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ECONOMIC POLICY UNCERTAINTY AND CREDIT RISK

A cross sectional analysis of company specific CDS spreads across nine industries in the U.S market

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ABSTRACT

We analyse the effects political uncertainty has on the credit risk embedded in the term structure of single name credit default swap spreads across nine industries in the United States. After running a set of panel regressions, we find that economic policy uncertainty has a widening effect on the spreads. Specifically, we find that one standard deviation change in economic policy uncertainty moves the spread about 0.4 % and has an additional trailing effect of 0.7 % the following month. We argue that the numbers reflect the opportunity cost of not being able to postpone the need of credit insurance during periods of political turmoil.

Furthermore, we make a comparison of the financial and the non-financial sectors and conclude that the financial sector is up to 3.4 times more sensible to shocks in policy uncertainty then non-financial sectors.

JEL Codes: C33, D84, D84, G18

Keywords: Credit Default Swap, Credit Risk, Policy Uncertainty, EPU, Policy Making

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1 INTRODUCTION

Policy uncertainty arises when agents are unable to predict the outcome of a policy-making process, and there is little or no knowledge about how fiscal or monetary policies will change. When policy uncertainty increases, the future development of the economy becomes harder to predict. From a policy maker's perspective, understanding how policy uncertainty affects different levels in society is crucial, as imperfect information in policy making might have not only direct consequences but substantial effects on long-term growth prospects and welfare, (Croce, Nguyen, and Schmid, 2012). Uncertainty about the Federal Reserve's future announcements may affect private investment, which indirectly have effects on the rate of unemployment, (Baker, Bloom, and Davis, 2013; Creal, 2014; Shoag, 2015). Moreover, policy uncertainty is negatively correlated with both investment and growth, and thus determining the pattern of economic development in society, (Aizenman and Marion, 1993).

In the last decade, economies and its financial markets all over the world have endured periods of significant political turbulence, such as the Global Financial Crisis, the Eurozone Crisis and the U.S. Debt-Ceiling Dispute. The high level of policy uncertainty during these periods had an adverse impact on the rate of recovery, (Hendrickson, 2015). To avoid making already unstable situations worse in the future, we need a better understanding of the relationship between financial markets and government institutions during periods of political turmoil, (IMF, 2012).

Even though the interest in studying the impact of policy uncertainty has grown, mainstream finance theory still lacks theoretical models taking it into account, (Pastor, 2013). It is nevertheless surprising that almost no research exist on how policy uncertainty affects credit risk to date. While some studies covering sovereign credit risk are provided: (Bekaert, Hoerova, and Duca, 2013; Cuadra and Sapriza, 2008; Manzo, 2013), the only published work on corporate credit risk is to our knowledge the study by Wisniewski (2015). Analysing the relationship between policy uncertainty and credit default swap (CDS) indices (Markit CDX IG and iTraxx), they found that economic policy uncertainty Granger-cause a positive movement in CDS spreads. However, as they merely looked at the relationship, the magnitude of this effect is yet to be quantified.

Given how central the concepts of risk and uncertainty is in finance and economic theory, we want to contribute the understanding of how they are interlinked. We, therefore, aim to fill to this void by looking at how different agents respond to changes in uncertainty, as well as how governmental inefficiency shape the economic landscape.

1.1 PURPOSE OF STUDY

While Wisniewski et al. primarily looked at how CDS spreads respond to shocks in policy risk, we want to capture and quantify how uncertainty alter perceptions of credit risk on a broader scale. To this end, instead of a Vector Autoregressive framework, we use a broad cross-section of single-name credit default swap spreads. By doing so, this study addresses two questions:

1. Does economic policy uncertainty impact risk perceptions of investors in the U.S economy?

2. If yes, how large is this effect?

Answering those questions, our study accomplishes two things: first, we confirm that a positive relationship between economic policy uncertainty and CDS spreads exist, thus making the findings by Wisniewski et al. more robust. Second, to our knowledge, this is the first study to quantify the effect varying political ambiguity has firm-specific CDS spreads.

After controlling for other market factors, a one standard deviation shock to the policy uncertainty index in our model, cause the CDS spread to change by approximately 0.4 %. We also identify a lagging effect the following month, which correspond to almost a 0.7 % change in the CDS spread. Moreover, we show that firms in the financial sector are several times more sensitive to shocks than other sectors, but that the lagging effect one month after is about the same in all industries. Our conclusion is that changes in policy uncertainty do alter the perceived risk-level in the economy, and we believe this is an expected behaviour due to the psychological mechanisms behind loss aversion. We finally argue that the coefficients are interpretable as the opportunity cost of being unable to postpone the need for credit protection during times of political instability.

The remainder of this paper is organised as follows: Chapter 2 provide an introductory explanation of what a Credit Default Swap is, together with a description of our proxy for policy uncertainty. Chapter 3 describe our sampling method, data, and selection criteria for explanatory variables. Chapter 4 contains a walk-through of the rationale behind our method and a short description of the model selection process. Lastly, Chapter 5 is where we conduct the analysis, interpret output, and discuss our conclusions.

2

THEORETICAL FRAMEWORK & PREVIOUS RESEARCH

The following sections describe the characteristics and dynamics of the CDS contract, as well as the components and construction of the Economic Policy Uncertainty Index (hereafter EPU). We also provide a brief summary of studies on policy uncertainty and its implications for the capital markets.

2.1 CREDIT DEFAULT SWAPS

A CDS is a credit derivative transferring credit risk of an underlying obligation from one party to another, (Lipton, 2011). Due to the prevalence of debt financing, CDS were originally designed to protect investors (buyers) against loans going bad. A CDS allows risk transferal from the buyer (the issuer of debt) to investors who are in a better position to bear that risk. The mechanics behind the swap is best described as a bilateral over-the-counter contract, consisting of two legs: the protection leg and the premium leg. As depicted in Figure 1, the protection buyer (premium leg) pays a quarterly or semi-annual premium to the protection seller (protection leg). In return, the protection seller guarantees to make the protection buyer whole in the case of a credit event, (Lipton, 2011). Two significant differences exist between a CDS and regular insurance. First, with insurance you typically have direct economic exposure to the underlying asset, with a CDS it is not necessary to hold the underlying bond. Second, insurance is not traded on the market, in opposite to CDS contracts, (Stulz, 2010).

The market for CDS has grown rapidly since the late 90's when the International Swap and Derivatives Association (ISDA) introduced their first standardised CDS contract, (Hull, Predescu, and White, 2004). However, The Dodd-Frank Wall Street Reform Act overhauled the swaps market and mandated central clearing, trading, and reporting. These new regulatory requirements, combined with higher capital requirements, have increased the costs of trading swaps, (Acharya, 2011). From being one of the most common derivative traded, (Lipton, 2011), the market of single name CDS has declined, but have still a gross value exceeding $16 trillion in late 2014, (International Settlements, 2015).

CDS makes the financial market more efficient in several ways. First, if an investor believes the default risk of a particular company will increase, it can be much easier to buy credit protection using a CDS than short-selling the company's bonds, (Stulz, 2010). Second, CDS contracts allow banks to hedge against their credit risks, (Amato, 2005). Put together, the possibility of risk transferal allows more companies to access credit markets since banks can lend more money without severely affecting their risk level, (Stulz, 2010). Moreover, the CDS market often more liquid than the corporate bond market, (Amato, 2005). The total notional amount outstanding of a CDS can often exceed to total amount of debt issued by the underlying company, (Stulz, 2010), which makes the data more accurate and hence more useful to analyse.

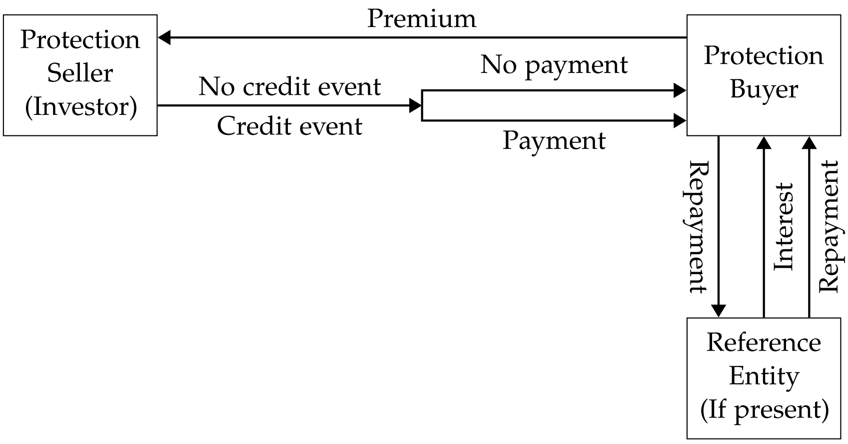


Figure 1: Schematic picture of the parts involved in a CDS. The protection buyer receives interest from the borrower, and in turn pay the protection seller a regular premium to get covered in case of a credit event.

