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FINANCIAL REGULATION POLICY UNCERTAINTY AND CREDIT SPREADS IN THE U.S.

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Abstract

This paper quantifies the macroeconomic effects of surprise movements in uncertainty about financial regulation policies in the U.S. economy. Within the context of a Structural VAR model, exogenous variations in financial regulation policy uncertainty lead to a widening in corporate credit spreads, and can potentially trigger flight to quality and flight to liquidity episodes. Financial regulation policy uncertainty shocks also induce a strong and persistent reduction of industrial production, an increase in unemployment and a deflationary phase, acting as negative demand shocks. A variance decomposition analysis underlines the contribution of the shock for the dynamics of the macro observables. These findings are supported by a variety of robustness checks.

JEL classification: E32, E44, E61, G18.

Keywords: Uncertainty shocks, financial regulation, government policy, credit spread dynamics.

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1 Introduction

The U.S. financial regulation system has come under criticism in the aftermath of the financial crisis of 2007-2009. Since then, policymakers have engaged in a variety of reforms, leading to a substantial increase in the level of uncertainty about the future financial regulatory framework. A clear warning has recently been launched by the IMF Managing Director, Christine Lagarde, who stated: "[...] *That is the first imperative I just mentioned, which is to follow through on the policies in order to eliminate the uncertainty. The second point, which is in our* [IMF] *view critical, because it has been at the heart of the latest development of the crisis, is to finish the reform of the financial sector. We recognize that there has been progress, but the process has been very time consuming, and continues to contribute to uncertainty*" (IMF New Year Press Briefing - January 17th, 2013).

Regulatory reforms play an important role in re-establishing trust in the financial system. Particularly, the reforms underway in the U.S. are aimed to make markets and institutions more transparent, less complex, and less leveraged, which should help to restore appropriate levels of credit growth to support the recovery. However, undesirable effects may arise when the policymaking process concerning implementation is surrounded by uncertainty, i.e., unclear future norms regulating financial institutions can increase the risk associated with lending activities, therefore raising the borrowing costs of capital and depressing real activity.

This paper quantifies the macroeconomic effects of financial regulation policy uncertainty within the context of a Structural Vector Autoregressive (SVAR) model. The empirical counterpart of uncertainty is the news-based financial regulation policy uncertainty index recently developed by Baker, Bloom and Davis (2013). Such index proxies *perceived* macroeconomic uncertainty concerning U.S. financial regulation policies. Precisely, I focus on the role of policy-specific uncertainty shocks in driving credit spreads and some key macroeconomic variables, namely industrial production, unemployment, inflation and the federal funds rate.

My baseline results show that an innovation of one standard deviation in the uncertainty index raises the Baa–Aaa credit spread by about 7 basis points. Although this increase may not seem particularly big, financial regulation policy uncertainty shocks of magnitude similar to the increases occurred during the recent financial crisis are estimated to raise credit spreads three times more.

The widening in the Baa–Aaa spread offers some evidence of flights to quality and flights to liquidity triggered by policy-specific uncertainty shocks. When expected default probabilities increase, investors tend to rebalance their portfolios towards less risky and more liquid securities, i.e., the well known flight to quality (Bernanke, Gertler and Gilchrist, 1996) and flight to liquidity (Longstaff, 2004) effects, respectively. To dip further into the financial regulation policy uncertainty–credit spread relationship, I consider alternative spread measures. These are the Aaa– and Baa–10 Year Treasury bond spreads (referred to as Aaa–GS10 and Baa–GS10), and the GZ spread recently developed by Gilchrist and Zakrajšek (2012). All the spread indicators are shown to positively react to uncertainty innovations. I then separately examine the reaction of the two distinct components of the GZ spread: a predicted component measuring movements in corporate credit risk and a residual part above and beyond the compensation for expected defaults—the excess bond premium. This exercise confirms that the shock hits the expected default component of credit spreads.

On the real side of the economy, my findings document a strong and persistent reduction of the industrial production index, whose cumulative growth rate is about 6 percent below its trend one year after the shock. Importantly, the inclusion of unemployment and inflation in the analysis allows to classify the financial regulation policy uncertainty shock as a negative aggregate demand shock, which causes prices to fall by more than 1 percent, and unemployment to increase by 0.15 percent. These results are in line with those of Leduc and Liu (2013), Caggiano, Castelnuovo and Groshenny (2013), Colombo (2013), and Kamber, Karagedikli, Ryan and Vehbi (2013), who also show that uncertainty shocks act as negative demand shocks.

