to 1995. We compare return dispersion with future volatility. We use traded implied volatility as a proxy of market expectations for future volatility.

## 6.1 Implied volatility and macroeconomic uncertainties

We first compare co-movements between implied volatility and return dispersion visually. We 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 2 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. For instance, during the ten-year period of 1992 to 2002, return dispersion is extremely high while implied volatility is around an average level.

*Please insert Figure 2 around here*

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

*Please insert Table 11 around here*

Next we test whether the implied volatility is also a risk measure for macroeconomic uncertainty. We use the implied volatility series in each country regress on business cycles, international political crisis and economic policy uncertainty, as we did for the return dispersion measure. Again, we only include global business cycle dummies in this regress due to the limitation of data and the local business cycle does not include recessions during this period. We run the regression in equation (10) where the independent variable is the implied volatility at month t ($VIX_t$) and the explanatory variables are global business cycle dummy at month t ($BC\_global_t$), ongoing crisis starting at month t ($Start_t$), during month t ($During_t$), ending at month t ($End_t$) and natural log of the economic policy uncertainty at time t ($EPU_t$):

$$VIX_t = \alpha + \beta_1 BC\_global_t + \beta_2 Start_t + \beta_3 During_t + \beta_4 End_t + \beta_5 \ln(EPU_t) + \varepsilon_t \qquad (9)$$

Table 12 shows the regression results for G5 countries. Implied volatility also seems to capture the uncertainty associated with these variables well. Implied volatility series in France, Japan and the US correlate with the global business cycle. Implied volatilities are significantly positive related to economic policy uncertainty. In fact, results for implied volatility seems stronger indicating that implied volatility is able to capture economic policy uncertainty better than return dispersion.

*Please insert Table 12 around here*

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

As we find implied volatility does a good job in capturing macroeconomic uncertainties, a logical question is whether or not the implied volatility also relates to the cross section of stock returns. We investigate this follow the same procedure of section 5 (again we report levels but we also consider changes, but these results are similar to the level). We test whether stocks with higher sensitivities to implied volatility produce higher average returns. We run the following time-series regression:

$$R_{i,t} = \alpha_i + \beta_{i,RMRF} RMRF_t + \beta_{i,vix} VIX_t + \varepsilon_{i,t} \qquad (10)$$

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 we use the largest 90% market capitalisation stocks (ranked at the end of the previous year). At the end of each month, we sort stocks into three portfolios (high, medium and low) based on the value of implied volatility risk loadings over the month. In table 13, Panel A 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, we 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 aggregate volatility innovations and portfolios that are least sensitive to aggregate volatility are statistically zero. However, the only exception in the US, the value-weighted portfolios that have the highest sensitivity generate higher four-factor alphas than portfolios that have the lowest sensitivity. The difference is 1.13% and statistically significant with a t-value of 2.4.

*Please insert Table 13 around here*

### 6.3 Compare return dispersion with implied volatility

In order to see more explicitly whether return dispersion and implied volatility are linked with certain types of uncertainty, we run a horse race between the two measures. We 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 11).

$$Uncertainty_t = \alpha + \beta_1 RD_t + \beta_2 IV_t + \varepsilon_t \quad (11)$$

where $Uncertainty_t$ is the local business cycle dummy, global business cycle dummy, ongoing crises and economic policy uncertainty in turn. Table 14 contains our results. Return dispersion seems to do a better job in capturing global business cycle and world crisis risk while implied volatility is better with capturing economic policy uncertainty. Return dispersion is higher during global recessions in every country. In contrast, only the implied volatility in Germany and Japan is significantly lower during global recession period. One unit increases in implied volatility reduce the probability that France and Germany in recession of 1.5% and 0.3% respectively. Higher return dispersion and implied volatility both imply higher probability that the US is in contraction, however, return dispersion has a much stronger effects. One unit increases in return dispersion leads to 3.15%

higher probability of recession compared with 0.01% of implied volatility. With regard to international political crises, return dispersion seems to be more sensitive to this type of risk compared to implied volatility. With respect to economic policy uncertainty, implied volatility does a better job than return dispersion. The implied volatility series of all countries are able to capture the country specific economic policy uncertainty. In contrast, only the return dispersion in France, UK and US is affected by the corresponding uncertainty associated with economic policy. To conclude, return dispersion and implied volatility seem to capture different types of uncertainties.

*Please insert Table 14 around here*

Moreover, we test if we control for implied volatility, is return dispersion still a measure of uncertainty? Table 15 reports our results. The effect of return dispersion is reduced but not eliminated. After controlling for implied volatility, return dispersion is higher during global recession but only in Germany, Japan and the US. Also, the international political crisis still significantly raises return dispersion in all countries except Germany. None of the economic policy uncertainty has a significant effect on return dispersion this time.

*Please insert Table 15 around here*

Additionally, we do the reverse and test whether implied volatility is able to capture those uncertainties if we control for return dispersion. Table 16 reports the results. We find implied volatility is significantly lower during global recession in all countries except France. Implied volatility is able to capture political crises risk in all countries but the US. The effect of the economic policy uncertainty on the implied volatility has not been reduced. We find that implied volatility is able to capture economic policy uncertainty in all countries.

*Please insert Table 16 around here*

## 7. Conclusion

Recent studies have highlighted the importance of macroeconomic uncertainty. This study links the return dispersion with different aspects of uncertainties in 18 countries. We 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 of the countries we tested.

Our evidence suggests that investors are able to capture the uncertainty of the economic condition by observing stock market return dispersion. Return dispersion can be considered as a risk measure for the overall systematic risk.

We further link return dispersion with the cross-sectional stock return. Stocks that are more sensitive to return dispersion result in higher average returns. It's the case not only in US but also in 13 international stock markets regardless whether we use raw return or CAPM alpha as the measure of performance. Additionally, we compare return dispersion with implied volatility which is a conventional volatility measure. We find that they capture different angles of uncertainty. Return dispersion is more sensitive to business cycle and world political crisis while implied volatility is closely linked to economic policy uncertainty.

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Table 1: Descriptive statistics

Table 1 reports the basic statistics (mean, median, max, min, standard deviation, skewness and kurtosis) of return dispersion and mean return for each country. The return dispersion is calculated as the cross-sectional standard deviation of stock returns at time t. Both return dispersion and mean returns are computed using the returns of 50 largest stocks within each countries. For US, the time period is from Jan 1926 to Dec 2013. The rest countries are using time period from Jan 1986 to Mar 2014.

Panel A: Basic characteristics of return dispersion

| RD50 | Mean | Median | Max | Min | Std. Dev. | Skewness | Kurtosis | Obs | Jarque-Bera | Probability | Sum | Sum Sq. Dev. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Australia | 0.07 | 0.06 | 0.30 | 0.02 | 0.03 | 3.51 | 19.80 | 339 | 4681.25 | 0.00 | 24.27 | 0.41 |
| Austria | 0.09 | 0.08 | 0.34 | 0.02 | 0.04 | 2.34 | 11.56 | 339 | 1345.66 | 0.00 | 29.06 | 0.51 |
| Belgium | 0.07 | 0.06 | 0.29 | 0.02 | 0.03 | 2.32 | 11.92 | 339 | 1428.64 | 0.00 | 23.26 | 0.34 |
| Denmark | 0.08 | 0.07 | 0.41 | 0.04 | 0.04 | 3.54 | 25.05 | 339 | 7574.93 | 0.00 | 27.6 | 0.48 |
| Finland | 0.09 | 0.08 | 0.28 | 0.03 | 0.03 | 1.51 | 6.68 | 339 | 320.51 | 0.00 | 30.24 | 0.41 |
| France | 0.07 | 0.06 | 0.20 | 0.01 | 0.03 | 1.86 | 8.29 | 339 | 591.28 | 0.00 | 23.04 | 0.23 |
| Germany | 0.07 | 0.06 | 0.26 | 0.01 | 0.03 | 2.21 | 10.75 | 339 | 1124.05 | 0.00 | 23.63 | 0.31 |
| Ireland | 0.11 | 0.09 | 0.41 | 0.04 | 0.05 | 1.96 | 8.37 | 339 | 623.59 | 0.00 | 35.98 | 1.02 |
| Italy | 0.07 | 0.07 | 0.45 | 0.03 | 0.03 | 5.02 | 53.08 | 339 | 36842.99 | 0.00 | 25.19 | 0.36 |
| Japan | 0.07 | 0.07 | 0.25 | 0.03 | 0.03 | 1.89 | 7.80 | 339 | 526.59 | 0.00 | 25.18 | 0.39 |
| Netherlands | 0.08 | 0.07 | 0.40 | 0.02 | 0.04 | 3.18 | 20.04 | 339 | 4674.83 | 0.00 | 25.94 | 0.51 |
| Norge | 0.10 | 0.09 | 0.43 | 0.02 | 0.04 | 2.54 | 14.82 | 339 | 2337.56 | 0.00 | 33.76 | 0.62 |
| New Zealand | 0.09 | 0.08 | 0.33 | 0.03 | 0.04 | 2.09 | 9.37 | 339 | 819.07 | 0.00 | 30.86 | 0.59 |
| Spain | 0.08 | 0.07 | 0.65 | 0.01 | 0.05 | 6.31 | 73.13 | 339 | 71723.96 | 0.00 | 26.6 | 0.71 |
| Sweden | 0.07 | 0.07 | 0.23 | 0.02 | 0.03 | 1.56 | 6.95 | 339 | 359.23 | 0.00 | 25.37 | 0.28 |
| Switzerland | 0.07 | 0.06 | 0.37 | 0.02 | 0.03 | 3.79 | 30.53 | 339 | 11518.58 | 0.00 | 23.04 | 0.31 |
| UK | 0.07 | 0.06 | 0.21 | 0.01 | 0.03 | 1.84 | 7.26 | 339 | 447.63 | 0.00 | 22.57 | 0.27 |
| US | 0.06 | 0.05 | 0.25 | 0.02 | 0.02 | 2.56 | 13.86 | 1056 | 6340.91 | 0.00 | 60.02 | 0.64 |