2.1.1 *CDS Pricing*

There is no initial cost in entering into a credit default swap. At inception, a premium (noted in basis points) is decided such that so that the present value for both parties equals each other, making the market value of the CDS zero, (Lipton, 2011). Thus, the value of the premium leg can be expressed as the sum of the present value of all remaining premium payments:

$$PV_{premuim} = N\frac{S}{f}\sum_{i=1}^{M}\left[1 - F(\Delta t_{i-1})\right] D(\Delta t_i)^1 \tag{1}$$

In the event of default within the time frame of the contract, the insurer is obliged to compensate the protection buyer for the loss from par. The value of the protection leg is the expected present value of the protection or the cost of default, Lipton (2011).

$$PV_{protection} = N(1 - R - cR)\sum_{i=1}^{M}\left[F(\Delta t_i) - F(\Delta t_{i-1})\right] D(\Delta t_i)^1 \tag{2}$$

1 N is the notional of the swap, S is the spread in basis points (premium paid by the protection buyer), f is the frequency of spread payments, F is the cumulative default probability function, c is the coupon of the underlying bond as an annual percentage, and R is the recovery rate of the underlying bond. $D = e^{r_{\Delta t}\Delta t}$, and represents the continuously compounded discount factor at the horizon $\Delta t = t - t_P$, where t_P is the pricing date and $r_{\Delta t}$ is the spot risk free rate prevailing over $[t_P, t]$.

The market value of a CDS is the difference between the premium and the protection legs, which constitute the spread. The size of this spread is a reflection of two factors. The first being the default probability, which reflects the likelihood that the issuer will default on its obligations. The second component is the recovery rate, indicating how much a bondholder will recover without having credit protection if the issuer defaults on its obligations.

$$S = \frac{f(1 - R - cR)\sum_{i=1}^{M}[F(\Delta t_i) - F(\Delta t_{i-1})]}{\sum_{i=1}^{M}[1 - F(\Delta t_{i-1})]} \tag{3}$$

A wider spread means that investors believe a default is more likely, which is why it is popular to use a CDS as a proxy for credit risk, (Avesani, Li, and Garcia Pascual, 2006; Chan-Lau, 2005; Goodhart, 2009). For information in further detail on the mathematical expressions of CDS spreads, see Hull (2000).

Empirical research on the pricing of CDS has shown that firm-specific factors best explain the size of the spread. Ericsson, Jacobs, and Oviedo (2009) found with their structural model that financial leverage and volatility of the underlying explain 60 % of the spread expressed in levels, and 23 % of the variation in spread changes. Galil et al. (2014) tested both market and firm-specific variables and concluded that market factors could help explain the spreads, but confirmed earlier findings that the firm-specific factors still provided most explanatory power.

2.2 THE ECONOMIC POLICY UNCERTAINTY INDEX

The overall level of policy uncertainty facing an economy depends on such a vast number of constantly changing factors that actual uncertainty level impossible to fully observe. However, to conduct this study, it is crucial to find a good enough proxy for the underlying level of policy uncertainty. The methods used to proxy policy uncertainty are many and have varied over time. One popular approach has been to study the time period surrounding major political events. We are however interested in a *ever present* kind of policy uncertainty, affecting e.g., non-election years as well, and need thus another kind of proxy.

As many before us[1], we use the EPU index of Baker, Bloom, and Davis. The EPU Index consists of three value-weighted components and measures the policy uncertainty level on a monthly basis.

The first component is an index of search results from ten large newspapers and measures the frequency which certain keywords appear in the articles[2]. The keywords are sorted into three groups: *Economy*, *Uncertainty* and *Policy*[3]. An article has to contain at least one word in each group to count. The collected articles are then

1 A complete list of works using Baker, Bloom, and Davis (2013) EPU index can be found here: http://www.policyuncertainty.com/research.html

2 The newspapers included in the EPU index are *USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle, the Dallas Morning News, the New York Times*, and *the Wall Street Journal*.

3 The index measures on basis on the following groups of (1) “economic” or “economy”; (2) “uncertain”, “uncertainty” or “uncertainties”; (3) “congress”, “deficit”, “Federal Reserve”, “The Fed”, “legislation”, “regulation” or “White House”

divided by the total number of articles published in the newspaper they appeared in, yielding separate series for each newspaper. Lastly, the figures are normalised and summed up to the newspaper index of that month, (Baker, Bloom, and Davis, 2013).

The second component of the index draws on reports by the Congressional Budget Office (CBO) that compile lists of temporary federal tax code provision. Temporary tax measures create uncertainty for both companies and households since Congress often decides whether or not to extend them at last minute. As such, the annual dollar-weighted numbers of tax code provisions measure the level of uncertainty regarding the path that the federal tax code will take in the future, (Baker, Bloom, and Davis, 2013).

The third component accounts for disagreement among forecasters. Each quarter the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters (SPF) give their view of a range of macroeconomic variables for the coming five quarters. Baker et al. use the dispersion between individual forecasters' predictions about future levels of the Consumer Price Index, Federal Expenditures, and State and Local Expenditures to construct indices of uncertainty about policy-related macroeconomic variables, (Baker, Bloom, and Davis, 2013).

2.3 POLICY UNCERTAINTY

Financial research on the effects of policy uncertainty has foremost been provided from two perspectives: (1) the relationship between policy uncertainty and investments and (2) policy uncertainty and the capital markets. The former relates to the theoretical idea that investments can be seen as real options and therefore there is value in waiting to invest during times of uncertainty. The latter is empirically tested over a multitude of financial asset, showing how policy uncertainty affects asset prices, volatility and risk premia.

On a macroeconomic level, research on how policy uncertainty impact factors such as GDP and employment is inconsistent, both supporting that is does have an effect, and the lack thereof, (Born, 2014). The time frame has shown to matter whether any impact can be seen or not, as policy uncertainty have a strong negative short-run impact on growth, reducing investment, hiring, and consumption. In the longer-run the impact of uncertainty was less clear, as uncertainty had some potentially positive effects on R&D, Bloom (2014).

Policy uncertainty was found by Foerster (2014) to affect the economy asymmetrically when investigating the symmetry of spikes in policy uncertainty. The reason behind this research was to determine if a subsequent decrease will entirely offset a temporary increase, or if increases will have more sizable effects. If symmetric, then the consequences of a spike will not have any long-lasting impact on the economy. The findings, however, showed the contrary. Upward spikes, as in higher levels of uncertainty, had more sizable effects than the downward spikes.

2.3.1 *Policy Uncertainty & Investments*

Bernanke was the first to show the negative relationship between high levels of uncertainty and investments. He argued that since firms' real investments often are irreversible, i.e., when a machine is purchased and produced it cannot be transformed into something else or sold without a substantial economic loss, the investments can be seen as real options. When seen as a real option, the value of waiting to invest increases and thereby investments simultaneously decreases during times of high uncertainty. He further showed that firms' earnings power are lower during periods of considerable uncertainty, (Bernanke, 1983).

These findings have been confirmed several times regardless of which proxy for uncertainty being used. Rajan and Marwah (1998) concluded that policy uncertainty has a negative impact on foreign direct investment. Julio (2012) showed that firms reduce investment expenditures by an average of 4.8 %, and that investment is 40 % less sensitive to stock prices, during election years compared to non-election years. Further, the drop in investment-to-price sensitivity is larger when election results are less precise. Durnev (2013) found that election uncertainty leads to inefficient capital allocation, reducing company performance. Gulen (2015) could finally attribute two-thirds of the drop in corporate investments during the financial crisis to policy related uncertainty.

2.3.2 *Policy Uncertainty & Capital Markets*

Pástor and Veronesi are prominent in both the theoretical and empirical research of policy uncertainty and its effects on the equity market. Due to the lack of theoretical guidance, they created a model of how stock prices react to political news (Pastor, 2013). With this they empirically proved that policy uncertainty makes stocks more volatile and more correlated. Further, they showed that heterogeneity among the potential new government policies increases risk premia since government-related risk cannot be fully diversified away, (Pastor, 2013). The model was later applied to a cross section of 20 countries to investigate if elections and global summits affected option pricing. By doing so, they showed that political uncertainty is priced in the options market in such a way that protection against price, variance, and tail risks is more expensive before a political event, (Kelly, Pastor, and Veronesi, 2014).

Brogaard and Detzel (2015) found similarly that EPU positively forecasts log excess market returns, and that innovations in during times of high EPU earn a significant negative risk premium. On the debt side of the market, Ulrich (2012) found that uncertainty about future government spending is a risk factor in the bond market and that a one standard deviation change in EPU increases the slope of the yield curve by 0.2 %.

3

DATA

The following sections describe our sampling methods, sampling criterion, and sources of data. We also provide a detailed description of the control variables included in our model and the rationale behind them.

3.1 DATA ON CREDIT DEFAULT SWAPS

Data on CDS spreads used in this study is obtained from Thomson Reuters Datastream. All spreads in our sample are daily mid-market, U.S. Dollar CDS contracts, quoted in basis points. We choose to concentrate the study to five-year bonds, partly due to availability, but also to ensure uniformity of the dataset. Moreover, five-year contracts have been the most frequently traded the last decade (Blanco, Brennan, and Marsh, 2005).

We decide only to cover CDS contracts referencing *modified restructuring*, and in that way make sure that each firm represented in the dataset only has one CDS spread tied to it. Further, to increase liquidity, we exclude all spreads showing zero trading activity in an accumulated number of six months or more. We also require each firm to be listed on a U.S. stock exchange, with data on both share price and PE-ratio available. Remaining after these selection criteria are 254 spreads from 254 different firms, stretching over a 1,781 day period. Thomson Reuters has already sorted the firms in nine different industries: Banks, Consumer Goods, Electrical Power, Energy Companies, Other Financial Companies, Manufacturing, Services, Telephone and Transportation, which we will stick to in this study. The time frame is selected such that we avoid the direct impact of the U.S. sub-prime mortgage crisis, and spans from June 2009 to January 2016. A complete list the firms included in our sample can be found in the appendix, A.2.4.