Overall, my results are qualitatively robust to variations of the baseline vector that allow to account for the presence of potentially omitted variables and anticipated effects in the identification of the structural shock. A variance decomposition analysis indicates that the financial regulation policy uncertainty shock importantly contributes to the dynamics of credit spreads. In the baseline model, the shock accounts for about 18 percent of the forecast error variance of the Baa–Aaa spread up to five years. In contrast, a monetary policy shock explains less than 7 percent of the variance of the spread within the same forecast horizon. Moreover, the uncertainty shock is estimated to be responsible of an important share of the variance of the unemployment rate, i.e., innovations in financial regulation policy uncertainty explain more than 25 percent of the unemployment's forecast error variance at a 12 month forecast horizon.

The early theoretical literature has extensively analyzed the real-options channel as a transmission mechanisms of uncertainty shocks to the real economy.[1] Bernanke (1983) and Dixit (1989) show that real-option effects materialize within the framework of irreversible investment, where uncertainty plays a role in delaying investment decisions. In particular, firms will defer investment decisions implying sunk costs whenever facing a highly uncertain environment, because uncertainty increases the option value of waiting (the real-option) until new information about the state of the economy arrives. As a result, the economy will experience an immediate drop in investment. More recently, Bloom (2009) extends the analysis of uncertainty shocks by providing a structural framework to investigate the joint reactions of investment, hiring and productivity. He finds that higher uncertainty generates a rapid drop, rebound and overshoot in economic activity, due to the fact that firms pause their investment and hiring, while productivity growth falls. These dynamics following the shock are commonly referred to as the "wait-and-see" effect.

Another growing strand of the literature focuses on financial frictions as an additional mechanism by which uncertainty interacts with the business cycle. Recent papers explore this channel, both empirically and theoretically, and find that financial distortions amplify the response of economic activity to uncertainty shocks. Some examples include Christiano, Motto and Rostagno (2010), Arellano, Bai and Kehoe (2012), and Bonciani and van Roye (2013). In particular, Gilchrist, Sim and Zakrajšek (2013) show that unanticipated increases in uncertainty (based on aggregate idiosyncratic volatility of stock returns) lead to a significant widening of corporate credit spreads. The underlying intuition is that a shock to uncertainty may cause an actual or perceived increase in the riskiness of firms, which—under imperfect capital markets—raises the expected probability of default and consequently makes outside borrowing more costly. My study adds to this strand of the literature by providing empirical evidence on the macroeconomic effects of uncertainty concerning a specific source: *financial regulation policies*.[2]

[1] Born and Pfeifer (2013) and Bonciani and van Roye (2013) provide a discussion about other channels for the propagation of uncertainty shocks, i.e., the precautionary savings channel and the Hartman-Abel effects.

[2] Studies investigating the links between financial markets and policy-related uncertainty include Pástor and Veronesi (2012), Brogaard and Detzel (2013), Antonakakis et al. (2013) and Sum (2012). However, they focus on *aggregate* economic policy uncertainty. On the other hand, the macroeconomic effects of *policy-specific* uncertainty shocks are assessed by Bauer (2012), Born and Pfeifer (2013), and Fernández-Villaverde et al. (2012), but they concentrate on uncertainty regarding fiscal and monetary policies.

Finally, from a methodological point of view, this paper is also related to the work of Alexopoulos and Cohen (2009), Bachmann, Elstner and Sims (2013), Baker, Bloom and Davis (2013), and Jurado, Ludvigson and Ng (2013). These studies also deal with linear VAR models to analyze the effects of uncertainty shocks.

The remainder of the paper develops as follows. Section 2 presents the financial regulation policy uncertainty index. Section 3 describes the SVAR model, whose estimation results are illustrated in section 4. A sensitivity analysis is conducted in section 5. A few concluding remarks appear in section 6.