Table 1. Continued

Panel B: Basic characteristics of mean returns

| Mean50 | Mean | Median | Max | Min | Std. Dev. | Skewness | Kurtosis | Obs | Jarque-Bera | Probability | Sum | Sum Sq. Dev. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Australia | 0.01 | 0.01 | 0.14 | -0.51 | 0.05 | -3.51 | 35.37 | 339 | 15491.91 | 0.00 | 1.78 | 0.84 |
| Austria | 0.00 | 0.01 | 0.17 | -0.33 | 0.06 | -1.11 | 8.33 | 339 | 470.14 | 0.00 | 0.67 | 1.09 |
| Belgium | 0.01 | 0.01 | 0.17 | -0.30 | 0.05 | -1.40 | 9.94 | 339 | 790.38 | 0.00 | 2.01 | 0.88 |
| Denmark | 0.00 | 0.01 | 0.18 | -0.29 | 0.05 | -1.27 | 7.76 | 339 | 410.18 | 0.00 | 1.57 | 0.99 |
| Finland | 0.01 | 0.01 | 0.28 | -0.20 | 0.06 | -0.18 | 4.67 | 339 | 41.08 | 0.00 | 2.06 | 1.39 |
| France | 0.00 | 0.02 | 0.20 | -0.27 | 0.06 | -0.79 | 5.10 | 339 | 97.08 | 0.00 | 1.63 | 1.23 |
| Germany | 0.00 | 0.01 | 0.15 | -0.25 | 0.06 | -1.17 | 6.26 | 339 | 227.07 | 0.00 | 1.17 | 1.05 |
| Ireland | 0.00 | 0.01 | 0.24 | -0.38 | 0.07 | -0.87 | 6.42 | 339 | 207.79 | 0.00 | 1.33 | 1.86 |
| Italy | 0.00 | 0.01 | 0.21 | -0.24 | 0.07 | -0.11 | 3.85 | 339 | 10.90 | 0.00 | 0.54 | 1.52 |
| Japan | 0.00 | 0.00 | 0.19 | -0.23 | 0.06 | -0.31 | 3.88 | 339 | 16.29 | 0.00 | -0.61 | 1.28 |
| Netherlands | 0.00 | 0.01 | 0.16 | -0.34 | 0.06 | -1.39 | 7.45 | 339 | 388.98 | 0.00 | 1.12 | 1.16 |
| Norge | 0.00 | 0.01 | 0.16 | -0.31 | 0.07 | -1.24 | 5.91 | 339 | 206.70 | 0.00 | 0.53 | 1.79 |
| New Zealand | 0.00 | 0.01 | 0.24 | -0.26 | 0.05 | -0.34 | 6.87 | 339 | 218.24 | 0.00 | 1.04 | 0.86 |
| Spain | 0.01 | 0.01 | 0.19 | -0.37 | 0.06 | -0.84 | 6.95 | 339 | 260.87 | 0.00 | 2.25 | 1.32 |
| Sweden | 0.01 | 0.01 | 0.23 | -0.24 | 0.06 | -0.62 | 5.02 | 339 | 79.32 | 0.00 | 2.72 | 1.35 |
| Switzerland | 0.00 | 0.01 | 0.13 | -0.29 | 0.05 | -1.56 | 8.21 | 339 | 521.33 | 0.00 | 1.36 | 1.00 |
| UK | 0.01 | 0.01 | 0.14 | -0.30 | 0.05 | -1.12 | 7.35 | 339 | 338.60 | 0.00 | 2.02 | 0.83 |
| US | 0.01 | 0.01 | 0.38 | -0.27 | 0.05 | 0.34 | 11.02 | 1056 | 2852.84 | 0.00 | 9.22 | 2.91 |

Table 2: Return dispersion over local business cycles

Table 2 reports the results of the univariate regression 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, $BC\_local_t$ is the dummy variable for each countries' local business cycle (1= recession, 0 = expansion), $\alpha$ is the constant and $\varepsilon_t$ is the error term.

| | constant | t-value | local BC | t-value | Adjusted R2 |
|---|---|---|---|---|---|
| Australia | 0.074 | **32.59** | 0.007 | 0.86 | 0.000 |
| Austria | 0.084 | **39.65** | 0.021 | **2.08** | 0.031 |
| Belgium | 0.065 | **35.14** | 0.013 | **1.98** | 0.021 |
| Denmark | 0.080 | **38.38** | 0.008 | 1.23 | 0.005 |
| Finland | 0.089 | **42.23** | 0.030 | **3.56** | 0.059 |
| France | 0.064 | **34.54** | 0.016 | **4.93** | 0.079 |
| Germany | 0.071 | **39.55** | 0.011 | 0.84 | 0.004 |
| Ireland | 0.097 | **30.80** | 0.039 | **3.95** | 0.078 |
| Italy | 0.074 | **33.80** | 0.006 | 1.14 | -0.001 |
| Japan | 0.074 | **31.18** | 0.008 | **1.79** | 0.005 |
| Netherlands | 0.071 | **37.27** | 0.038 | **4.34** | 0.133 |
| Norge | 0.101 | **37.42** | 0.026 | **2.49** | 0.025 |
| New Zealand | 0.098 | **33.67** | -0.017 | **-3.39** | 0.016 |
| Spain | 0.076 | **34.22** | 0.017 | **3.14** | 0.025 |
| Sweden | 0.078 | **39.04** | 0.002 | 0.50 | -0.003 |
| Switzerland | 0.066 | **43.04** | 0.027 | **3.25** | 0.089 |
| UK | 0.067 | **35.21** | 0.003 | 0.69 | -0.001 |
| US | 0.062 | **39.73** | 0.030 | **5.10** | 0.139 |
| System | | | 0.016 | **11.38** | |
| Sur | | | 0.006 | **5.88** | |

Table 3: Return dispersion over local and global business cycles

Table 3 reports the coefficients estimates and t-statistics of the regression in the form of $RD_t = \alpha + \beta_1 BC\_local_t + \beta_2 BC\_global_t + \varepsilon_t$, where $RD_t$ is the return dispersion of the largest 50 market capitalization stocks at time t, $BC\_local_t$ and $BC\_global_t$ are the contemporaneous dummy variable for business cycle (1= recession, 0 = expansion) in local country and global respectively.

| | constant | t-value | local BC | t-value | global BC | t-value | Adjusted R2 |
|---|---|---|---|---|---|---|---|
| Australia | 0.071 | **34.48** | -0.008 | -1.01 | 0.049 | **3.81** | 0.115 |
| Austria | 0.083 | **37.82** | 0.008 | 1.08 | 0.041 | **3.10** | 0.097 |
| Belgium | 0.063 | **35.34** | 0.006 | 0.99 | 0.046 | **4.38** | 0.155 |
| Denmark | 0.077 | **33.76** | 0.002 | 0.48 | 0.056 | **3.43** | 0.150 |
| Finland | 0.089 | **40.80** | 0.025 | **3.24** | 0.016 | **1.88** | 0.069 |
| France | 0.064 | **34.80** | 0.014 | **3.91** | 0.014 | **2.10** | 0.093 |
| Germany | 0.068 | **41.76** | -0.012 | -1.39 | 0.058 | **5.87** | 0.214 |
| Ireland | 0.095 | **29.53** | 0.030 | **3.25** | 0.037 | **2.31** | 0.105 |
| Italy | 0.073 | **32.65** | 0.004 | 0.69 | 0.006 | 1.13 | -0.003 |
| Japan | 0.073 | **31.17** | -0.001 | -0.20 | 0.033 | **4.63** | 0.058 |
| Netherlands | 0.071 | **36.64** | 0.037 | **3.46** | 0.005 | 0.45 | 0.130 |
| Norge | 0.099 | **37.57** | 0.020 | **1.76** | 0.035 | **3.05** | 0.066 |
| New Zealand | 0.099 | **31.74** | -0.017 | **-3.40** | -0.007 | -1.59 | 0.014 |
| Spain | 0.075 | **33.96** | 0.014 | **2.10** | 0.007 | 0.99 | 0.024 |
| Sweden | 0.077 | **37.84** | -0.001 | -0.36 | 0.028 | **4.72** | 0.058 |
| Switzerland | 0.066 | **42.97** | 0.028 | **1.75** | -0.002 | -0.09 | 0.086 |
| UK | 0.066 | **34.86** | -0.008 | **-2.29** | 0.046 | **5.04** | 0.145 |
| US | 0.062 | **39.66** | 0.009 | 1.38 | 0.040 | **4.25** | 0.210 |
| | | | | | | | |
| System | | | 0.008 | **5.56** | 0.030 | **15.38** | |
| Sur | | | 0.004 | **3.76** | 0.030 | **7.37** | |

Table 4: Basic statistics of crisis data

Table 4 reports the summary statistics for the international political crisis data from January 1986 to December 2006. 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. We 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_S, WCI_D and WCI_E 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 | 0.34 | 1.44 | 0.35 | 1.08 | 5.06 | 1.11 |
| Median | 0 | 1 | 0 | 0 | 4 | 0 |
| Maximum | 3 | 5 | 3 | 12 | 20 | 11 |
| Minimum | 0 | 0 | 0 | 0 | 0 | 0 |
| Std. Dev. | 0.59 | 1.18 | 0.64 | 2.10 | 4.31 | 2.13 |
| Skewness | 1.80 | 0.42 | 1.89 | 2.39 | 0.45 | 2.06 |
| Kurtosis | 6.16 | 2.56 | 6.31 | 9.41 | 2.42 | 6.86 |
| Jarque-Bera | 240.34 | 9.53 | 264.85 | 671.88 | 12.04 | 335.27 |
| Probability | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| Sum | 85 | 364 | 88 | 271 | 1275 | 279 |
| Sum Sq. Dev. | 88.33 | 350.22 | 101.27 | 1105.57 | 4666.11 | 1140.11 |
| Observations | 252 | 252 | 252 | 252 | 252 | 252 |