3.2 DATA ON ECONOMIC POLICY UNCERTAINTY

Data on economic policy uncertainty (described in 2.2) is publicly available on the website of Baker, Bloom and Davis. We use the monthly index, constructed of three components, and cover the whole sampling period.

3.3 DATA ON CONTROL VARIABLES

To rinse for market information already embedded in the CDS spreads, one has to choose the control variables with care, since factors related to the credit risk within in different industries are nearly infinite. We determine which variables to include in the model based on three criterion:

1. There should be both company-specific and global variables included in our model.

2. The variables should be selected such that they altogether remove as much of already embedded market information in the CDS spread movements as possible.

3. While still achieving the two first criterion, the correlation between our variables should be as low as possible to avoid multicollinearity.

COMPANY SPECIFIC VARIABLES We use the negative correlation between equity and its default probability, first suggested by Merton (1974), to capture the economic state of the specific firm. By including each firm's corresponding share price and price-earnings ratio, we try to capture any changes in their equity premium. Share prices are also proved to be significant factors in explaining the CDS spread, (Galil et al., 2014). We further believe that the accumulated stock price movements will partly reflect the overall state of the economy, due to the variety and number of companies included in our dataset. Our data source of share prices and PE-ratios is Thomson Reuters Datastream.

CORPORATE YIELD SPREAD Inspired by Longstaff et al. (2011), we use changes in the spreads of investment-grade bonds, specifically the five-year Thomson Reuters BBB and AAA bond indices. By doing so, we aim to catch the range of variation in investment-grade bond yields and thus purge the CDS spreads from movements tied to changes in the systematic risk within the economy.

THE STATE OF THE ECONOMY Another factor that might reflect the global state of the economy is the changes of the Standard and Poor's Goldman Sachs Commodity Index (GSGC), since gold is a hedge against stocks on average and a safe-haven in extreme stock market conditions, (Baur, 2010).

Trying to capture any other external economic factors that might influence the credit spread, we use the fact that sovereign credit risk is more correlated across countries than the equity index returns for the same countries, (Longstaff et al., 2011). Since the U.S economy affects financial markets all over the world, we choose to include the U.S sovereign CDS spread as a control variable as well. We retrieve data on GSGC and U.S. Sovereign CDS's from Thomson Reuters Datastream.

PARTISAN CONFLICT INDEX The last control variable we chose to include is the Partisan Conflict Index (PCI), constructed by Azzimonti (2013). To measure PCI, Azzimonti used a methodology very similar to that of Baker, Bloom, and Davis (2013). The main difference between PCI and EPU is that PCI measures government dysfunction rather than the degree of economic policy uncertainty.

Under extreme values of the PCI, such as during a shutdown, disagreement is intense, which means that agents ought to know with high certainty that the status-quo will remain unchanged, (Azzimonti, 2013). By including PCI in our model, we hope to rinse for periods where the two indices overlap and thus isolate the effects of EPU yet further. Data on the PC Index is publicly available on the website of the Federal Reserve Bank of Philadelphia.

4

METHODOLOGY

In the following sections, we describe our methodological approach and the rationale behind it. We also give a detailed description of the data tidying process and provide summary statistics on some of the data used in the study.

4.1 PANEL REGRESSIONS

This study aims to first answer is if economic policy uncertainty impacts risk perceptions of investors in the U.S economy. If present, the second purpose is to quantify this effect. We address this by constructing panel data frame, and then regress the changes in CDS spreads on the EPU index. Empirical evidence suggests that the impact of uncertainty is asymmetric, meaning that that a sudden peak in the EPU index may very well have sustained effects, (Foerster, 2014). We, therefore, include EPU from both the current and the previous month in our model. Besides, adding potential explanatory power to the model, there is a value from investor perspective to add the latter. Since EPU is published with one month delay, the lagged version is the most currently available to investors.

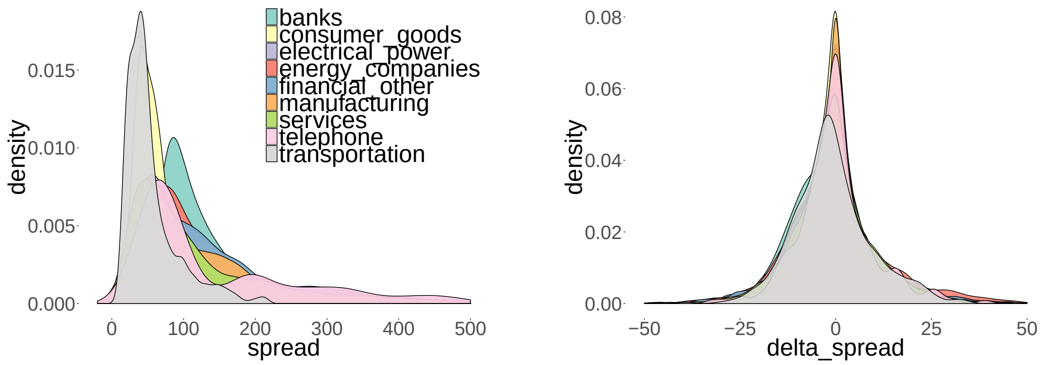
The first regression is performed on the index alone; we then add the control variables step by step. This allows us to dodge some of the criticism of the EPU index; its composition catches not only political uncertainty but uncertainty embedded in the financial markets as well. Including stock, credit and commodity markets in the model enable us to clean the EPU index from financial and economic information, leaving out only the political part.

Since the financial sector is more exposed to policy making, one can assume that this industry also is more sensible to policy uncertainty. We will investigate this by extending our model with a set of dummy variables: *financials*, covering *banks* and *financial_other*, and *non_financials* representing the rest of the industries included in our dataset.

To make interpretation easier, we choose to demean and scale both EPU and PCI, such that their mean take a value of zero, and their standard deviation is one. We can thus measure the impact of EPU on CDS spreads in terms of standard error movements, and hence, avoid any arbitrary metrics for a *normal* shocks to the policy uncertainty index.

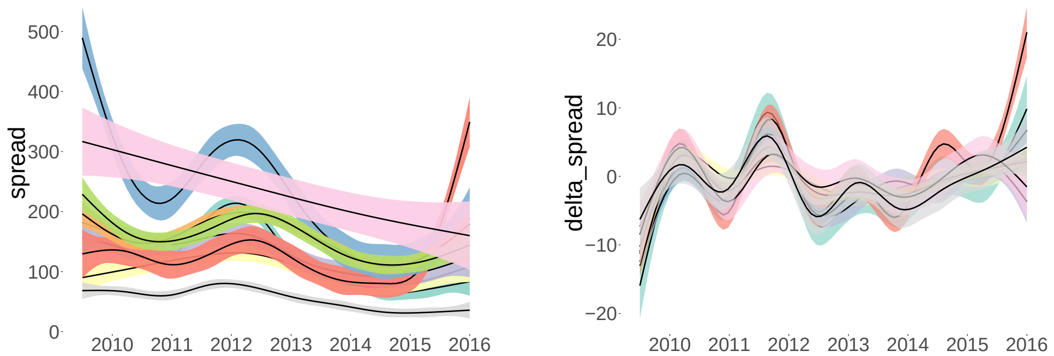
CDS spreads, stock prices, leverage, and stock volatility are non-stationary in levels but stationary in first differences, (Galil et al., 2014). We, therefore, apply first log-differences to all variables and thus remove any firm-specific trends. The outcome of these measures is illustrated in Figure 5.

We use logarithms for two reasons. First, we want to scale the variables such that any exceptional values do not absorb all variance. Secondly, log-differences can be interpreted as percentage changes later in the regression output. This applies to all variables except PE-ratios, PCI and EPU. PE-ratios are not logarithmised due to the presence of negative values.



(a) (b)

Figure 2: Density plots of the firm-specific CDS spreads grouped by industry, expressed in levels to the left and log-differences to the right. The log changes are scaled such that they are interpretable as percentage points.



(a) (b)

Figure 3: Smoothed trends of firm-specific CDS spreads, grouped by industry over the sampling period. Spreads are expressed in levels to the left and log changes to the right, where the log changes are scaled such that they are interpretable as percentage points. The shaded area represents the standard error bounds for each industry and month.

For each firm, we compute the monthly CDS spread by first creating monthly mid-spreads. We do this by collapsing the daily spreads for each firm into monthly averages. Then, we calculate the log-difference between present and previous month, such that the monthly log-difference of firm i at time t can be expressed as:

$$\Delta \ln(CDS_{i,t}) = \ln(CDS_{i,t}) - \ln(CDS_{i,t-1}) \tag{4}$$

4.2 MODEL SELECTION

To select the most suitable panel method for our sample, we rely on the guidance from a set of different tests. The following section will give a short description and purpose of the tests performed.

TEST OF POOLABILITY First, we conduct a standard F-test under the hypothesis that the fixed effect are equal across all units. Rejecting this assumption means that the fixed effects are non-zero. A significant F-test tells us that a pooled OLS regression will be biassed, which is the outcome we expect to get.

BREUSCH-PAGAN TEST We make sure that the assumption of heteroskedasticity applies to our dataset by performing a Breusch-Pagan Test. The Breusch–Pagan Test tests for conditional heteroscedasticity, with a null hypothesis of homoscedasticity. If chi-squared is significant, the null hypothesis of homoscedasticity is rejected and heteroskedasticity assumed.