2 The FRPU index

Baker, Bloom and Davis (2013) create a news-based empirical proxy for U.S. Financial Regulation Policy Uncertainty (henceforth referred to as FRPU index) by analyzing the Newsbank Access World News, a database covering about 2,000 U.S. newspapers. Specifically, they perform monthly searches for articles containing jointly references to financial regulation policies, uncertainty and the economy.[3] To deal with changing volumes of articles, they divide the raw counts (in each newspaper) by the total number of news articles in the same newspapers for each given month. They then normalize each newspaper index to have a unit standard deviation over the period 1985-2010 and add up the indices for all papers. The monthly index is then rescaled to have an average value of 100.[4]

Figure 1 plots the FRPU index, showing the evolution of uncertainty associated with financial regulation policies in the U.S. economy since 1985. The variations of the index are substantial, and clearly capture noticeable financial-related events. However, it is worth stressing that the FRPU index proxies *perceived* policy uncertainty. Thus, it also shows peaks in correspondence of events not strictly connected with financial regulation, such as the 9/11 terrorist attack. Other relevant increases of the index cor-

[3] The key terms are the following: uncertainty, uncertain, economic, economy, regulation, banking supervision, Glass-Steagall, tarp, bank supervision, thrift supervision, Dodd-frank, financial reform, commodity futures trading commission, cftc, house financial services committee, Basel, capital requirement, Volcker rule, bank stress test, securities and exchange commission, sec, deposit insurance, fdic, fslic, ots, occ, firrea, truth in lending.

[4] The FRPU index is a sub-category of the "Newsbank" EPU index, an aggregate measure of economic policy uncertainty identically constructed, with the exception that the selected articles do not contain terms related to any specific-policy area. The correlation between the two is 0.62, meaning that the former contains specific information about *financial regulation* policy uncertainty.

respond to: the "Boesky Day" (November, 1986), which documents one of the largest insider trading scandals and is considered a defining moment in the history of federal securities law enforcement; the Black Monday (October, 1987); the "Friday the 13th minicrash", which refers to a stock market crash dated October, 1989; the Japanese Asset Price and the Dot.com bubbles; the WorldCom's collapse in July, 2002; and more recently, the Great Recession.

Another commonly used proxy for economic uncertainty is the Chicago Board Options Exchange Market Volatility Index (the VIX index).[5] The VIX index is an indicator representing implied volatility of S&P500 index options, and as so directly related to uncertainty in financial markets. Indeed, the correlation between the FRPU index and the VIX is equal to 0.54. Although I do not use this index as a proxy for financial regulation policy uncertainty—because it moves for reasons beyond potential future changes in the financial regulatory framework—in the robustness checks' section I show that the results conditional on FRPU shocks survive to the addition of the VIX to the baseline vector.

3 Empirical Analysis

Figure 2 plots the FRPU index along with the corporate yield spread between Baa- and Aaa-rated bonds. The picture points to positive co-movements between financial regulation uncertainty and credit spread dynamics, in particular during recessions. Looking at the period from 1985 to 2012, the correlation coefficient between the two is equal to 0.55. Increases in the Baa–Aaa spread are sometimes preceded by increases in the FRPU index. As for this point, table 1 displays the results from some Granger-causality tests considering different lag lengths. The null hypothesis that financial regulation policy uncertainty does not Granger-cause the Baa–Aaa spread is always rejected. Differently, the Baa–Aaa credit spread does not Granger-cause the FRPU index for lags ranging from 4 to 6 (at a 95% confidence level). These results provide some evidence in favor of unidirectional Granger-causality from financial regulation uncertainty to credit spreads and support the lag length used in the SVAR model, which is equal to 6 to get rid of serial correlation in the residuals.[6]

[5] Studies using the VIX index as a proxy for uncertainty include Bloom (2009), Leduc and Liu (2013), Caggiano et al. (2013), Kamber et al. (2013).

[6] The VAR(6) is stable, since the eigenvalues of the (companion form) coefficient matrix are all less than one in absolute terms. The results, however, are robust to using 2 lags, as suggested by the commonly

3.1 The SVAR model

I work with the following Structural-VAR model:

$$B_0 \boldsymbol{x}_t = \sum_{i=1}^{p} B_i \boldsymbol{x}_{t-i} + \boldsymbol{\varepsilon}_t \tag{1}$$

which is estimated using U.S. monthly data spanning the period 1985:1 – 2012:10. The choice of the sample is due to the availability of the uncertainty indicator by Baker et al. (2013). I model the vector $\boldsymbol{x}_t = [frpu_t, \Delta y_t, \pi_t, u_t, i_t, s_t]'$, where $frpu_t$ is the financial regulation policy uncertainty index, Δy_t denotes the annualized monthly log-difference of real industrial production, π_t stands for the annualized monthly CPI inflation rate, u_t represents the total civilian unemployment rate, i_t is the nominal effective federal funds rate, and s_t is the difference between the Moody's Baa- and Aaa-rated corporate bond yields.[7] The Baa–Aaa spread is a widely used aggregate credit spread indicator in the corporate bond pricing literature (e.g., Chen, Collin-Dufresne and Goldstein, 2009). Apart from the FRPU index, the source of these data is the Federal Reserve Bank of St. Louis' database.