Table 5: Return dispersion and international political crises

Table 5 provides the results of return dispersion regress on world crisis index with the control of business cycle in each country ($RD_t = \alpha + \beta_1 BC\_local_t + \beta_2 BC\_global_t + \beta_3 Start_t + \beta_4 During_t + \beta_5 End_t + \varepsilon_t$). $RD_t$ 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. $Start_t$, $During_t$ and $End_t$ are ongoing crisis starting at month t, during month t and ending at month t.

| | 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 | 0.063 | **25.95** | -0.007 | -1.25 | 0.011 | **1.70** | 0.002 | 1.37 | 0.001 | **2.13** | 0.000 | 0.61 | 0.019 |
| Austria | 0.079 | **24.53** | -0.006 | -0.84 | 0.030 | **2.24** | -0.001 | -0.80 | 0.000 | 0.88 | 0.002 | 1.23 | 0.029 |
| Belgium | 0.055 | **21.59** | 0.007 | 1.30 | 0.026 | **2.47** | 0.001 | 0.73 | 0.001 | **1.97** | 0.001 | 1.07 | 0.059 |
| Denmark | 0.070 | **29.52** | -0.003 | -0.78 | 0.037 | **3.52** | 0.001 | 0.90 | 0.002 | **4.34** | -0.001 | **-2.03** | 0.131 |
| Finland | 0.073 | **22.62** | 0.031 | **3.57** | 0.030 | **1.66** | 0.002 | **2.21** | 0.003 | **5.95** | 0.000 | -0.09 | 0.201 |
| France | 0.055 | **28.87** | 0.014 | **3.76** | 0.006 | 0.76 | 0.001 | 0.91 | 0.001 | **3.97** | 0.001 | 0.82 | 0.141 |
| Germany | 0.061 | **30.31** | -0.016 | **-4.46** | 0.054 | **4.36** | 0.001 | 1.54 | 0.001 | **2.37** | 0.000 | 0.33 | 0.162 |
| Ireland | 0.079 | **17.73** | 0.008 | 1.18 | -0.004 | -0.70 | 0.002 | 1.10 | 0.003 | **4.64** | -0.001 | -1.09 | 0.081 |
| Italy | 0.067 | **16.90** | -0.001 | -0.12 | 0.000 | 0.04 | 0.000 | -0.47 | 0.001 | **2.08** | 0.001 | 0.90 | 0.003 |
| Japan | 0.063 | **20.29** | 0.001 | 0.30 | 0.051 | **5.90** | 0.002 | 1.45 | 0.002 | **3.15** | 0.000 | 0.31 | 0.102 |
| Netherlands | 0.062 | **22.60** | 0.036 | **3.04** | 0.005 | 0.32 | 0.002 | 1.51 | 0.001 | **3.50** | 0.000 | -0.36 | 0.142 |
| Norge | 0.090 | **17.84** | 0.032 | **2.14** | 0.037 | **2.40** | 0.002 | 1.21 | 0.002 | **2.78** | -0.001 | -1.10 | 0.077 |
| New Zealand | 0.084 | **18.19** | -0.015 | **-2.80** | -0.005 | -0.65 | 0.003 | **1.66** | 0.002 | **4.14** | -0.001 | -0.49 | 0.068 |
| Spain | 0.057 | **23.72** | 0.013 | 1.58 | 0.014 | 1.38 | 0.004 | **3.85** | 0.002 | **4.19** | 0.002 | **2.09** | 0.187 |
| Sweden | 0.060 | **25.31** | 0.001 | 0.19 | 0.035 | **4.17** | 0.002 | **1.76** | 0.002 | **6.55** | 0.001 | 1.24 | 0.202 |
| Switzerland | 0.059 | **25.87** | 0.033 | **1.78** | -0.021 | -1.10 | 0.000 | -0.35 | 0.001 | **2.60** | 0.001 | 1.25 | 0.083 |
| UK | 0.059 | **24.89** | -0.007 | **-2.33** | 0.036 | **4.56** | 0.002 | **2.29** | 0.001 | **4.27** | -0.002 | **-2.29** | 0.147 |
| US | 0.054 | **34.95** | 0.006 | 0.87 | 0.057 | **5.73** | 0.000 | -0.08 | 0.001 | **4.12** | 0.000 | 0.57 | 0.251 |
| System | | | 0.006 | **4.02** | 0.025 | **9.01** | 0.001 | **5.74** | 0.002 | **13.99** | 0.000 | 1.19 | |
| Sur | | | 0.003 | **3.53** | 0.030 | **5.68** | 0.001 | **2.28** | 0.001 | **6.53** | 0.001 | 1.09 | |

Table 6: Return dispersion and economic policy uncertainty

Table 6 presents the characteristics of economic policy uncertainty. We shows the regression result of $RD_t = \alpha + \beta_1 BC\_global_t + \beta_2 Start_t + \beta_3 During_t + \beta_4 End_t + \beta_5 \ln(EPU_t) + \varepsilon_t$. $RD_t$ 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. $Start_t$, $During_t$ and $End_t$ are ongoing crisis starting at month t, during month t and ending at month t. The coefficients are in percentage.

| Uncertainties | France | Germany | Italy | Japan | Spain | UK | US |
|---|---|---|---|---|---|---|---|
| Constant | 7.062*** | -1.876 | -2.265 | 0.927 | 0.044 | 2.435 | 4.451 |
| | (2.080) | (2.563) | (3.710) | (2.786) | (1.775) | (3.311) | (3.211) |
| Global business cycles | 1.307 | 5.060*** | -0.552 | 4.969*** | 4.580*** | 1.881* | 6.293*** |
| | (0.814) | (1.187) | (0.780) | (0.919) | (0.672) | (0.950) | (0.723) |
| Start crisis | 0.115 | 0.173 | 0.012 | -0.011 | 0.482* | 0.377* | -0.012 |
| | (0.119) | (0.156) | (0.157) | (0.124) | (0.256) | (0.206) | (0.057) |
| During crisis | 0.184*** | 0.115*** | 0.214* | 0.156*** | 0.259*** | 0.368*** | 0.140*** |
| | (0.038) | (0.044) | (0.112) | (0.053) | (0.072) | (0.065) | (0.036) |
| End crisis | 0.047 | 0.111 | 0.190 | -0.129 | 0.133 | -0.037 | 0.036 |
| | (0.106) | (0.181) | (0.319) | (0.101) | (0.214) | (0.145) | (0.082) |
| ln(EPU) | -0.319 | 1.797*** | 1.978** | 1.215* | 1.064** | 0.762 | 0.225 |
| | (0.464) | (0.585) | (0.790) | (0.637) | (0.403) | (0.768) | (0.724) |
| | | | | | | | |
| Obs. | 240 | 168 | 120 | 223 | 72 | 120 | 252 |
| R-squared | 0.116 | 0.246 | 0.083 | 0.159 | 0.510 | 0.350 | 0.264 |

Table 7: Return dispersion and word count uncertainty

Table 7 reports the regression of return dispersion on word count uncertainty around the world. We count the number of Bloomberg reports in every months that contains the word "uncertainty" and take a log of it. We consider these word counts as proxy for uncertainty. We run the regression in the form of $RD_t = \alpha + \beta_1 BC_{local_t} + \beta_2 BC_{global_t} + \beta_3 Start_t + \beta_4 During_t + \beta_5 End_t + \beta_6 \, ln(word\ count)_t + \varepsilon_t$ 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.