THE HAUSMAN TEST We use the Hausman Test to investigate how the non-zero fixed effects are correlated with the time-varying explanatory variables. The purpose of this test is to compare the fixed and the random effects models, under which the null hypothesis is that the random effects model is the more efficient (has the smallest asymptotic variance).

BREUSCH-GODFREY/WOOLDRIDGE TEST With this test, we investigate the presence of general serial correlation excluded from the proposed model. If present, the conclusions drawn from other tests, or the estimates of model parameters could be misleading and should be interpreted carefully. If the original model's errors are uncorrelated then fixed effect residuals are negatively serially correlated.

ROBUST COVARIANCE MATRIX ESTIMATION Bertrand, Duflo, and Mullainathan (2004) show that the usual standard errors of the fixed effects estimator are drastically understated in the presence of serial correlation. We will, therefore, estimate the regression model without control for within-cluster error correlation, and then post-estimate cluster-robust standard errors. We use agglomerative clustering on a firm level. In the fixed effect model, the Arellano estimation is preferred, which allows a full general structure w.r.t. heteroskedasticity and serial correlation, (Marcellino, Stock, and Watson, 2006).

5

RESULTS

5.1 TEST OUTCOME & MODEL SELECTION

The outcome of the F-test allows us to accept the alternative hypothesis of instability and confirm the presence of non-zero fixed effects. Following the F-test is the Breusch-Pagan test, which allows us to assume heteroskedasticity at an equally high significance level.

When performing the Hausman-test, we conclude that a fixed effects model is preferable to a random effects model. The Breusch-Godfrey/Wooldridge-test indicate that the idiosyncratic error terms are serially correlated. The model used in the upcoming regressions will thus have the following expression:

$$\Delta \ln(Y_{t,i}) = \beta_1 \Delta EPU_t + \beta_2 \Delta EPU_{t-1} + \gamma \chi_{i,t} + \alpha_i + u_{i,t} \tag{5}$$

where $Y_{i,t}$ is the firm specific change in the CDS spread at time t, EPU is the economic policy uncertainty index, $\chi_{t,i}$ is our set of control variables, and α_i is the firm-specific fixed effects. To control for serial correlation and heteroscedasticity, we post-cluster all error terms by group on a firm-level. Complete output of all test is included the appendix, A.2.

5.2 DESCRIPTIVE STATISTICS

Presented in Table 4, the average CDS spread between June 2009 and January 2016 was 161.00 basis points, and the corresponding mean change per month was -0.62 bps. The overall trend is negative, as in decreasing spread sizes. This pattern is expected since our sample period begins at the end of the global financial crisis. As Oh (2016) showed, distress for individual firms has reduced since the crisis, although the joint probability of distress is higher now than before the crisis. The CDS spreads expressed in levels show high positive skewness, meaning that their distribution has a longer and flatter right tail and shorter and fatter left tail. This indicates a bigger disparity among the larger spreads.

Table 5 displays the correlation matrix of all variables in our model, where the first column represents the relationship between the independent variable and the dependent variables. We note that *delta_spread* and *delta_share_price* are the most correlated, with a negative relationship. Among the explanatory variables, *delta_share_price* and *delta_PE_ratio* have the highest correlation, but only about 0.35. Hence, we assume that the risk of multicollinearity is rather low, and will not interfere with our conclusions below.

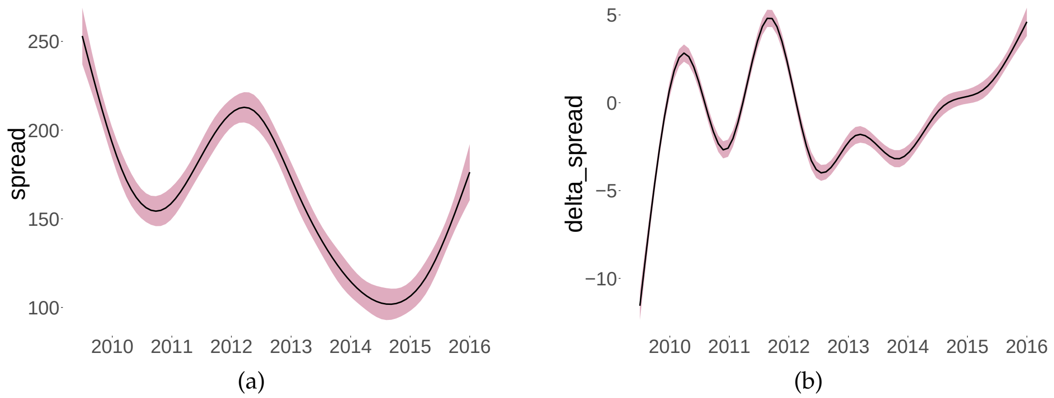


Figure 4: Illustration of trends in CDS spreads across all 254 firms over the sampling period. Spreads are expressed in levels to the left and log-changes to the right, log changes are scaled such that they are interpretable as percentage points. The shaded area represents the standard error bounds for each industry and month.

5.3 PANEL REGRESSIONS

5.3.1 *Regression Over All Firms & Industries*

Regression output found in Table 1 shows overall high statistical significance. In the first regression (column 1), *delta_EPU* and the *lag(delta_EPU,1)* are roughly equal in size. A change of one standard deviation in *delta_EPU* leads to 1.3 % change in the CDS spreads, both in the present and the forthcoming month. The adjusted R^2 is low at 0.02.

In the following regressions (columns 2–5) the remaining variables are successively added to account for information already embedded in the financial market. When adding the first control variable, *delta_PCI*, the EPU coefficients increases somewhat. As PCI measure government inaction, it serves to clean the EPU Index from shocks where turbulence might be high, but the true ambiguity is low. In our third regression, the firm-specific variables are added, which increases R^2 with more than a factor seven. This substantial increase (from 0.03 to 0.20) confirms the findings by Ericsson, Jacobs, and Oviedo (2009) and Galil et al. (2014) et al., that firm-specific variables are the most useful to explain CDS spreads. The inclusion of the firm-specific variables further reduce the coefficients to 0.50 and 0.87 respectively. Lastly, the global variables are added which lowers the effects of EPU further, down to 0.38 and 0.67 the following month. Conclusively, our model suggests that shocks of policy uncertainty with the magnitude of a standard deviation will have a widening effect on a given CDS spread of 0.4 % immediately, and 0.7 % the following month. As expressed in basis points, one can interpret the median spread as increasing first from 91.58 basis points to 91.93 basis points, and then to 92.54 in the month after (*ceteris paribus*).

We believe the results to be reasonable since policy uncertainty makes it harder for investors to value the collateral. Accordingly, creditors will demand higher interest rates and limit their lending, (IMF, 2012). Further, Bernanke (1983) showed that firms’ earnings power are lower during times of high uncertainty, and when uncertainty increases, firms and consumers postpone their decisions, lowering economic activity. The market value of equity should thus go down and the probability of default should go up. By the same logic, investors demand a higher premium during periods of increasing uncertainty as compensation for the *possibility* of greater default risk. In the light of previous research, we also regard the magnitude as plausible. Our estimates of 0.4 % and 0.7 % (lagged) are in the same region as the results of Ulrich (2012), who showed that one standard deviation shock to EPU increases the slope of the yield curve by 0.2 %. Further, it can be compared to the findings of Born (2014), who concluded that a two standard-deviations shock generates a 0.025 % drop in company output. The lagging effect is in line with Foerster (2014), who showed that the impact of uncertainty is asymmetric and that a decrease in uncertainty not necessarily offset the effects of a preceding increase. As a result, spikes in uncertainty may produce persistent declines in economic activity, (Foerster, 2014).

Although not our main focus, we examine the remaining variables to see if the model works as expected. PCI improves the fit somewhat. An increase in share price by 1 % reduces the CDS spreads with about -0.6 % seems plausible given that Galil et al. (2014) found about twice the magnitude when using fewer controlling variables. The change in PE-ratio seems at first glance to have more impact on the spreads, but it is important to remember the unit differences. One unit of *delta_share_price* is approximately 1 % change whereas one unit of *delta_PE_ratio* is the absolute change in PE-ratios, i. e., from 12 to 13. Since the former is much more common than the latter, share price still is the greater impact. The remaining global variables have overall lower coefficients, with gold being the largest with 0.2.