The VAR reduced-form specification includes a constant and 6 lags, as previously mentioned. The identification of the financial regulation policy uncertainty shock is achieved by appealing to short-run restrictions, i.e., the standard Cholesky approach. Thus, a recursive structure is assumed, with the ordering being the one indicated above. By placing the uncertainty measure first, I assume that financial regulation policy uncertainty responds with a lag to changes in the remaining variables, a very common restriction in the literature, see e.g., Alexopoulos and Cohen (2009), Bachmann et al. (2013), Baker et al. (2013), Bloom (2009), Caggiano et al. (2013) and Jurado et al. (2013). One potential weakness related to this ordering may be that it does not allow for uncertainty to contemporaneously react to macroeconomic shocks. Section 5 presents a robustness check in which the FRPU index is ordered last and suggests that the results are qualitatively unchanged.

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used selection criteria, i.e., the Akaike Information criterion (AIC), the Schwarz criterion (BIC) and the Hannan-Quinn information criterion (HQC), see robustness checks' section.

[7] The results are robust to the employment of yearly-on-yearly growth rates as well as levels of the industrial production and the CPI indices.

4 Estimation Results

Figure 3 reports the impulse response functions following a one standard deviation shock to the FRPU index, along with the 90 percent confidence bands calculated via Kilian's (1998) bias-corrected bootstrap-after-bootstrap procedure.

An unanticipated increase in financial regulation policy uncertainty causes a significant and persistent increase in the Baa–Aaa spread, which reaches a peak near to 7 basis points after three months. Although the magnitude of the response is relatively low, one should consider the extent of the observed variation in the FRPU index. A one standard deviation shock amounts to 90 points, whereas the index has increased by 280 points from the end of 2007 to the end of 2008. Such a shock would cause credit spreads to raise by more than 20 basis points according to the SVAR estimates. Gilchrist, Sim and Zakrajšek (2013), in their SVAR exercise, find a similar increase in the 10-year BBB–Treasury spread following a shock to uncertainty, proxied by the volatility of aggregate firm-level stock returns.

As for economic activity, the cumulative growth rate of industrial production bottoms out about 6 percent below trend roughly one year after the shock. This substantial decrease is persistent, and there is no evidence of long-run overshooting effect. Long-lasting negative effects of uncertainty shocks on industrial production are also found by Bachmann et al. (2013), Baker et al. (2013), and Jurado et al. (2013). As pointed out by Bachmann et al. (2013), persistent effects may highlight the relevance of additional channels through which uncertainty shocks propagate, other than the "wait and see" mechanism. Indeed, including credit spreads in the SVAR model—a commonly-used indicator of the degree of financial distortions (Gilchrist et al., 2013)—allows to shed some light on the financial frictions mechanism.

Importantly, the FRPU shock has the features of a negative demand shock, in that it decreases economic activity and induces a negative co-movement between the responses of inflation and unemployment in the short-run. Specifically, a surprise increase in financial regulation policy uncertainty leads to a disinflation of more than 1 percent, while the unemployment rate is estimated to increase by about 0.15 percent. These findings corroborate previous results in the literature. For example, Leduc and Liu (2013) and Caggiano et al. (2013) study the effects of uncertainty shocks following a "within-the-U.S.-country" approach, whereas Colombo (2013) and Kamber et al. (2013) investigate international spillovers of U.S. uncertainty shocks to the Euro area and to the New Zealand economy, respectively. All these papers document macroeconomic dynamics similar to those following negative demand shocks.

In contrast to the above result, Born and Pfeifer (2013) study fiscal policy uncertainty and find that shocks to capital tax risk feature the characteristics of a positive demand shock, whereas increases in labor tax risk induce the same effects of a negative supply shock. Additionally, Fernández-Villaverde et al. (2012) find fiscal volatility shocks to be "stagflationary", i.e., they create inflation while output falls. These different results highlight the relevance of distinguishing between the sources of economic uncertainty while studying its effects on the economy.