| | constant | t-stat | local BC | t-stat | global BC | t-stat | start Crisis | t-stat | during Crisis | t-stat | end Crisis | t-stat | Word count uncertainty | t-stat | Adjusted $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Australia | 0.106 | **8.31** | -0.011 | **-2.09** | 0.024 | **3.67** | 0.001 | 0.73 | 0.001 | **1.79** | 0.000 | -0.42 | -0.007 | **-3.57** | 0.08 |
| Austria | 0.049 | **3.95** | -0.006 | -0.87 | 0.022 | 1.64 | 0.000 | -0.22 | 0.001 | 1.21 | 0.003 | 1.59 | 0.005 | **2.60** | 0.06 |
| Belgium | 0.013 | 1.24 | 0.012 | **2.19** | 0.012 | 1.15 | 0.001 | **1.69** | 0.001 | **2.51** | 0.002 | **2.06** | 0.006 | **4.48** | 0.14 |
| Denmark | 0.018 | **1.98** | 0.001 | 0.31 | 0.022 | **2.09** | 0.002 | **2.01** | 0.002 | **5.09** | 0.000 | -0.62 | 0.008 | **5.78** | 0.21 |
| Finland | 0.056 | **3.69** | 0.034 | **3.76** | 0.025 | 1.39 | 0.002 | **2.40** | 0.003 | **5.91** | 0.000 | 0.28 | 0.003 | 1.18 | 0.20 |
| France | 0.021 | **2.19** | 0.015 | **4.28** | -0.004 | -0.48 | 0.002 | 1.56 | 0.002 | **4.38** | 0.001 | 1.55 | 0.005 | **3.62** | 0.20 |
| Germany | 0.013 | 1.58 | -0.004 | -1.04 | 0.042 | **3.45** | 0.002 | **2.67** | 0.001 | **3.00** | 0.001 | 1.28 | 0.007 | **5.67** | 0.27 |
| Ireland | 0.054 | **3.21** | 0.006 | 0.89 | -0.011 | -1.36 | 0.003 | 1.27 | 0.003 | **4.71** | -0.001 | -0.73 | 0.004 | 1.52 | 0.09 |
| Italy | 0.031 | **3.42** | 0.005 | 0.67 | -0.009 | -1.20 | 0.000 | 0.22 | 0.001 | **2.36** | 0.002 | 1.44 | 0.006 | **3.30** | 0.04 |
| Japan | 0.027 | **2.22** | 0.003 | 0.75 | 0.040 | **4.23** | 0.002 | **2.09** | 0.002 | **3.33** | 0.001 | 0.99 | 0.005 | **3.11** | 0.13 |
| Netherlands | -0.008 | -0.60 | 0.035 | **3.26** | -0.013 | -0.73 | 0.003 | **2.60** | 0.002 | **4.62** | 0.001 | 0.80 | 0.011 | **4.96** | 0.25 |
| Norge | 0.061 | **3.58** | 0.032 | **2.35** | 0.029 | **1.88** | 0.002 | 1.50 | 0.002 | **2.90** | -0.001 | -0.59 | 0.004 | **1.84** | 0.09 |
| New Zealand | 0.168 | **9.90** | -0.011 | **-2.19** | 0.018 | **2.10** | 0.001 | 0.82 | 0.002 | **3.68** | -0.002 | **-1.91** | -0.013 | **-5.42** | 0.20 |
| Spain | 0.094 | **8.86** | 0.011 | 1.19 | 0.024 | **2.28** | 0.004 | **3.36** | 0.002 | **4.03** | 0.002 | 1.48 | -0.006 | **-3.70** | 0.23 |
| Sweden | 0.048 | **5.25** | 0.001 | 0.19 | 0.031 | **3.65** | 0.002 | **1.93** | 0.003 | **6.61** | 0.002 | 1.38 | 0.002 | 1.26 | 0.20 |
| Switzerland | 0.005 | 0.42 | 0.026 | 1.62 | -0.030 | -1.60 | 0.001 | 1.05 | 0.001 | **3.05** | 0.002 | **2.48** | 0.008 | **4.99** | 0.19 |
| UK | 0.006 | 0.64 | 0.000 | 0.00 | 0.020 | **2.25** | 0.003 | **3.80** | 0.002 | **5.37** | -0.001 | -0.87 | 0.008 | **5.45** | 0.27 |
| US | -0.007 | -0.87 | 0.017 | **3.52** | 0.031 | **3.39** | 0.001 | **2.27** | 0.002 | **5.40** | 0.002 | **2.36** | 0.009 | **7.55** | 0.43 |
| | | | | | | | | | | | | | | | |
| System | | | 0.007 | **4.86** | 0.018 | **6.33** | 0.002 | **7.53** | 0.002 | **15.05** | 0.001 | **3.08** | 0.004 | **9.38** | |
| Sur | | | 0.004 | **3.90** | 0.026 | **4.79** | 0.001 | **2.89** | 0.002 | **7.10** | 0.001 | **1.83** | 0.004 | **5.43** | |

Table 8: Economic forecast dispersion in US

Table 8 reports the univariate regression of return dispersion on the forecast dispersion of each macroeconomic variable. The regression is in the form of $RD_t = \alpha + \beta_1 z_t + \varepsilon_t$ where $RD_t$ is either the return dispersion of the largest 50 stocks on CRSP dataset (Panel A and Panel C) or the return dispersion of all constitutes in S&P 500 (Panel B and Panel D). The forecast dispersion variables are nominal GDP (GDP), 3-month treasury bill rate (TBL), unemployment rate (UNE), industrial production growth (IPD), corporate profits (CPF), real GDP growth (GDPG), real consumption growth (CSM), real non-residential investment growth (NRI), real residential investment growth (RSI), real federal government spending growth (FGS), real state and local government spending growth (LGS), consumer price index (CPI), personal consumption expenditure (PCE), term spread (TSP), AAA ranked government bond yield (TBY), real t-bill pgdp (PGDP), real t-bill CPI (RTB, CPI), long-term CPI (LPCPI).

Macroeconomic variable forecast for current quarter

| | Panel A: CRSP top50 | | | | | | Panel B: S&P 500 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Macro variables | β | SE(β) | Constant | SE(constant) | Obs. | $R^2$ | β | SE(β) | Constant | SE(constant) | Obs. | $R^2$ |
| GDP | 0.000*** | (0.000) | 0.053*** | (0.002) | 181 | 0.082 | 0.000*** | (0.000) | 0.074*** | (0.003) | 179 | 0.096 |
| TBL | 0.011** | (0.005) | 0.061*** | (0.002) | 130 | 0.010 | 0.006 | (0.005) | 0.084*** | (0.003) | 128 | 0.003 |
| UNE | 0.020 | (0.014) | 0.059*** | (0.003) | 181 | 0.010 | 0.027* | (0.016) | 0.080*** | (0.003) | 179 | 0.018 |
| IPD | 0.001 | (0.001) | 0.058*** | (0.003) | 181 | 0.010 | 0.002** | (0.001) | 0.078*** | (0.003) | 179 | 0.027 |
| CPF | 0.000 | (0.000) | 0.060*** | (0.002) | 181 | 0.014 | 0.000 | (0.000) | 0.083*** | (0.002) | 179 | 0.004 |
| GDPG | 0.000 | (0.002) | 0.061*** | (0.003) | 181 | 0.000 | 0.002 | (0.002) | 0.081*** | (0.003) | 179 | 0.005 |
| CSM | 0.003 | (0.003) | 0.060*** | (0.004) | 130 | 0.007 | 0.006** | (0.003) | 0.078*** | (0.004) | 128 | 0.033 |
| NRI | 0.004*** | (0.001) | 0.045*** | (0.005) | 130 | 0.064 | 0.004*** | (0.001) | 0.065*** | (0.006) | 128 | 0.070 |
| RSI | 0.000 | (0.000) | 0.062*** | (0.003) | 130 | 0.001 | 0.000 | (0.000) | 0.082*** | (0.003) | 128 | 0.006 |
| FGS | -0.000 | (0.000) | 0.066*** | (0.003) | 130 | 0.004 | 0.000 | (0.000) | 0.084*** | (0.003) | 128 | 0.001 |
| LGS | 0.003 | (0.002) | 0.059*** | (0.004) | 130 | 0.008 | 0.005** | (0.002) | 0.076*** | (0.004) | 128 | 0.037 |
| CPI | 0.002 | (0.004) | 0.061*** | (0.005) | 130 | 0.004 | 0.005 | (0.005) | 0.080*** | (0.005) | 128 | 0.015 |
| PCE | 0.021*** | (0.004) | 0.037*** | (0.004) | 28 | 0.337 | 0.026*** | (0.003) | 0.053*** | (0.005) | 26 | 0.378 |
| TSP | 0.080** | (0.033) | 0.051*** | (0.006) | 88 | 0.059 | 0.088** | (0.035) | 0.069*** | (0.007) | 86 | 0.068 |
| TBY | 0.075*** | (0.026) | 0.054*** | (0.005) | 88 | 0.097 | 0.096*** | (0.024) | 0.069*** | (0.005) | 86 | 0.156 |
| PGDP | 0.007 | (0.007) | 0.057*** | (0.006) | 130 | 0.011 | 0.010 | (0.006) | 0.076*** | (0.006) | 128 | 0.024 |
| RTB, CPI | 0.002 | (0.004) | 0.061*** | (0.004) | 130 | 0.003 | 0.004 | (0.004) | 0.081*** | (0.005) | 128 | 0.010 |
| LTCPI | -0.028** | (0.013) | 0.082*** | (0.008) | 89 | 0.037 | -0.022 | (0.014) | 0.099*** | (0.008) | 87 | 0.022 |

Table 8. Continued

| Macroeconomic variable forecast for next quarter | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Panel C: CRSP top50 | | | | | | Panel D: S&P 500 | | | | | |
| Macro variables | β | SE(β) | Constant | SE(constant) | Obs. | $R^2$ | β | SE(β) | Constant | SE(constant) | Obs. | $R^2$ |
| GDP | 0.000*** | (0.000) | 0.053*** | (0.002) | 181 | 0.075 | 0.000*** | (0.000) | 0.075*** | | 179 | 0.088 |
| TBL | 0.004 | (0.003) | 0.062*** | (0.003) | 130 | 0.004 | 0.001 | (0.003) | 0.085*** | | 128 | 0.001 |
| UNE | 0.017 | (0.014) | 0.057*** | (0.004) | 181 | 0.008 | 0.034** | (0.014) | 0.075*** | | 179 | 0.034 |
| IPD | 0.001 | (0.001) | 0.059*** | (0.003) | 181 | 0.009 | 0.002** | (0.001) | 0.077*** | | 179 | 0.041 |
| CPF | 0.000 | (0.000) | 0.060*** | (0.002) | 181 | 0.012 | 0.000 | (0.000) | 0.083*** | | 179 | 0.005 |
| GDPG | 0.001 | (0.002) | 0.060*** | (0.003) | 181 | 0.001 | 0.003* | (0.001) | 0.080*** | | 179 | 0.011 |
| CSM | 0.013** | (0.006) | 0.050*** | (0.006) | 130 | 0.077 | 0.015*** | (0.005) | 0.069*** | | 128 | 0.104 |
| NRI | 0.004** | (0.002) | 0.049*** | (0.006) | 130 | 0.055 | 0.004** | (0.002) | 0.070*** | | 128 | 0.058 |
| RSI | 0.001** | (0.000) | 0.058*** | (0.003) | 130 | 0.017 | 0.001 | (0.000) | 0.081*** | | 128 | 0.010 |
| FGS | -0.001* | (0.001) | 0.068*** | (0.004) | 130 | 0.014 | -0.000 | (0.001) | 0.086*** | | 128 | 0.000 |
| LGS | 0.000 | (0.003) | 0.063*** | (0.004) | 130 | 0.000 | 0.005* | (0.003) | 0.079*** | | 128 | 0.021 |
| CPI | 0.005 | (0.005) | 0.059*** | (0.005) | 130 | 0.007 | 0.007 | (0.006) | 0.079*** | | 128 | 0.014 |
| PCE | 0.048*** | (0.009) | 0.013 | (0.008) | 28 | 0.654 | 0.059*** | (0.011) | 0.019* | | 26 | 0.648 |
| TSP | 0.066** | (0.033) | 0.047*** | (0.009) | 88 | 0.057 | 0.065* | (0.033) | 0.067*** | | 86 | 0.054 |
| TBY | 0.084*** | (0.026) | 0.047*** | (0.006) | 88 | 0.121 | 0.117*** | (0.027) | 0.059*** | | 86 | 0.226 |
| PGDP | 0.002 | (0.003) | 0.062*** | (0.004) | 130 | 0.002 | 0.001 | (0.003) | 0.084*** | | 128 | 0.001 |
| RTB, CPI LTCPI | 0.005 | (0.004) | 0.059*** | (0.004) | 130 | 0.009 | 0.005 | (0.005) | 0.080*** | | 128 | 0.010 |