	(1)	(2)	(3)	(4)	(5)
delta_EPU	1.318***	1.638***	0.501***	0.374***	0.381***
	(0.079)	(0.096)	(0.108)	(0.109)	(0.110)
lag(delta_EPU, 1)	1.343***	1.459***	0.870***	0.635***	0.672***
	(0.072)	(0.074)	(0.069)	(0.072)	(0.068)
delta_PCI		−0.772***	−0.273***	−0.522***	−0.543***
		(0.072)	(0.072)	(0.073)	(0.072)
delta_share_price			−0.645***	−0.620***	−0.620***
			(0.042)	(0.042)	(0.042)
delta_PE_ratio			−1.098***	−1.157***	−1.175***
			(0.149)	(0.151)	(0.150)
GSGC				0.200***	0.208***
				(0.021)	(0.023)
US_CDS				0.094***	0.094***
				(0.007)	(0.007)
CB_diff					−0.017*
					(0.010)
Observations	20,653	20,653	20,653	20,653	20,653
R^2	0.024	0.028	0.202	0.213	0.213
Adjusted R^2	0.023	0.027	0.199	0.210	0.210
F Statistic	246.979*** (df = 2; 20368)	192.756*** (df = 3; 20367)	1,030.388*** (df = 5; 20365)	787.943*** (df = 7; 20363)	689.966*** (df = 8; 20362)

Table 1: Panel regressions of CDS spread changes on the policy uncertainty index (EPU), Partisan Conflict Index (PCI), firm-specific stock returns (share_price), PE-ratios (PE_ratio), the GSGC Gold Price Index (GSGC), U.S. Sovereign CDS spreads (US_CDS), and the monthly difference between AAA and BBB grade corporate bonds (CB_diff). All variables are in log-differences, except PE-ratios which is unaltered, EPU and PCI, which are standardised. Those in log changes are scaled such that they are interpretable as percentage points. Firm fixed effects included. Arellano post-estimated robust standard errors grouped across firms. Monthly sample period July 2009 to January 2016, *p<0.1; **p<0.05; ***p<0.01

5.3.2 *A Comparision of Financials & Non-financials*

We already know that uncertainty affects different firms in varying degrees, depending on factors such as investment irreversibility and reliance on government spending, (Bernanke, 1983; Gulen, 2015). Monetary policy is mainly implemented through the financial sector, which makes it more exposed to economic policy decisions, both in a regulatory way and more direct to changing interest rate levels. Further has the financial sector endured hefty turmoil and frequent government intervention in the last decade.

Common for banks and other financial services is that both have, on average, a high debt-to-equity ratio, and a balance sheet mainly consisting of intangibles. When modelling the term structure of credit spreads using the structural approach of Merton (1974), one assumes that leverage is a major source of financial distress; with higher leverage comes higher probability of default. The volatility of the underlying assets is also an important factor when valuing investments and securities, and the financial sector is one of the most volatile on the market. It is also said that ambiguity averse investors dislike assets for which information quality is poor, especially when the underlying are volatile, (Epstein and Schneider, 2008). We, therefore, intuitively believe that the intangibility of assets in financial organisations, combined with increased mistrust towards the industry in general, should make the sector more sensible to shocks in policy uncertainty. We use this intuition to test our model's robustness by expecting larger EPU-coefficients for the financial companies compared to the non-financial companies. To investigate this, we perform a second set of regressions. We modify the model by adding dummies which takes the value of 1 (0) for *banks* or *financial_other* (other sectors), and 1 (0) for other sectors (*banks* or *financial_other*). The new econometric expression is thus:

$$\begin{aligned}\Delta \ln(Y_{t,i}) = \beta_1(\mathit{financial} \cdot \Delta EPU_t) + \beta_2(\mathit{financial} \cdot \Delta EPU_{t-1}) \\ + (\mathit{non\_financial} \cdot \Delta EPU_t) + \beta_2(\mathit{non\_financial} \cdot \Delta EPU_{t-1}) \\ + \gamma\chi_{i,t} + \alpha_i + u_{i,t}\end{aligned} \tag{6}$$

Regression output, presented in Table 2, shows that the financial firms indeed are much more sensitive to the immediate economic policy uncertainty, which is the expected outcome. Interestingly though, the financial sector seems not to be considerably more susceptible the following month. According to our model, a one standard deviation change in EPU lead to a 1.02 % change in CDS spreads for the financial companies compared to 0.30 % for non-financial companies. This difference is only 0.03% one month after: 0.70 % for financials compared to 0.67 % for non-financials. It seems like the effect of a shock in policy uncertainty first hits the financial sector, and then transfers with a lag to other sectors, but before we can draw any conclusions regarding this, further analysis is required. Although beyond our scope, one explanation could be the leading role of banks and financial services regarding price discovery, and the fact that these sectors are net transmitters of volatility, (Tamakoshi and Hamori, 2014, 2016).

	(1)	(2)	(3)	(4)	(5)
financials:delta_EPU	1.840***	2.170***	1.112***	1.008***	1.015***
	(0.284)	(0.287)	(0.257)	(0.257)	(0.258)
financials:lag(delta_EPU, 1)	1.431***	1.538***	0.893***	0.667***	0.701***
	(0.221)	(0.220)	(0.176)	(0.176)	(0.174)
delta_EPU:non_financials	1.251***	1.570***	0.422***	0.291***	0.298***
	(0.083)	(0.098)	(0.109)	(0.111)	(0.111)
lag(delta_EPU, 1):non_financials	1.333***	1.451***	0.870***	0.633***	0.670***
	(0.081)	(0.083)	(0.074)	(0.076)	(0.074)
delta_PCI		−0.773***	−0.274***	−0.523***	−0.544***
		(0.072)	(0.073)	(0.073)	(0.072)
delta_share_price			−0.646***	−0.620***	−0.620***
			(0.042)	(0.042)	(0.042)
delta_PE_ratio			−1.095***	−1.155***	−1.173***
			(0.149)	(0.150)	(0.150)
GSGC				0.201***	0.208***
				(0.021)	(0.023)
US_CDS				0.094***	0.094***
				(0.007)	(0.007)
CB_diff					−0.017*
					(0.010)
Observations	20,653	20,653	20,653	20,653	20,653
R^2	0.024	0.028	0.202	0.214	0.214
Adjusted R^2	0.024	0.027	0.199	0.211	0.211
F Statistic	124.879*** (df = 4; 20366)	116.812*** (df = 5; 20365)	737.573*** (df = 7; 20363)	614.208*** (df = 9; 20361)	553.202*** (df = 10; 20360)

Table 2: Panel regressions using sector-specific dummies of CDS spread changes on the policy uncertainty index (EPU), Partisan Conflict Index (PCI), firm-specific stock returns (share_price), PE-ratios (PE_ratio), the GSGC Gold Price Index (GSGC), U.S. Sovereign CDS spreads (US_CDS), and the monthly difference between AAA and BBB grade corporate bonds (CB_diff). All variables are in log-differences, except PE-ratios which is unaltered, EPU and PCI, which are standardised. Those in log changes are scaled such that they are interpretable as percentage points. Firm fixed effects included. Arellano post-estimated robust standard errors grouped across firms. Monthly sample period July 2009 to January 2016, *p<0.1; **p<0.05; ***p<0.01.

5.4 DISCUSSION

It is said that an agent experiencing uncertainty can neither be optimistic or pessimistic, which invokes consideration of security, (Damghani, Taghavifard, and Moghaddam, 2009). To cope with doubts, she slants probabilities pessimistically, which adds an uncertainty premia to the market price of risk, (Hansen and Sargent, 2006). Our results suggest accordingly that political indecisiveness induces a higher degree of mistrust in the economy. Given that periods with much uncertainty present depress private investment, we argue that our coefficients can proxy for the opportunity cost of waiting during times of political ambiguity. If an investor in need of credit protection is unable to postpone her investment until turbulence abates, the price she has to pay for insurance is 0.4 % higher on average and has a trailing effect of 0.7%. It aligns with Slovic's theories about uncertainty and trust: uncertainty erodes confidence in our financial systems and catalyses the perceived risk among investors, which accordingly demands higher risk premia as compensation.

One should however interpret our results conservative; they apply in a post-financial-crisis setting and for one proxy of policy uncertainty. During the sampling period, the liquidity of CDS markets decrease substantially. The implication of this is that the instrument could lose some value as a *economy-wide* proxy for credit risk. On the other side, before the financial crisis, CD's were exposed to a high degree of pure speculation. One important discussion is also whether the uncertainty index of Baker, Bloom, and Davis (2013) measures anything different than the uncertainty associated with bad states of the economy. If one assume that policy makers respond to economic conditions, and a lot of uncertainty is present in the economy, the outcome of policy making processes may be uncertain as well. It could thus be hard to argue for a distinction between economic policy uncertainty and economic uncertainty. Another aspect of it is that readers of newspapers have an economically significant preference for like-minded news, (Gentzkow and Shapiro, 2010), which means that the index could be biassed towards what the public want to read. Hence, when the index peak, the real uncertainty of the policy making process might not be higher, but still attain higher values.

While our findings may or may not be applicable in pricing models or trading strategies, they serve foremost to make current research on policy uncertainty more robust. There are certainly a large set of additional variables we could have included in our model, both firm-specific and global. One should however always worry about the pitfall of *omitted variable bias*, as one never works with a *correctly* specified model. Every additional control variable would make this bias stronger.

We hope to draw more attention to this field of study, especially to encourage exploration of the relationship between government and the economy. It is a mere truism to state that policymakers should avoid ambiguity, still it is important to emphasise how damaging the lack of coherence and determination are. Policy uncertainty hit our economies on a broad scale and have a sustained impact on many levels within society. Even the most desirable reforms recoil if they induce doubts, (Rodrik, 1991). As the eminent Robert S. Pindyck already concluded two decades ago: "[Thus] if a policy goal is to stimulate investment, stability and credibility may be more important than tax incentives or interest rates." (Pindyck, 1990).

5.5 CONCLUSION

Political uncertainty is proved to have an impact on many levels in the economy but has hitherto been difficult to quantify. When Baker, Bloom, and Davis (2013) constructed the EPU index, they opened a whole new dimension of tools to work with. This study aim to quantify the impact changes in EPU has on CDS movements and thus complement the findings by Wisniewski (2015). Using CDS data for a cross-section of 254 firms in nine industries within the U.S., we run a set of fixed effects panel regressions, adding explanatory variables one by one.