Finally, to counteract these adverse economic developments, and in order to return inflation to its target, monetary policy is eased. The nominal federal funds rate is decreased by 0.2 percent after fifteen months. Indeed, monetary policy in the U.S. is designed to promote the primary goals of maximum employment and stable prices.

4.1 Flight to quality and flight to liquidity effects

The seminal paper on the financial accelerator theory by Bernanke, Gertler and Gilchrist (1996) shows that the spending and production effects of adverse shocks to the economy, to the extent that these shocks reduce the net worth of borrowers, may be amplified by worsening credit market conditions. Accordingly, one implication is that following negative macroeconomic shocks, low-net-worth borrowers should experience reduced access to credit relative to high-net-worth borrowers, i.e., the flight to quality effect. Another related phenomenon is the flight to liquidity effect, which occurs when a mass of investors, concerned about the future state of the economy, exit illiquid investments and turn to secondary markets to buy easily saleable securities (Longstaff, 2004).

Increases in credit spreads can be viewed as an indication of these two phenomena to the extent which they reflect credit risk and liquidity premia. The Baa–Aaa spread is considered as a proxy for the credit risk premium, see e.g., Friedman and Kuttner (1993) and Güntay and Hackbarth (2010), and as so its increases are a signal of potential flights to quality. On the other hand, the yield spread between Aaa-rated bonds and the 10-year U.S. Treasury bonds (the Aaa–GS10 spread) has been used in the literature as a proxy for liquidity premium.[8] Assessing the reaction of the Aaa–GS10 spread to FRPU

[8] Chen, Collin-Dufresne and Goldstein (2009) show that the time variation of the Aaa–GS10 spread is mostly due to factors independent of credit risk, while Hakkio and Keeton (2009) argue that a widening

shocks helps to shed some light on potential flights to liquidity.

Additionally, I consider two spread indicators to provide a basis of comparison against the reaction of the Baa–Aaa spread. These are the yield difference between Baa-rated bonds and 10-year U.S. Treasury bonds (the Baa–GS10 spread), and the GZ spread. The former reflects both a liquidity premium and a safety premium (Krishnamurthy and Vissing-Jorgensen, 2011), whereas the latter is a micro-founded spread indicator recently elaborated by Gilchrist and Zakrajšek (2012).

In particular, the GZ spread aggregates micro-level information on bonds issued by U.S. non-financial corporations, and thus represents an accurate measure of credit spreads.[9] Interestingly, the authors decompose the GZ spread into two components: one capturing systematic changes in default risk (the predicted part), and a residual component representing a risk premium above and beyond expected losses (the excess bond premium). They then show that the excess bond premium fluctuates closely in response to movements in capital and balance sheet conditions of key financial intermediaries. I analyze the reaction of the overall GZ spread, as well as of each of its two components separately, to a surprise increase in the FRPU index.

The left panel in figure 4 plots the impulse responses of the different spreads to a one standard deviation shock to the FRPU index.[10] The Baa–GS10 and the GZ spreads increase by almost 15 basis points. Moreover, FRPU shocks mainly induce a change in the expected default risk (middle panel), and have only a mild effect on the excess bond premium (right panel), meaning that in the short-run financial regulation-related uncertainty shocks are very likely to influence agents' expectations. The Aaa–GS10 spread follows a path similar to the benchmark indicator, suggesting that FRPU shocks may play a role in driving variations in liquidity premia as well.

Flights to quality triggered by uncertainty about financial regulation policies, and not necessarily reflecting an actual deterioration in borrowers' net worth, can disrupt credit, implying that even firms featuring good fundamentals may find it difficult to afford the costs related to external finance. Nonetheless, FRPU shocks may also worsen the macroeconomic effects of liquidity crises by pushing further market participants to

in the Aaa–GS10 spread captures decreased willingness to hold illiquid assets, and use this spread to construct the Kansas City Financial Stress Index (KCFSI).

[9] The reader is refereed to Gilchrist and Zakrajšek (2012) for further details about the construction of the GZ spread.

[10] I model the baseline vector, where the spread is in turn replaced by the alternative indicators. Due to data availability, the VAR models including the GZ spread and its components are estimated over the period from 1985:1 to 2010:9, while the remaining estimations follow the baseline sample period.

disengage from illiquid assets.