Table 9: Raw returns of portfolios sorted by their sensitivity to return dispersion

Table 9 reports the raw returns of portfolios sorted by their sensitivity to return dispersion. We use daily stock returns from January 1986 to March 2014. We first regress the daily stock return on the contemporaneous mean return of the largest 50 stocks and the return dispersion of the largest 50 stocks. Then we obtain the coefficients for the return dispersion and sorted all stocks based on their coefficients. Group 1 consists of stock with the smallest 20% return dispersion coefficients whereas Group 5 consists of stocks with the largest 20% return dispersion coefficients. We report the monthly value-weighted portfolio returns in panel A and equal-weighted portfolio returns in panel B.

| Panel A: value 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 | -0.031 | **-6.60** | -0.001 | -0.30 | 0.006 | **2.11** | 0.015 | **4.91** | 0.030 | **6.68** | 0.061 | **9.38** |
| Belgium | -0.017 | **-3.71** | 0.003 | 0.97 | 0.006 | **2.28** | 0.014 | **5.20** | 0.029 | **6.73** | 0.047 | **7.31** |
| France | -0.021 | **-4.82** | -0.003 | -0.95 | 0.005 | 1.57 | 0.012 | **3.79** | 0.028 | **7.47** | 0.049 | **8.57** |
| Germany | -0.022 | **-4.78** | -0.005 | -1.41 | 0.002 | 0.65 | 0.010 | **3.11** | 0.028 | **6.82** | 0.049 | **8.10** |
| Italy | -0.020 | **-4.75** | -0.005 | -1.43 | 0.001 | 0.20 | 0.008 | **2.01** | 0.027 | **6.35** | 0.048 | **7.85** |
| Japan | -0.027 | **-6.53** | -0.014 | **-4.24** | -0.005 | **-1.67** | 0.006 | **2.10** | 0.028 | **7.20** | 0.055 | **9.68** |
| Netherland | -0.029 | **-6.33** | -0.000 | -0.01 | 0.005 | 1.52 | 0.011 | **3.54** | 0.029 | **7.12** | 0.058 | **9.46** |
| Norway | -0.028 | **-4.88** | 0.001 | 0.21 | 0.004 | 1.06 | 0.017 | **4.46** | 0.036 | **6.25** | 0.064 | **7.86** |
| Spain | -0.019 | **-4.05** | 0.002 | 0.53 | 0.006 | 1.64 | 0.012 | **2.91** | 0.035 | **7.93** | 0.053 | **8.40** |
| Sweden | -0.025 | **-4.78** | 0.002 | 0.47 | 0.008 | **2.38** | 0.017 | **4.46** | 0.037 | **8.26** | 0.063 | **9.01** |
| Switzerland | -0.021 | **-5.04** | 0.000 | 0.03 | 0.005 | **1.75** | 0.011 | **3.45** | 0.028 | **7.50** | 0.049 | **8.80** |
| UK | -0.023 | **-5.65** | 0.000 | 0.01 | 0.006 | **2.06** | 0.011 | **4.19** | 0.028 | **8.65** | 0.051 | **9.81** |
| US | -0.013 | **-3.62** | 0.003 | 1.35 | 0.010 | **4.23** | 0.016 | **6.43** | 0.031 | **8.44** | 0.044 | **8.54** |
| | | | | | | | | | | | | |
| average | -0.023 | | -0.001 | | 0.005 | | 0.012 | | 0.030 | | 0.053 | |
| min | -0.031 | | -0.014 | | -0.005 | | 0.006 | | 0.027 | | 0.044 | |
| max | -0.013 | | 0.003 | | 0.01 | | 0.017 | | 0.037 | | 0.064 | |
| median | -0.022 | | 0 | | 0.005 | | 0.012 | | 0.029 | | 0.051 | |

Table 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 | -0.012 | **-2.48** | -0.002 | -0.67 | 0.001 | 0.39 | 0.002 | 0.63 | 0.012 | **2.43** | 0.024 | **3.47** |
| Belgium | -0.004 | -1.11 | 0.004 | 1.39 | 0.005 | **1.93** | 0.010 | **4.03** | 0.021 | **5.74** | 0.025 | **4.97** |
| France | -0.003 | -0.77 | -0.001 | -0.34 | 0.002 | 0.76 | 0.004 | 1.56 | 0.012 | **3.38** | 0.015 | **2.87** |
| Germany | -0.008 | **-2.29** | -0.003 | -1.26 | -0.001 | -0.51 | -0.001 | -0.49 | 0.001 | 0.22 | 0.009 | **1.76** |
| Italy | -0.008 | **-1.90** | -0.006 | **-1.84** | -0.003 | -1.07 | 0.001 | 0.38 | 0.017 | **4.07** | 0.025 | **4.21** |
| Japan | -0.005 | -1.24 | -0.008 | **-2.44** | -0.005 | -1.56 | 0.001 | 0.34 | 0.019 | **4.63** | 0.024 | **4.06** |
| Netherland | -0.008 | **-2.10** | 0.001 | 0.38 | 0.004 | 1.45 | 0.005 | 1.62 | 0.015 | **4.02** | 0.023 | **4.33** |
| Norway | -0.015 | **-2.81** | 0.000 | 0.09 | 0.004 | 1.01 | 0.012 | **3.07** | 0.025 | **4.46** | 0.041 | **5.16** |
| Spain | -0.009 | **-1.96** | 0.001 | 0.25 | 0.003 | 1.00 | 0.009 | **2.54** | 0.026 | **6.09** | 0.035 | **5.64** |
| Sweden | -0.009 | **-1.82** | 0.001 | 0.23 | 0.004 | 1.19 | 0.010 | **2.82** | 0.020 | **4.34** | 0.029 | **4.35** |
| Switzerland | -0.008 | **-2.25** | 0.001 | 0.34 | 0.004 | 1.50 | 0.007 | **2.51** | 0.019 | **5.27** | 0.027 | **5.27** |
| UK | -0.003 | -0.79 | 0.002 | 0.77 | 0.002 | 0.85 | 0.004 | 1.37 | 0.011 | **2.82** | 0.014 | **2.55** |
| US | 0.008 | **2.26** | 0.007 | **2.80** | 0.009 | **3.78** | 0.011 | **4.22** | 0.022 | **5.99** | 0.014 | **2.64** |
| | | | | | | | | | | | | |
| average | -0.0065 | | -0.0003 | | 0.0022 | | 0.0058 | | 0.0170 | | 0.0235 | |
| min | -0.0155 | | -0.0082 | | -0.0049 | | -0.0012 | | 0.0008 | | 0.0093 | |
| max | 0.0082 | | 0.0074 | | 0.0090 | | 0.0124 | | 0.0263 | | 0.0409 | |
| median | -0.0079 | | 0.0008 | | 0.0033 | | 0.0046 | | 0.0187 | | 0.0244 | |

Table 10: CAPM alphas of portfolios sorted by their sensitivity to return dispersion

Table 10 reports the CAPM alphas of portfolios sorted by their sensitivity to return dispersion. We report the monthly value-weighted portfolio returns in panel A and equal-weighted portfolio returns in panel B.

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

Table 10. 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 | **-4.75** | -0.007 | **-3.50** | -0.004 | **-2.00** | -0.003 | -1.50 | 0.006 | 1.50 | 0.025 | **5.00** |
| Belgium | -0.010 | **-5.00** | -0.001 | -1.00 | -0.000 | 0.00 | 0.005 | **5.00** | 0.014 | **7.00** | 0.024 | **8.00** |
| France | -0.008 | **-4.00** | -0.005 | **-5.00** | -0.001 | -1.00 | 0.001 | 1.00 | 0.008 | **4.00** | 0.016 | **5.33** |
| Germany | -0.012 | **-6.00** | -0.006 | **-6.00** | -0.004 | **-4.00** | -0.004 | **-4.00** | -0.003 | -1.50 | 0.009 | **3.00** |
| Italy | -0.010 | **-5.00** | -0.008 | **-8.00** | -0.005 | **-5.00** | -0.000 | 0.00 | 0.015 | **7.50** | 0.025 | **8.33** |
| Japan | -0.004 | -1.33 | -0.007 | **-3.50** | -0.004 | **-2.00** | 0.002 | 1.00 | 0.020 | **6.67** | 0.024 | **6.00** |
| Netherland | -0.011 | **-5.50** | -0.002 | **-2.00** | 0.001 | 1.00 | 0.002 | **2.00** | 0.012 | **6.00** | 0.023 | **7.67** |
| Norway | -0.018 | **-6.00** | -0.001 | -0.50 | 0.002 | 1.00 | 0.010 | **5.00** | 0.023 | **7.67** | 0.041 | **10.25** |
| Spain | -0.016 | **-8.00** | -0.005 | **-2.50** | -0.003 | **-3.00** | 0.003 | 1.50 | 0.019 | **9.50** | 0.035 | **11.67** |
| Sweden | -0.018 | **-6.00** | -0.007 | **-3.50** | -0.003 | **-3.00** | 0.003 | **3.00** | 0.011 | **3.67** | 0.028 | **7.00** |
| Switzerland | -0.013 | **-6.50** | -0.003 | **-3.00** | 0.001 | 1.00 | 0.003 | **3.00** | 0.014 | **7.00** | 0.027 | **13.50** |
| UK | -0.010 | **-3.33** | -0.003 | -1.50 | -0.003 | **-3.00** | -0.001 | -1.00 | 0.004 | 1.33 | 0.014 | **3.50** |
| US | -0.003 | -1.00 | -0.001 | -0.50 | 0.001 | 0.50 | 0.002 | 1.00 | 0.011 | **3.67** | 0.014 | **3.50** |
| | | | | | | | | | | | | |
| 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 11: Basic characteristics of implied volatility