First, we confirm the findings of Wisniewski (2015), i. e., that changes in levels of EPU indeed has a widening effect on the CDS spreads. Secondly, after controlling for other market effects, we show that the magnitude of this effect is about 0.4 % the same month and 0.7 % the following month. We argue that our results can be viewed as an opportunity cost of being unable to postpone the need for credit protection during times of uncertainty. As expected proved firm-specific factors to have a strong explanatory value in our model as well.

Our findings are meant to ignite further interest in the subject. The effects EPU has on credit risk and risk perceptions is yet an unknown field, in need of more research. It would, for example, be interesting to extend the study by applying the model of Pan and Singleton (2008) to decompose the CDS spread into the risk premium and default risk component. Especially the premium component co-vary with several economic measures of global event risk, financial market volatility, and macroeconomic policy, (Pan and Singleton, 2008).

One could also perform another study on CDX indices by decomposing the CDX theoretical fair spread, which provides interesting diagnostics when spreads widen. In particular, by measuring how fast the fair average spread and the CDX spread change indicate if the likelihood of default of a given name increase, or if the global credit market deteriorates, (Couderc, 2007).

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A

APPENDIX

A.1 SUMMARY STATISTICS

INDUSTRY	N	MEAN	SD	MEDIAN	MIN	MAX	RANGE	SKEW	KURTOSIS
banks	542	−0.919	11.584	−1.382	−34.348	56.822	91.170	1.042	2.776
consumer_goods	1,847	−0.421	9.796	−0.391	−46.484	59.001	105.485	0.424	4.472
electrical_power	946	−1.322	9.305	−0.453	−31.231	30.141	61.373	−0.003	1.122
energy_companies	1,768	0.764	15.340	−0.444	−58.892	178.815	237.707	2.097	15.259
financial_other	4,426	−1.130	12.009	−0.840	−83.043	88.400	171.443	0.673	4.973
manufacturing	6,640	−0.586	10.950	−0.254	−99.105	72.495	171.600	0.007	5.594
services	4,297	−0.632	11.281	−0.709	−77.454	67.017	144.471	0.299	3.741
telephone	472	−0.168	9.838	−0.076	−32.670	39.565	72.235	0.449	1.936
transportation	548	−0.800	10.554	−1.586	−39.104	64.551	103.656	0.756	3.016
all	21,486	−0.619	11.497	−0.535	−99.105	178.815	277.921	0.718	8.069

Table 3: Summary statistics of log-changes in 5-year Credit Default Swap spreads over the monthly period from July 2009 to January 2016. The last row reports summary statistics for all industries combined. The numbers are scaled such that they are interpretable as percentage points.

INDUSTRY	N	MEAN	SD	MEDIAN	MIN	MAX	RANGE	SKEW	KURTOSIS
banks	542	122.923	70.976	101.794	36.270	460.863	424.593	1.942	4.320
consumer_goods	1,847	103.057	142.520	57.933	17.521	1,229.096	1,211.575	4.141	20.279
electrical_power	946	131.431	121.936	87.890	11.672	736.927	725.255	2.208	5.459
energy_companies	1,768	129.275	177.218	93.347	13.490	4,422.029	4,408.539	13.509	274.746
financial_other	4,426	224.933	371.390	122.620	11.261	6,120.432	6,109.171	6.138	58.506
manufacturing	6,640	157.421	188.117	94.526	10.786	3,056.197	3,045.411	4.147	29.800
services	4,297	155.533	207.033	88.344	11.213	5,078.964	5,067.750	6.016	88.253
telephone	472	233.067	286.145	90.788	40.758	1,574.841	1,534.084	2.383	6.004
transportation	548	55.002	37.191	43.812	14.561	214.520	199.959	1.798	3.335
all	21,486	160.996	237.806	91.582	10.786	6,120.432	6,109.647	7.256	99.680

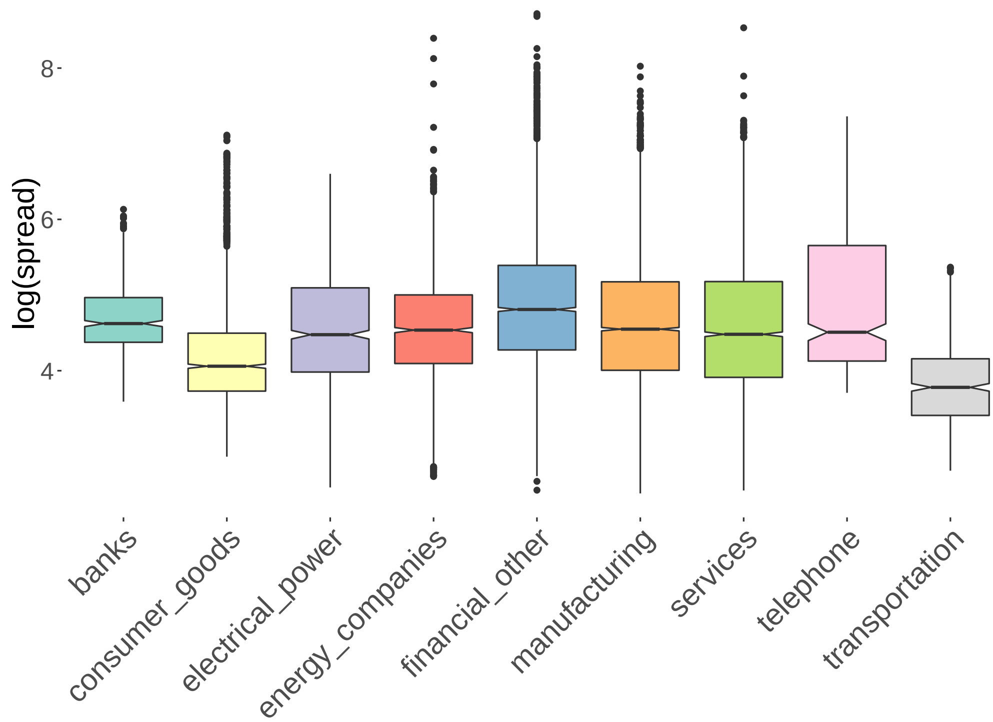
Table 4: Summary statistics of 5-year Credit Default Swap spread sizes over the monthly period from July 2009 to January 2016. The last row reports summary statistics for all industries combined.

	delta_spread	delta_share_price	delta_PE_ratio	CB_diff	delta_EPU	delta_PCI	GSGC	US_CDS
delta_spread	1	-0.427	-0.213	0.068	0.098	-0.002	0.082	0.159
delta_share_price	-0.427	1	0.347	-0.068	-0.167	0.014	-0.052	-0.133
delta_PE_ratio	-0.213	0.347	1	-0.093	-0.068	-0.063	-0.016	-0.035
CB_diff	0.068	-0.068	-0.093	1	0.003	-0.093	0.235	0.035
delta_EPU	0.098	-0.167	-0.068	0.003	1	0.383	0.148	0.103
delta_PCI	-0.002	0.014	-0.063	-0.093	0.383	1	0.043	0.238
GSGC	0.082	-0.052	-0.016	0.235	0.148	0.043	1	-0.103
US_CDS	0.159	-0.133	-0.035	0.035	0.103	0.238	-0.103	1

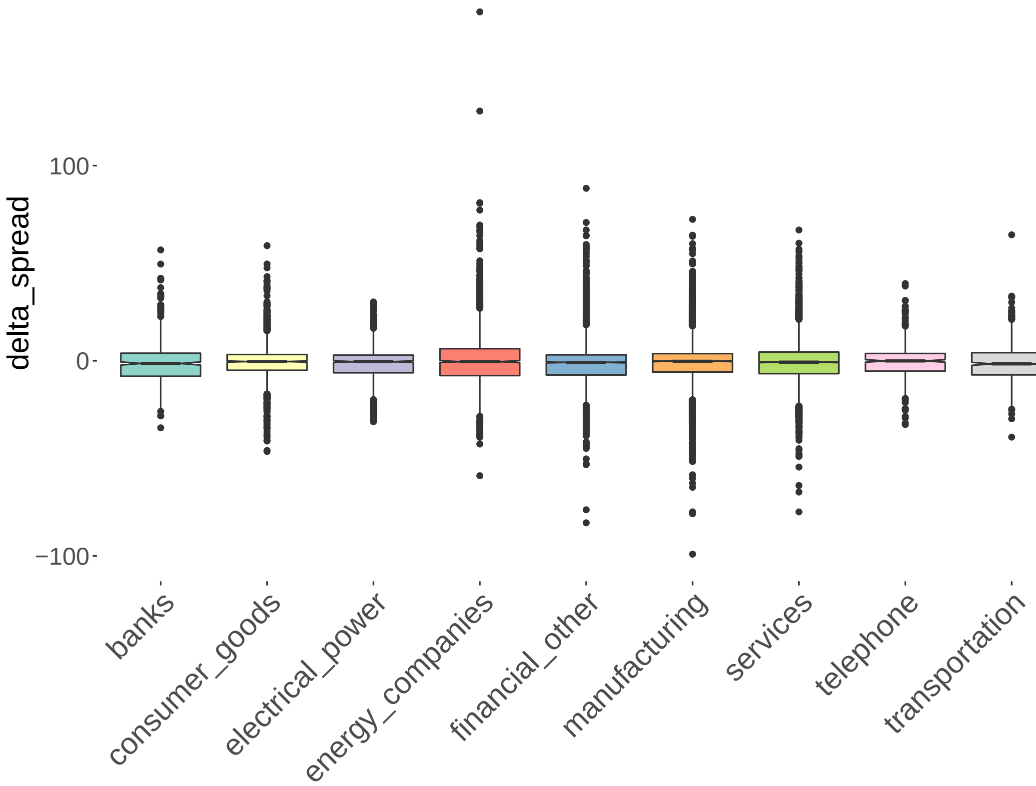
Table 5: Correlation matrix of monthly changes between July 2009 and January 2016 between CDS spreads, the policy uncertainty index (EPU), Partisan Conflict Index (PCI), firm-specific stock returns (share_price), PE-ratios (PE_ratio), the GSGC Gold Price Index (GSGC), U.S. Sovereign CDS spreads (US_CDS), and the monthly difference between AAA and BBB grade corporate bonds (CB_diff). All variables are in log-differences, except PE-ratios which is unaltered, EPU and PCI, which are standardised. Those in log changes are scaled such that they are interpretable as percentage points.