4.2 Variance Decomposition Analysis

The contribution of the financial regulation policy uncertainty shock to fluctuations in macroeconomic aggregates can be scrutinized via a forecast error variance decomposition. Table 2 reports the forecast error variance of the variables under investigation for different forecast horizons. As for the Baa–Aaa spread, FRPU shocks account for about 18 percent. By comparing this percentage to those explained by the other shocks modeled within the SVAR, innovations in financial regulation uncertainty are estimated to be quantitatively relevant for movements in the spread. Moreover, they explain important shares of variations in the unemployment and the federal funds rate, respectively more than 25 and 16 percent. The magnitude of the variation relative to the unemployment is remarkably high and similar to those reported by Alexopoulos and Cohen (2009), using a news-based indicator of general economic uncertainty, and by Caggiano et al. (2013), conditional on their linear VAR model, using the VIX index. However, it is worth noting that when enlarging the baseline vector with the S&P500 and the VIX indices (in the next section), FRPU shocks are relatively less important (they account for about 19 percent of the unemployment's forecast error variance at a 12 month horizon).

Table 3 further underlines the contribution of FRPU shocks for the dynamics of credit spreads. These shocks are responsible for important shares of the variance decomposition of the alternative measures so far considered. For example, at a 12 month horizon, financial regulation policy uncertainty picks up about 10, 17 and 13 percent of the variation in the GZ spread, the Baa–GS10, and the Aaa–GS10, respectively. On the other hand, monetary policy shocks, for instance, account for much smaller fractions. Exogenous variations in the federal funds rate explain just 2, 4, 5 percent of the above spread indicators at the same forecast horizon.

5 Robustness checks

This section deals with the robustness of my results to variations of the baseline vector. I start by controlling for broader economic conditions in the financial market. To this end, I add the S&P500 and the VIX indices as the first variables in the VAR. The

VIX index is a proxy for volatility risk (Ang et al., 2006) and contains important information about economic uncertainty. Moreover, taking into account stock-market levels allows to control for the impact of first-moment shocks, i.e., variations in uncertainty may confound variations in the level of the stock market index, see e.g., Bloom (2009) and Caggiano et al. (2013). Following these studies, the log of the S&P500 index is HP detrended to capture its cyclical component.[11] Therefore, I model the vector $\boldsymbol{x}_t^{s\&p} = [sp_t, vix_t, frpu_t, \Delta y_t, \pi_t, u_t, i_t, s_t]'$.

Flights to quality and liquidity occur due to changes in agents' preferences, which in turn are triggered by different reasons. In this regard, my baseline results evidence that financial regulation policy uncertainty is a possible candidate. However, it may be that instead of uncertain, agents become more confident about the future, see e.g., Longstaff (2004) and Tang and Yan (2010). In such a case, surprise movements in the FRPU index would simply reflect confidence shocks. I address this issue by augmenting the baseline VAR with the Consumer Confidence Index, which consists of an average of responses to different questions concerning the future evolution of the business cycle.[12] I thus estimate the following vector: $\boldsymbol{x}_t^{conf} = [conf_t, frpu_t, \Delta y_t, \pi_t, u_t, i_t, s_t]'$.

It is worth stressing that the Consumer Confidence Index and the VIX are forward-looking measures, and as so allow to account for potential anticipated effects not captured by the baseline VAR system, i.e., available information about future economic developments may induce agents to react to anticipated changes in exogenous fundamentals, usually before such changes materialize, leading to a not fully exogenous variation in uncertainty related to financial regulation.

Another concern could be that the FRPU index is capturing aggregate economic policy uncertainty. To deal with this issue, I estimate a VAR including the "Newsbank" EPU index by Baker et al. (2013), which captures uncertainty about economic policies in general, and as previously mentioned, has been constructed in the same way as the FRPU index. I place the "Newsbank" EPU before the FRPU index in the Cholesky ordering, such that movements in the latter are already purged from uncertainty not related to the financial system, i.e., $\boldsymbol{x}_t^{N\_epu} = [N\_epu_t, frpu_t, \Delta y_t, \pi_t, u_t, i_t, s_t]'$.

The final robustness exercises I undertake consist in variations of the number of lags, a sub-sample analysis, and an alternative Cholesky ordering. Although a VAR(6)

[11] The results, however, are robust even using the level of the S&P500 index.