Table 11 reports the summary statistics of the implied volatility series in five countries. For France we use the CAC40 volatility index from January 2000 to December 2013. For Germany we use the VDAX new volatility index from January 1992 to December 2013. For Japan we use the NIKKEI stock average volatility index from January 1998 to December 2013. For the UK we use the FTSE 100 volatility index from January 2000 to December 2013. For the US we use the COBE 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 |
| ρ(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 |

Table 12: implied volatility and the macroeconomic uncertainties

Table 12 exhibits the characteristics of implied volatility in G5 countries. Panel A exhibits the basic statistics of the implied volatility series. Panel B shows the regression result of $VIX_t = \alpha + \beta_1 BC\_global_t + \beta_2 Start_t + \beta_3 During_t + \beta_4 End_t + \beta_5 \ln(EPU_t) + \varepsilon_t$. $VIX_t$ is the implied volatility indices 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. $Start_t$, $During_t$ and $End_t$ are ongoing crisis starting at month t, during month t and ending at month t. $EPU_t$ is the economic policy uncertainty index at time t. The coefficients are in percentage.

| VARIABLES | France | Germany | Japan | UK | US |
|---|---|---|---|---|---|
| Constant | -6.854 | -12.964 | -7.848 | -19.219*** | -20.681** |
| | (7.745) | (8.752) | (5.968) | (5.567) | (8.302) |
| Global business cycles | -3.980* | -1.396 | -3.160** | -3.566 | 3.418*** |
| | (2.129) | (1.215) | (1.234) | (2.232) | (1.163) |
| Start crisis | 0.168 | 0.633 | 0.646** | 0.292 | 0.193 |
| | (0.536) | (0.559) | (0.304) | (0.575) | (0.279) |
| During crisis | 1.802*** | 0.476*** | 0.379*** | 1.684*** | 0.190* |
| | (0.267) | (0.156) | (0.114) | (0.217) | (0.107) |
| End crisis | 1.695*** | 0.656 | 0.119 | 1.186** | 0.027 |
| | (0.558) | (0.611) | (0.252) | (0.487) | (0.284) |
| ln(EPU) | 5.274*** | 7.250*** | 6.926*** | 7.479*** | 8.470*** |
| | (1.730) | (2.035) | (1.368) | (1.274) | (1.890) |
| Observations | 84 | 168 | 108 | 84 | 204 |
| R-squared | 0.515 | 0.174 | 0.364 | 0.637 | 0.165 |

Table 13: Implied volatility and cross-sectional stock returns

Table 13 reports the average raw returns, CAPM alphas and four factor alphas for the portfolios sorted by implied volatility loadings. We run the time-series regression using individual stock return regress on market return and implied volatility: $R_{i,t} = \alpha_i + \beta_{i,RMRF} RMRF_t + \beta_{i,vix} VIX_t + \varepsilon_{i,t}$. Then we sort portfolios based on the implied volatility loadings. "Low", "Medium", "High" represent the portfolios that contains stocks that are most, medium and least sensitive to implied volatility loadings. The results for the four factor alphas are in percentage.

| **Countries** | **Low** | **Medium** | **High** | **H-L** | **Low** | **Medium** | **High** | **H-L** | **Low** | **Medium** | **High** | **H-L** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***Panel A: value weighted*** | | | | | | | | | | | | |
| | **Raw average return** | | | | **CAPM - alpha** | | | | **4 factors - alpha in %** | | | |
| | **Low** | **Medium** | **High** | **H-L** | **Low** | **Medium** | **High** | **H-L** | **Low** | **Medium** | **High** | **H-L** |
| **Australia** | -0.0137 | -0.0007 | -0.0060 | 0.0078 | -0.011 | 0.001 | -0.004 | 0.007 | -1.523 | -0.461 | -0.755 | 0.768 |
| t-stat | (-1.423) | (-0.126) | (-0.829) | (0.644) | (-1.837) | (0.587) | (-1.001) | (1.061) | (-2.596) | (-1.578) | (-1.668) | (1.036) |
| **France** | -0.0017 | 0.0002 | 0.0018 | 0.0035 | -0.003 | -0.001 | 0.001 | 0.004 | -0.616 | -0.332 | -0.248 | 0.367 |
| t-stat | (-0.272) | (0.052) | (0.368) | (0.444) | (-1.269) | (-0.792) | (0.236) | (1.110) | (-1.595) | (-1.344) | (-0.840) | (0.755) |
| **Germany** | -0.0009 | 0.0034 | 0.0052 | 0.0062 | -0.006 | -0.000 | 0.001 | 0.007 | -0.804 | -0.250 | -0.103 | 0.701 |
| t-stat | (-0.207) | (1.102) | (1.421) | (1.059) | (-2.260) | (-0.173) | (0.665) | (2.178) | (-2.000) | (-0.952) | (-0.311) | (1.343) |
| **Japan** | -0.0017 | -0.0038 | -0.0005 | 0.0012 | 0.002 | -0.001 | 0.003 | 0.001 | -0.508 | -0.788 | -0.493 | 0.015 |
| t-stat | (-0.355) | (-1.093) | (-0.106) | (0.189) | (0.714) | (-1.140) | (1.328) | (0.342) | (-1.705) | (-3.606) | (-1.618) | (0.036) |
| **Netherlands** | -0.0010 | -0.0017 | 0.0045 | 0.0055 | -0.002 | -0.002 | 0.004 | 0.005 | -0.485 | -0.572 | 0.217 | 0.701 |
| t-stat | (-0.141) | (-0.374) | (0.740) | (0.587) | (-0.393) | (-1.095) | (1.433) | (1.096) | (-0.870) | (-1.717) | (0.521) | (1.009) |
| **Sweden** | 0.0058 | 0.0081 | 0.0060 | 0.0002 | -0.002 | 0.001 | -0.001 | 0.001 | -0.254 | 0.164 | 0.024 | 0.278 |
| t-stat | (0.929) | (1.609) | (1.182) | (0.026) | (-0.668) | (0.478) | (-0.416) | (0.326) | (-0.490) | (0.430) | (0.063) | (0.430) |
| **Switzerland** | 0.0004 | 0.0015 | 0.0008 | 0.0004 | -0.002 | 0.000 | -0.001 | 0.001 | -0.041 | -0.075 | -0.213 | -0.172 |
| t-stat | (0.080) | (0.454) | (0.228) | (0.074) | (-0.689) | (0.136) | (-0.273) | (0.332) | (-0.128) | (-0.279) | (-0.764) | (-0.403) |
| **United Kingdom** | -0.0066 | 0.0009 | 0.0037 | 0.0102 | -0.008 | -0.000 | 0.002 | 0.011 | -1.053 | -0.287 | 0.073 | 1.126 |
| t-stat | (-1.261) | (0.263) | (0.967) | (1.589) | (-2.790) | (-0.311) | (1.247) | (3.037) | (-2.660) | (-1.157) | (0.294) | (2.406) |
| **United States** | 0.0077 | 0.0095 | 0.0089 | 0.0012 | -0.002 | 0.002 | -0.000 | 0.001 | -0.314 | 0.108 | 0.035 | 0.349 |
| t-stat | (2.520) | (4.127) | (3.203) | (0.283) | (-0.891) | (1.963) | (-0.059) | (0.664) | (-2.105) | (1.831) | (0.255) | (1.721) |

Table 13 continued.

***Panel B: Equally weighted***

| | Raw average return | | | | CAPM - alpha | | | | 4 factors - alpha in % | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Low** | **Medium** | **High** | **H-L** | **Low** | **Medium** | **High** | **H-L** | **Low** | **Medium** | **High** | **H-L** |
| **Australia** | -0.0203 | -0.0187 | -0.0161 | 0.0043 | -0.017 | -0.016 | -0.013 | 0.004 | -2.124 | -2.073 | -1.699 | 0.425 |
| t-stat | (-1.803) | (-2.636) | (-1.467) | (0.271) | (-2.341) | (-5.076) | (-1.883) | (0.444) | (-3.866) | (-6.034) | (-2.993) | (0.538) |
| **France** | 0.0010 | -0.0037 | -0.0006 | -0.0017 | -0.000 | -0.005 | -0.002 | -0.001 | -0.209 | -0.710 | -0.398 | -0.189 |
| t-stat | (0.162) | (-0.959) | (-0.125) | (-0.205) | (-0.100) | (-2.462) | (-0.613) | (-0.278) | (-0.537) | (-3.211) | (-1.352) | (-0.388) |
| **Germany** | -0.0053 | -0.0032 | -0.0048 | 0.0005 | -0.009 | -0.005 | -0.008 | 0.001 | -0.878 | -0.724 | -0.832 | 0.046 |
| t-stat | (-1.396) | (-1.524) | (-1.340) | (0.094) | (-3.716) | (-5.422) | (-3.840) | (0.200) | (-2.701) | (-4.084) | (-2.785) | (0.104) |
| **Japan** | 0.0029 | -0.0039 | 0.0060 | 0.0030 | 0.006 | -0.002 | 0.009 | 0.003 | -0.465 | -1.048 | -0.137 | 0.327 |
| t-stat | (0.593) | (-1.149) | (1.277) | (0.449) | (1.762) | (-0.872) | (2.846) | (0.656) | (-1.720) | (-5.561) | (-0.497) | (0.848) |
| **Netherlands** | -0.0019 | -0.0016 | -0.0005 | 0.0014 | -0.002 | -0.002 | -0.001 | 0.001 | -0.624 | -0.539 | -0.384 | 0.240 |
| t-stat | (-0.322) | (-0.388) | (-0.082) | (0.171) | (-0.781) | (-1.312) | (-0.403) | (0.312) | (-1.520) | (-2.243) | (-1.080) | (0.443) |
| **Sweden** | 0.0007 | -0.0004 | 0.0002 | -0.0005 | -0.006 | -0.007 | -0.006 | -0.000 | -0.630 | -0.656 | -0.603 | 0.027 |
| t-stat | (0.110) | (-0.079) | (0.031) | (-0.062) | (-1.320) | (-2.856) | (-2.117) | (-0.053) | (-1.541) | (-2.356) | (-1.721) | (0.050) |
| **Switzerland** | 0.0008 | 0.0016 | 0.0037 | 0.0029 | -0.001 | 0.000 | 0.002 | 0.003 | -0.163 | -0.172 | 0.163 | 0.326 |
| t-stat | (0.174) | (0.574) | (0.884) | (0.455) | (-0.611) | (0.453) | (1.280) | (1.263) | (-0.543) | (-0.915) | (0.618) | (0.816) |
| **United Kingdom** | -0.0044 | -0.0033 | -0.0036 | 0.0008 | -0.006 | -0.005 | -0.005 | 0.001 | -0.730 | -0.662 | -0.584 | 0.146 |
| t-stat | (-0.809) | (-1.007) | (-0.787) | (0.117) | (-1.566) | (-2.562) | (-1.735) | (0.207) | (-2.594) | (-3.626) | (-2.369) | (0.389) |
| **United States** | 0.0134 | 0.0078 | 0.0141 | 0.0007 | 0.004 | 0.000 | 0.005 | 0.001 | 0.167 | -0.199 | 0.342 | 0.175 |
| t-stat | (3.703) | (3.068) | (4.056) | (0.133) | (1.525) | (0.261) | (1.998) | (0.335) | (1.184) | (-2.593) | (2.222) | (0.840) |