INDUSTRY	MEAN	SD	MEDIAN	MIN	MAX	RANGE	SKEW	KURTOSIS
delta_spread	−0.619	11.497	−0.535	−99.105	178.815	277.921	0.718	8.069
delta_share_price	0.709	7.192	1.055	−122.216	108.783	230.999	−0.540	18.457
delta_PE_ratio	0.049	0.754	0.060	−2.820	2.770	5.590	−0.197	1.588
CB_diff	0.011	8.654	−1.028	−21.515	21.870	43.385	−0.117	0.155
delta_EPU	0.002	0.984	−0.034	−3.421	2.001	5.422	−0.403	0.667
delta_PCI	−0.009	1.007	0.009	−4.718	3.386	8.105	−0.711	5.738
GSGC	0.120	3.586	−0.134	−7.050	11.192	18.242	0.278	−0.047
US_CDS	−1.148	12.440	−1.165	−29.939	30.452	60.391	0.271	0.627

Table 6: Descriptive statistics of monthly changes between July 2009 and January in CDS spreads, the policy uncertainty index (EPU), Partisan Conflict Index (PCI), firm-specific stock returns (share_price), PE-ratios (PE_ratio), the GSGC Gold Price Index (GSGC), U.S. Sovereign CDS spreads (US_CDS), and the monthly difference between AAA and BBB grade corporate bonds (CB_diff). All variables are in log-differences, except PE-ratios which is unaltered, EPU and PCI, which are standardised. Those expressed in log changes are scaled such that they are interpretable as percentage points.

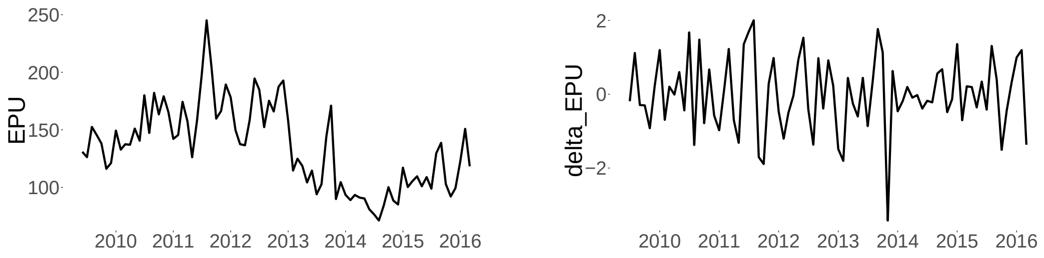


(a)



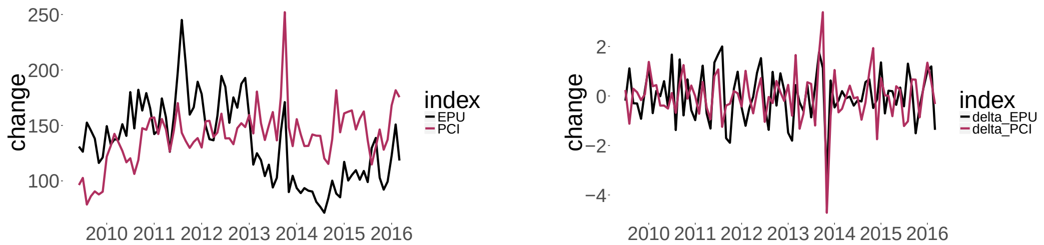
(b)

Figure 5: Notched boxplots of the firm-specific CDS spreads grouped by industry, expressed in levels on the top and log-differences on the bottom. The log changes are scaled such that they are interpretable as percentage points.



(a) (b)

Figure 6: Figure illustrating the movements of the EPU index over the sampling period. The left graph shows monthly levels (index points), the right graph displays the corresponding monthly changes, demeaned and standardized (sd = 1, mean = 0).



(a) (b)

Figure 7: Figure illustrating the movements of the EPU index and the PCI index over the sampling period. The left graph displays monthly levels (index points), the right graph shows the corresponding monthly changes, demeaned and standardised (sd = 1, mean = 0).

A.2 TESTS

A.2.1 *Standard F-test*

```
    F-statistic

data:  delta_spread ~ delta_EPU + lag(delta_EPU, 1)
+ delta_PCI + delta_share_price + delta_PE_ratio
+ GSGC + US_CDS + CB_diff

F = 1.6597, df1 = 2256, df2 = 18106, p-value < 2.2e-16
alternative hypothesis: unstability
```

A.2.2 *Breusch-Pagan Test*

```
    studentized Breusch-Pagan test

data:  delta_spread ~ delta_EPU + lag(delta_EPU, 1)
+ delta_PCI + delta_share_price + delta_PE_ratio
+ GSGC + US_CDS + CB_diff

BP = 182.52, df = 8, p-value < 2.2e-16
```

A.2.3 *Hausman Test*

```
    Hausman Test

data:  delta_spread ~ delta_EPU + lag(delta_EPU, 1)
+ delta_PCI + delta_share_price + delta_PE_ratio
+ GSGC + US_CDS + CB_diff

chisq = 36.986, df = 8, p-value = 1.158e-05
alternative hypothesis: one model is inconsistent
```

A.2.4 *Breusch-Godfrey/Wooldridge Test*

```
    Breusch-Godfrey/Wooldridge:
test for serial correlation in panel models

data:  delta_spread ~ delta_EPU + lag(delta_EPU, 1)
+ delta_PCI + delta_share_price + delta_PE_ratio
+ GSGC + US_CDS + CB_diff

chisq = 960.11, df = 7, p-value < 2.2e-16
alternative hypothesis: serial correlation in idiosyncratic errors
```

B

APPENDIX II - LIST OF COMPANIES

	Code	Name	Code	Name
1	ABC5.AR	AMERISOURCEBERGEN	ITW5.AR	ILLINOIS TOOL WORKS
2	ABT5.AR	ABBOTT LABORATORIES	JCI5.AR	JOHNSON CONTROLS
3	ADM5.AR	ARCHER-DANLS.-MIDL.	JNJ5.AR	JOHNSON & JOHNSON
4	AEP5.AR	AMER.ELEC.PWR.	JPM5.AR	JP MORGAN CHASE & CO.
5	AET5.AR	AETNA	K..5.AR	KELLOGG
6	AFG5.AR	AMERICAN FINL.GP.OHIO	KFT5.AR	MONDELEZ INTERNATIONAL CL.A
7	AIG5.AR	AMERICAN INTL.GP.	KIM5.AR	KIMCO REALTY
8	AIZ5.AR	ASSURANT	KMB5.AR	KIMBERLY-CLARK
9	ALL5.AR	ALLSTATE	KMG5.AR	KMG CHEMICALS
10	AMS5.AR	AMER.SHARED HOSP.SVS.	KO.5.AR	COCA COLA
11	AOC5.AR	AON CLASS A	KR.5.AR	KROGER
12	APA5.AR	APACHE	KSS5.AR	KOHL'S
13	APD5.AR	AIR PRDS.& CHEMS.	LEN5.AR	LENNAR 'A'
14	ARW5.AR	ARROW ELECTRONICS	LMT5.AR	LOCKHEED MARTIN
15	ASH5.AR	ASHLAND	LNC5.AR	LINCOLN NATIONAL
16	AVB5.AR	AVALONBAY COMMNS.	LOW5.AR	LOWE'S COMPANIES
17	AVP5.AR	AVON PRODUCTS	LUV5.AR	SOUTHWEST AIRLINES
18	AVT5.AR	AVNET	LVL5.AR	LEVEL 3 COMMS.
19	AX.5.AR	AGILENT TECHS.	LXK5.AR	LEXMARK INTL.
20	AXP5.AR	AMERICAN EXPRESS	MAR5.AR	MARRIOTT INTL.'A'
21	AZO5.AR	AUTOZONE	MAS5.AR	MASCO
22	BAC5.AR	BANK OF AMERICA	MAT5.AR	MATTEL
23	BAX5.AR	BAXTER INTL.	MCD5.AR	MCDONALDS
24	BBY5.AR	BEST BUY	MCK5.AR	MCKESSON
25	BDK5.AR	STANLEY BLACK & DECKER	MDT5.AR	MEDTRONIC
26	BDX5.AR	BECTON DICKINSON	MET5.AR	METLIFE
27	BGG5.AR	BRIGGS & STRATTON	MLM5.AR	MARTIN MRTA.MATS.
28	BHI5.AR	BAKER HUGHES	MMC5.AR	MARSH & MCLENNAN
29	BKE5.AR	BUCKLE	MMM5.AR	3M
30	BLK5.AR	BLACKROCK	MO.5.AR	ALTRIA GROUP
31	BLL5.AR	BALL	MOH5.AR	MOLINA HEALTHCARE
32	BRK5.AR	BERKSHIRE HATHAWAY 'A'	MOP5.AR	PHILIP MORRIS INTL.
33	BUD5.AR	ANHEUSER-BUSCH INBEV SPN.ADR	MOT5.AR	MOTOROLA SOLUTIONS
34	BWA5.AR	BORGWARNER	MRO5.AR	MARATHON OIL
35	BXP5.AR	BOSTON PROPERTIES	MS.5.AR	MORGAN STANLEY
36	C..5.AR	CITIGROUP	MSF5.AR	MICROSOFT
37	CA.5.AR	CA	MTC5.AR	MONSANTO
38	CAG5.AR	CONAGRA FOODS	MUR5.AR	MURPHY OIL
39	CAH5.AR	CARDINAL HEALTH	MYL5.AR	MYLAN
40	CAT5.AR	CATERPILLAR	NEM5.AR	NEWMONT MINING
41	CB.5.AR	CHUBB	NEU5.AR	NEWMARKET
42	CBS5.AR	CBS 'B'	NKE5.AR	NIKE 'B'
43	CCC5.AR	CALGON CARBON	NOB5.AR	NORDSTROM
44	CCE5.AR	COCA COLA ENTS.	NRG5.AR	NRG ENERGY
45	CGG5.AR	CGG ADR	NSC5.AR	NORFOLK SOUTHERN
46	CHK5.AR	CHESAPEAKE ENERGY	NUE5.AR	NUCOR
47	CI.5.AR	CIGNA	NVR5.AR	NVR
48	CL.5.AR	COLGATE-PALM.	NWL5.AR	NEWELL BRANDS
49	CLC5.AR	CLARCOR	NYT5.AR	NEW YORK TIMES 'A'
50	CLI5.AR	MACK CALI REALTY	OCA5.AR	OWENS CORNING
51	CLX5.AR	CLOROX	OI.5.AR	OWENS ILLINOIS NEW
52	CMC5.AR	COMMERCIAL MTLS.	OLN5.AR	OLIN
53	CMS5.AR	CMS ENERGY	OMC5.AR	OMNICOM GROUP
54	CNP5.AR	CENTERPOINT EN.	OXY5.AR	OCCIDENTAL PTL.
55	COF5.AR	CAPITAL ONE FINL.	PAA5.AR	PLAINS ALL AMER.PIPE.LP. UNIT
56	COP5.AR	CONOCOPHILLIPS	PBI5.AR	PITNEY-BOWES
57	COT5.AR	COSTCO WHOLESALE	PEP5.AR	PEPSICO
58	CPB5.AR	CAMPBELL SOUP	PG.5.AR	PROCTER & GAMBLE
59	CPT5.AR	CAMDEN PROPERTY TST.	PHH5.AR	PHH