[12] The Consumer Confidence Index is based on information collected via the Michigan Survey of Consumers, for further details, see http://www.sca.isr.umich.edu

has been selected to ensure no serial correlation in the residuals, I control whether the results are robust to using 2 and 12 lags. I then run the baseline model over the sub-sample 1985:1-2008:6. This time period excludes from the sample the acceleration of the financial crisis, which began with the bankruptcy of Lehman Brothers in September 2008. Finally, to account for the potential criticism to the Cholesky approach, I consider a VAR specification that changes the causal ordering, where the FRUP index is placed last, i.e., $\boldsymbol{x}_t^{frpu\_last} = [\Delta y_t, \pi_t, u_t, i_t, s_t, frpu_t]'$.

The alternative scheme, in which credit spreads are ordered before the financial regulation policy uncertainty measure, allows to shed additional light on the financial transmission channel of uncertainty shocks. Indeed, an unanticipated increase in uncertainty conditional on the information contained in the contemporaneous level of credit spreads has a noticeably less adverse effect on the real economy. This finding is in line with those of Gilchrist et al. (2013).

Figure 5 shows the results of these robustness checks. Overall, the estimated macroeconomic effects of financial regulation policy uncertainty shocks are qualitatively similar. Not surprisingly, conditional on the sub-sample analysis the magnitude of the reactions for all variables is lower than otherwise. This indicates that periods of crises contain much more information on uncertainty than "normal times", see e.g., Jurado et al. (2013) and Caggiano et al. (2013).

6 Conclusion

This paper analyzes the macroeconomic effects of uncertainty surrounding government actions in the financial regulation system. Particular attention is given to its impact on U.S. corporate credit spreads. In a SVAR model, financial regulation uncertainty shocks, as proxied by exogenous variations in the FRPU index recently developed by Baker, Bloom, and Davis (2013), raise the cost of external finance by increasing the expected probability of firms' default. Specifically, the estimated impulse response functions document robust evidence that a surprise movement in financial regulation-related uncertainty leads to a widening of credit spreads and can potentially induce flight to quality as well as flight to liquidity effects.

On the real side of the economy, the FRPU shock is shown to have a persistent negative impact on economic activity, strongly reducing the cumulative growth rate of industrial production. My results also document an increase in the unemployment rate and a fall in prices. These findings support previous empirical evidence showing that uncertainty shocks act as negative demand shocks.

From a theoretical point of view, this work provides additional empirical support for financial frictions as a channel through which uncertainty shocks propagate to the real economy (Gilchrist, Sim and Zakrajšek, 2013). From a policy perspective, while the need for financial reforms is not object of discussion here, further attention should be given to their design, specially in terms of policy management and credibility. Temporary lack of transparency in economic policy design is not beneficial for the economy as a whole. As highlighted by Bloom (2009), there may be a potential trade-off between policy "correctness" and "decisiveness". It may be desirable for governments to act decisively, but occasionally incorrectly, rather than being deliberately ambiguous on policies which many economic agents depend on for purposeful production and spending decisions.

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Tables

Table 1: Granger Causality Test, H_0:*absence of Granger causality*

Direction of causality	Number of lags 2	3	4	5	6	7
FRPU → Baa-Aaa	13.47	8.86	10.49	9.21	7.79	7.29
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Baa-Aaa → FRPU	6.37	3.43	2.17	1.60	1.87	2.34
	(0.001)	(0.017)	(0.071)	(0.158)	(0.085)	(0.024)

NOTES: The table reports the F-statistics for the Granger causality test, their p-values are reported in parentheses. Sample period from 1985:1 to 2012:10.

Table 2: Variance decomposition (baseline model)

Horizon	shock: ε^{frpu}				Baa-Aaa spread					
	Δy	π	u	i	ε^{frpu}	$\varepsilon^{\Delta y}$	ε^{π}	ε^{u}	ε^{i}	ε^{s}
6	7.96	7.21	19.64	16.14	17.99	6.15	2.32	0.87	0.13	72.54
12	8.26	7.21	26.88	17.11	17.82	7.05	5.25	1.04	2.43	66.40
36	8.53	7.25	29.57	18.37	18.29	7.24	7.54	0.99	6.35	59.59
60	9.08	7.55	29.70	17.79	18.51	7.61	7.52	1.26	6.63	58.46

NOTES: The left part of the table shows the fractions (as percentages) of the total forecast error variance due to innovations in financial regulation policy uncertainty. The right part displays the total forecast error variance decomposition of the spread, i.e., the percentage explained by each shock within the baseline VAR.