Table 14: Horserace between return dispersion and implied volatility in G5 countries

Table 14 shows the horserace between return dispersion (RD) and implied volatility (IV) in G5 countries. We 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 (During) and economic policy uncertainty (EPU) in turn.

| | France | | Germany | | Japan | | UK | | US | |
|---|---|---|---|---|---|---|---|---|---|---|
| | RD | VIX | RD | VIX | RD | VIX | RD | VIX | RD | VIX |
| Local BC | 7.252 | -0.015 | 1.955 | -0.003 | 0.898 | 0.005 | 2.214 | -0.003 | 3.145 | 0.009 |
| t-value | **4.430** | **-3.410** | **2.110** | **-1.720** | 1.100 | 1.300 | 1.630 | -0.590 | **2.340** | **2.260** |
| Global BC | 3.143 | -0.002 | 5.334 | -0.008 | 1.790 | 0.010 | 3.663 | 0.002 | 4.077 | 0.003 |
| t-value | **1.860** | -0.440 | **7.030** | **-2.910** | **1.920** | **2.850** | **2.750** | 0.280 | **3.280** | 0.640 |
| Start crisis | 10.059 | -0.001 | -2.443 | 0.021 | -1.065 | 0.081 | 9.436 | 0.007 | -6.065 | 0.036 |
| t-value | 1.200 | -0.060 | -0.400 | 1.010 | -0.370 | **2.690** | 1.210 | 0.240 | -1.210 | 1.400 |
| During crisis | 53.733 | 0.059 | 15.473 | 0.045 | 48.541 | 0.206 | 45.147 | 0.164 | 29.428 | 0.088 |
| t-value | **5.300** | 1.340 | 1.420 | 1.140 | **8.990** | **4.230** | **4.160** | **4.310** | **2.710** | **1.760** |
| End crisis | -2.638 | 0.059 | -1.389 | 0.022 | 0.272 | 0.040 | -4.730 | 0.060 | 4.242 | -0.002 |
| t-value | -0.500 | 1.630 | -0.200 | 0.890 | 0.090 | 1.320 | -1.260 | 1.400 | 0.690 | -0.070 |
| ln(EPU) | -7.795 | 0.032 | 0.614 | 0.014 | 0.087 | 0.016 | -3.432 | 0.026 | -1.918 | 0.020 |
| t-value | **-3.610** | **5.690** | 0.660 | **4.030** | 0.160 | **5.720** | **-2.170** | **4.320** | **-2.220** | **7.650** |

Table 15: Return dispersion and macroeconomic uncertainties with the control of implied volatility

Table 15 reports the results of the regression: $RD_t = \alpha + \beta_1 BC\_local_t + \beta_2 BC\_global_t + \beta_3 Start_t + \beta_4 During_t + \beta_5 End_t + \beta_6 WordCount_t + \beta_7 \ln(EPU_t) + \beta_8 VIX_t + \varepsilon_t$. We use return dispersion ($RD_t$) regress on the global business cycle dummy ($BC\_global_t$), international political crisis starting in a month ($Start_t$), during a month ($During_t$), ending in a month ($End_t$), log value of the word count uncertainty ($WordCount_t$), log value of the economic policy uncertainty ($EPU_t$) and implied volatility ($VIX_t$). Coefficients are in percentage.

| | Constant | Local BC | Global BC | Start WCI | during WCI | end WCI | Word Count Uncertainty | ln(EPU) | VIX | N | Adjusted R2 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *France* | | | | | | | | | | | |
| Coefficient | 7.03 | 0.76 | -0.79 | 0.51 | 0.40 | 0.04 | -0.37 | -0.59 | 0.16 | 84 | 0.58 |
| t-statistics | 1.05 | 0.60 | -0.64 | **1.66** | **2.37** | 0.20 | -0.39 | -0.98 | **3.68** | | |
| *Germany* | | | | | | | | | | | |
| Coefficient | -2.64 | - | 4.60 | 0.08 | 0.06 | 0.03 | 0.60 | 0.29 | 0.16 | 168 | 0.54 |
| t-statistics | -0.96 | - | **3.76** | 0.61 | 1.55 | 0.24 | **2.22** | 0.61 | **6.15** | | |
| *Japan* | | | | | | | | | | | |
| Coefficient | -3.39 | 0.29 | 2.08 | -0.03 | 0.46 | 0.00 | 0.87 | 0.84 | -0.02 | 108 | 0.26 |
| t-statistics | -0.53 | 0.46 | 1.51 | -0.14 | **3.66** | 0.00 | 1.20 | 0.93 | -0.24 | | |
| *UK* | | | | | | | | | | | |
| Coefficient | -7.18 | -1.12 | 0.80 | 0.55 | 0.45 | -0.03 | 1.75 | -0.36 | 0.06 | 84 | 0.47 |
| t-statistics | -0.91 | **-1.90** | 0.68 | 1.56 | **2.89** | -0.19 | 1.43 | -0.31 | 0.99 | | |
| *US* | | | | | | | | | | | |
| Coefficient | -0.17 | 0.94 | 3.41 | 0.04 | 0.16 | 0.19 | 0.82 | -0.64 | 0.17 | 204 | 0.54 |
| t-statistics | -0.04 | 1.60 | **3.63** | 0.59 | **4.46** | **1.87** | **5.33** | -0.81 | **6.33** | | |

Table 16: Implied volatility and macroeconomic uncertainties with the control of return dispersion

Table 16 reports the results of the regression: $VIX_t = \alpha + \beta_1 BC\_local_t + \beta_2 BC\_global_t + \beta_3 Start_t + \beta_4 During_t + \beta_5 End_t + \beta_6 WordCount_t + \beta_7 \ln(EPU_t) + \beta_8 RD_t + \varepsilon_t$. We use implied volatility ($VIX_t$) regress on the global business cycle dummy ($BC\_global_t$), international political crisis starting in a month ($Start_t$), during a month ($During_t$), ending in a month ($End_t$), log value of the word count uncertainty ($WordCount_t$), log value of the economic policy uncertainty ($EPU_t$) and return dispersion ($RD_t$).

| | Constant | Local BC | Global BC | Start WCI | during WCI | end WCI | Word Count Uncertainty | ln(EPU) | RD | N | Adjusted R2 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *France* | | | | | | | | | | | |
| Coefficient | -4.69 | -1.11 | -1.68 | -0.45 | 1.05 | 1.30 | -0.91 | 5.17 | 116.94 | 84 | 0.57 |
| t-statistics | -0.30 | -0.40 | -0.82 | -0.88 | **2.47** | **3.88** | -0.39 | **2.89** | **3.62** | | |
| *Germany* | | | | | | | | | | | |
| Coefficient | -28.48 | - | -14.00 | 0.43 | 0.46 | 0.62 | 3.85 | 2.32 | 162.18 | 168 | 0.54 |
| t-statistics | **-3.43** | - | **-5.42** | 0.92 | **3.19** | **1.77** | **5.23** | 1.57 | **7.04** | | |
| *Japan* | | | | | | | | | | | |
| Coefficient | -12.63 | 3.71 | -5.66 | 0.71 | 0.45 | 0.18 | 1.05 | 6.15 | -3.90 | 108 | 0.35 |
| t-statistics | -1.12 | **3.18** | **-3.84** | **2.36** | **3.27** | 0.70 | 0.83 | **4.72** | -0.25 | | |
| *UK* | | | | | | | | | | | |
| Coefficient | 12.48 | -2.42 | -1.27 | 0.17 | 1.72 | 1.03 | -4.95 | 8.52 | 24.51 | 84 | 0.65 |
| t-statistics | 0.91 | -1.59 | -0.51 | 0.31 | **5.21** | **2.09** | **-2.34** | **6.22** | 0.93 | | |
| *US* | | | | | | | | | | | |
| Coefficient | -28.58 | 4.37 | -8.58 | 0.31 | 0.12 | 0.05 | 1.16 | 7.05 | 103.54 | 204 | 0.42 |
| t-statistics | **-3.18** | **3.09** | **-4.27** | 1.33 | 1.15 | 0.22 | **2.72** | **4.02** | **5.04** | | |