60	CR.5.AR	CRANE	PKG5.AR	PACKAGING CORP.OF AM.
61	CSC5.AR	COMPUTER SCIS.	PKI5.AR	PERKINELMER
62	CSO5.AR	CISCO SYSTEMS	PNC5.AR	PNC FINL.SVS.GP.
63	CTB5.AR	COOPER TIRE & RUB.	POM5.AR	PEPCO HOLDINGS
64	CUM5.AR	CUMMINS	PPC5.AR	PPL
65	CVX5.AR	CHEVRON	PPG5.AR	PPG INDUSTRIES
66	CZN5.AR	FRONTIER COMMUNICATIONS	PRX5.AR	PRUDENTIAL FINL.
67	D..5.AR	DOMINION RESOURCES	PX.5.AR	PRAXAIR
68	DD.5.AR	E I DU PONT DE NEMOURS	PXD5.AR	PIONEER NTRL.RES.
69	DDR5.AR	DDR	R..5.AR	RYDER SYSTEM
70	DDS5.AR	DILLARDS 'A'	ROK5.AR	ROCKWELL AUTOMATION
71	DE.5.AR	DEERE	RRD5.AR	R R DONNELLEY & SONS
72	DEL5.AR	DELTIC TIMBER	RSG5.AR	REPUBLIC SVS.'A'
73	DGX5.AR	QUEST DIAGNOSTICS	RTN5.AR	RAYTHEON 'B'
74	DHI5.AR	D R HORTON	SHW5.AR	SHERWIN-WILLIAMS
75	DHR5.AR	DANAHER	SON5.AR	SONOCO PRODUCTS
76	DIA5.AR	DISH NETWORK 'A'	SPG5.AR	SIMON PROPERTY GROUP
77	DIS5.AR	WALT DISNEY	SPL5.AR	STAPLES
78	DLX5.AR	DELUXE	STZ5.AR	CONSTELLATION BRANDS 'A'
79	DOV5.AR	DOVER	SVU5.AR	SUPERVALU
80	DOW5.AR	DOW CHEMICAL	SXH5.AR	SEAGATE TECH.
81	DRE5.AR	DUKE REALTY	SYY5.AR	SYSCO
82	DRI5.AR	DARDEN RESTAURANTS	T..5.AR	AT&T
83	DTE5.AR	DTE ENERGY	TAP5.AR	MOLSON COORS BREWING 'B'
84	DUD5.AR	DUKE ENERGY	TDS5.AR	TELEPHONE & DATA SYS.
85	DVN5.AR	DEVON ENERGY	TE.5.AR	TECO ENERGY
86	EEP5.AR	ENBRIDGE ENERGY PTNS.LP	TGT5.AR	TARGET
87	EMN5.AR	EASTMAN CHEMICAL	THC5.AR	TENET HEALTHCARE
88	EMR5.AR	EMERSON ELECTRIC	TJX5.AR	TJX
89	EOG5.AR	EOG RES.	TOL5.AR	TOLL BROTHERS
90	EPD5.AR	ENTERPRISE PRDS.PTNS.LP.	TRV5.AR	TRAVELERS COS.
91	EQR5.AR	EQUITY RESD.TST.PROPS. SHBI	TSN5.AR	TYSON FOODS 'A'
92	ETN5.AR	EATON	TSO5.AR	TESORO
93	ETP5.AR	ENERGY TRANSFER PTNS.	TWD5.AR	TIME WARNER CABLE
94	ETR5.AR	ENTERGY	TWX5.AR	TIME WARNER
95	EXC5.AR	EXELON	TXT5.AR	TEXTRON
96	FDX5.AR	FEDEX	UDR5.AR	UDR
97	FE.5.AR	FIRSTENERGY	UFX5.AR	UNIFLEX
98	FMR5.AR	FORD MOTOR	UHS5.AR	UNIVERSAL HEALTH SVS.'B'
99	GD.5.AR	GENERAL DYNAMICS	UIS5.AR	UNISYS
100	GIS5.AR	GENERAL MILLS	UNH5.AR	UNITEDHEALTH GROUP
101	GLW5.AR	CORNING	UNM5.AR	UNUM GROUP
102	GMT5.AR	GATX	UNP5.AR	UNION PACIFIC
103	GNW5.AR	GENWORTH FINANCIAL CL.A	UPS5.AR	UNITED PARCEL SER.'B'
104	GPS5.AR	GAP	URI5.AR	UNITED RENTALS
105	GR.5.AR	GOODRICH PTL.	USM5.AR	UNITED STATES CELLULAR
106	GS.5.AR	GOLDMAN SACHS GP.	UTX5.AR	UNITED TECHNOLOGIES
107	HAL5.AR	HALLIBURTON	UVV5.AR	UNIVERSAL
108	HAS5.AR	HASBRO	VFC5.AR	V F
109	HCN5.AR	WELLTOWER	VIA5.AR	VIACOM 'B'
110	HCP5.AR	HCP	VLO5.AR	VALERO ENERGY
111	HD.5.AR	HOME DEPOT	VZ.5.AR	VERIZON COMMUNICATIONS
112	HES5.AR	HESS	WEN5.AR	WENDY'S CLASS A
113	HIG5.AR	HARTFORD FINL.SVS.GP.	WFC5.AR	WELLS FARGO & CO
114	HIW5.AR	HIGHWOODS PROPERTIES	WHR5.AR	WHIRLPOOL
115	HNT5.AR	HEALTH NET	WLB5.AR	ANTHEM
116	HON5.AR	HONEYWELL INTL.	WMB5.AR	WILLIAMS
117	HOT5.AR	STARWOOD H&R.WORLDWIDE	WMI5.AR	WASTE MANAGEMENT
118	HPQ5.AR	HP	WMT5.AR	WAL MART STORES
119	HPT5.AR	HOSPITALITY PROPS.TST. SHRE.BENL.INT.	WOR5.AR	WORTHINGTON INDS.
120	HSL5.AR	HOST HOTELS & RESORTS	WRE5.AR	WASHINGTON RLST.INV. SHRE.BENEFIT INT.
121	HSY5.AR	HERSHEY	WRI5.AR	WEINGARTEN REALTY INVRS.
122	HUM5.AR	HUMANA	WU.5.AR	WESTERN UNION
123	IBM5.AR	INTERNATIONAL BUS.MCHS.	WY.5.AR	WEYERHAEUSER
124	INU5.AR	INTUIT	XCE5.AR	XCEL ENERGY
125	IP.5.AR	INTERNATIONAL PAPER	XOM5.AR	EXXON MOBIL
126	IPG5.AR	INTERPUBLIC GROUP	XRX5.AR	XEROX
127	IRC5.AR	INLAND REAL ESTATE	YUM5.AR	YUM! BRANDS