Figure 1: Return dispersion in US and events

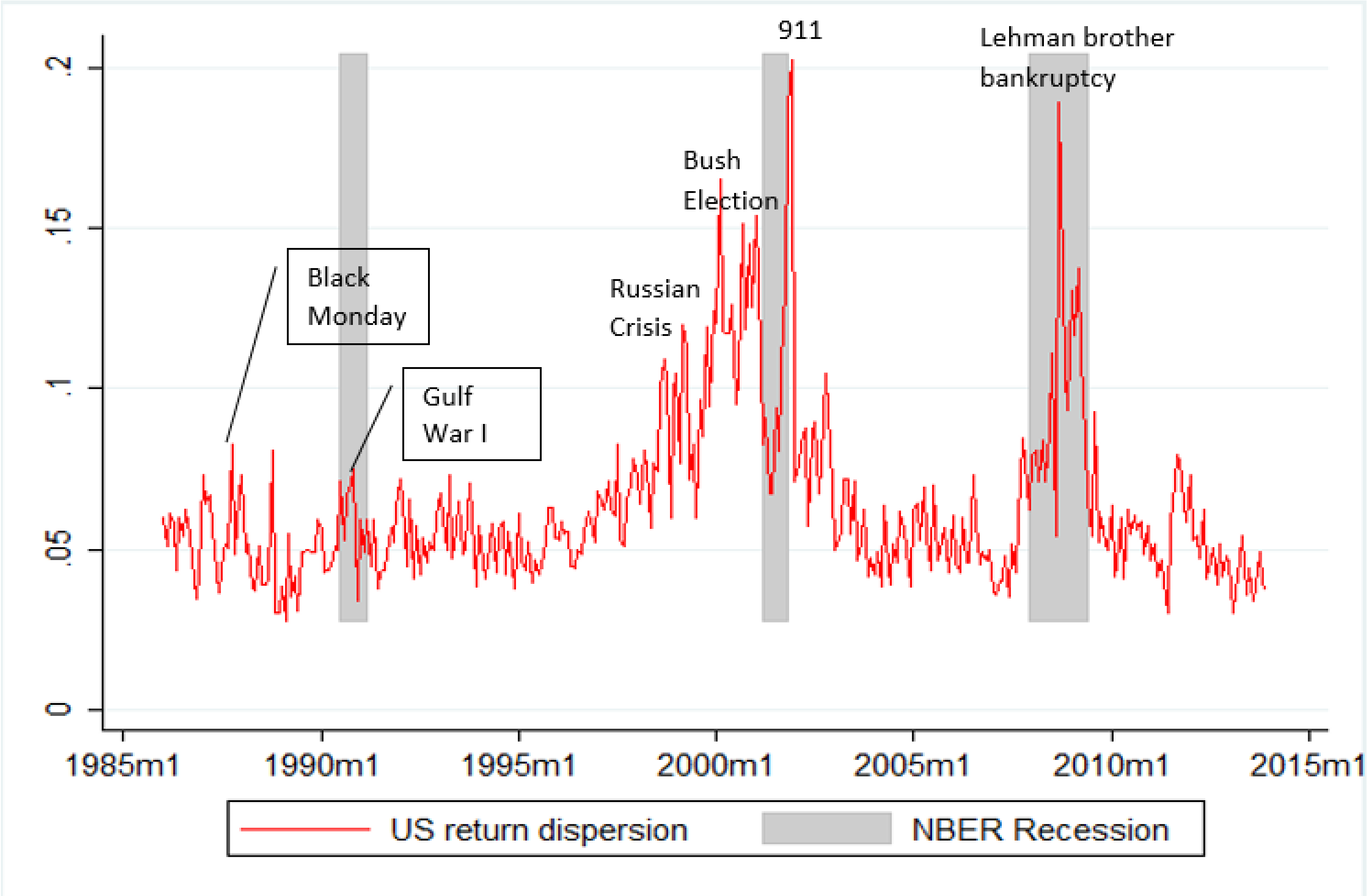


Figure 1 plots the return dispersion of the largest 50 US stocks from January 1985 to December 2013.

Figure 2: Return dispersion and implied volatility

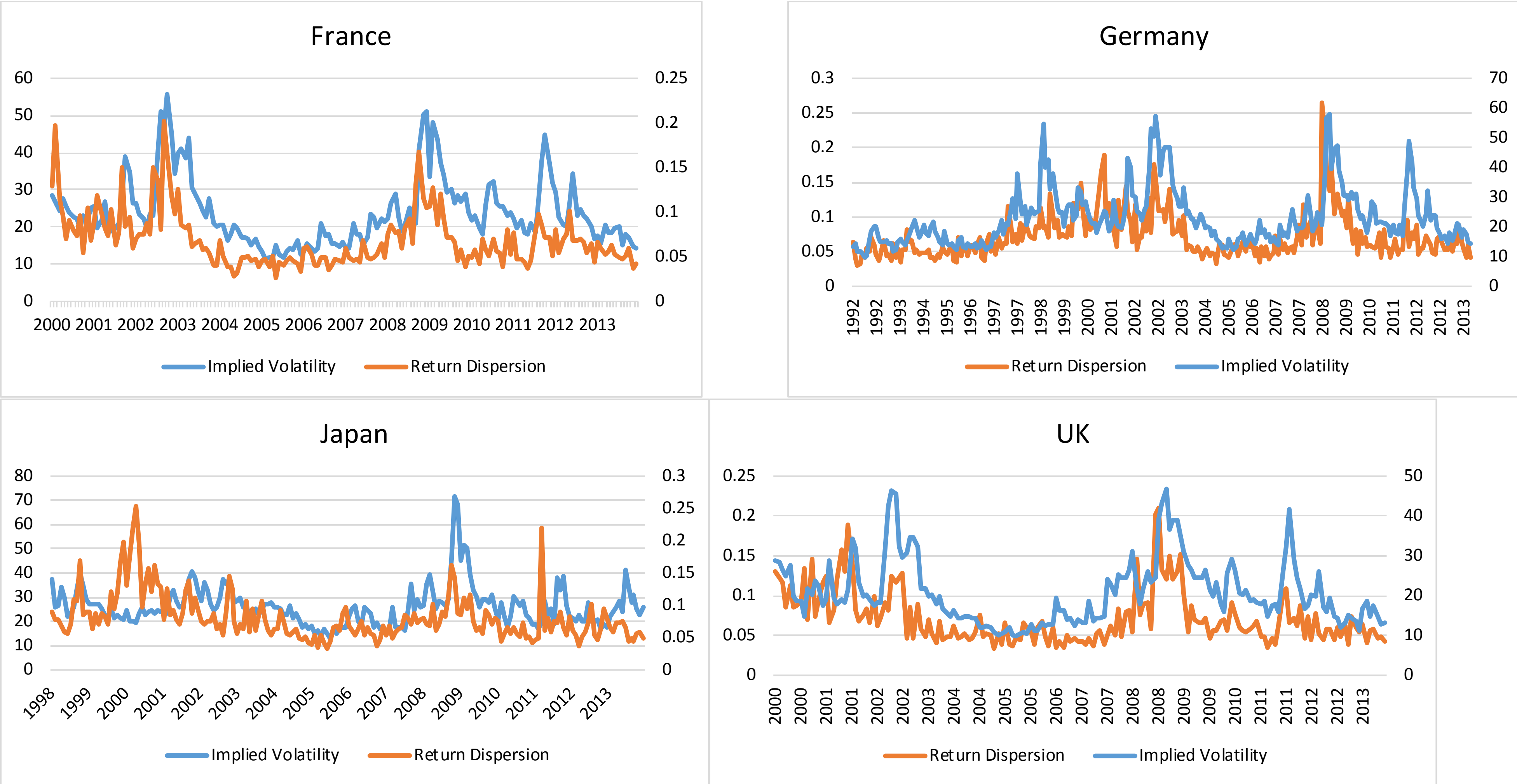

Figure 2. Continued

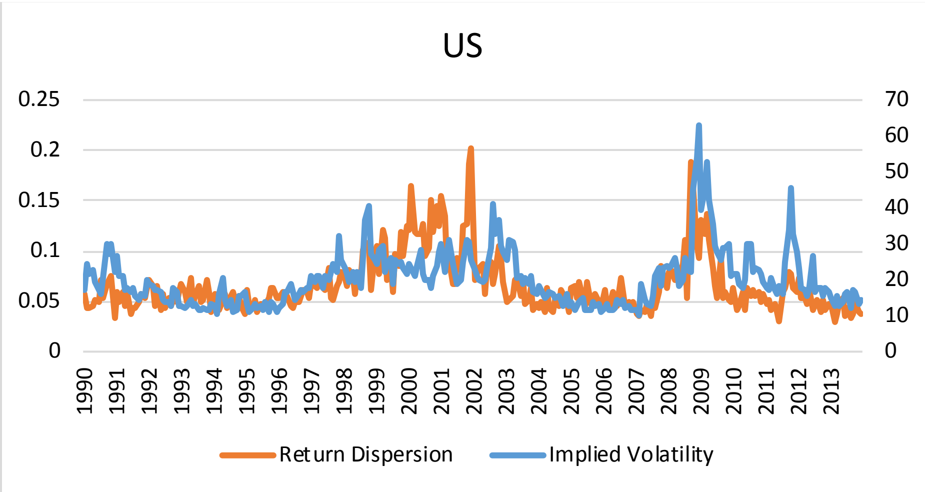


Figure 2 plots the return dispersion and its contemporaneous implied volatility index for each country. The return dispersion is calculated using the largest 50 stock returns. The implied volatility indices we use include CAC40 Volatility Index (France), VDAX New Volatility Index (Germany), NIKKEI Stock Average Volatility Index (Japan), FTSE 100 Volatility Index (UK) and CBOE SPX Volatility VIX (US).