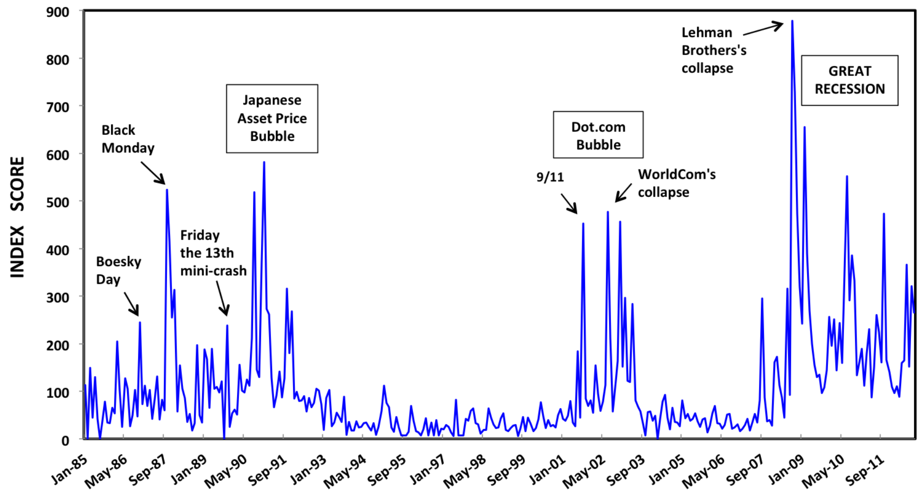
Table 3: Variance decomposition of alternative credit spreads

Horizon	GZ spread		Baa–GS10 spread		Aaa–GS10 spread	
	ε^{frpu}	ε^{i}	ε^{frpu}	ε^{i}	ε^{frpu}	ε^{i}
6	14.46	1.89	20.49	0.43	15.42	1.60
12	9.76	1.72	17.08	3.89	13.15	4.75
36	11.52	4.59	14.00	11.94	9.97	9.51
60	14.96	3.79	14.01	12.26	9.66	10.06

NOTES: The table shows the fractions (as percentages) of the total forecast error variance of alternative measures for the credit spread due to innovations in the financial regulation policy uncertainty index (ε^{frpu}) and in the federal funds rate (ε^{i}), estimated within the baseline VAR model.

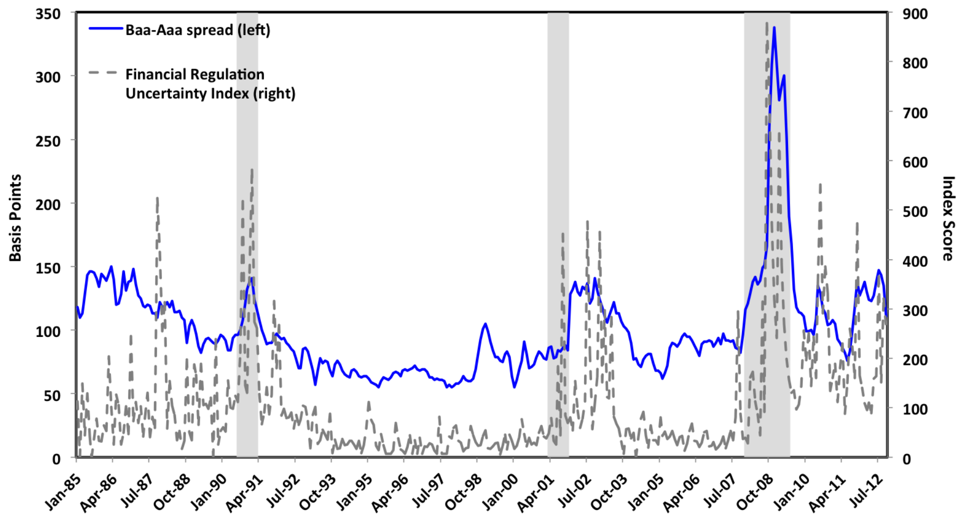
Figures

Figure 1: Financial Regulation Policy Uncertainty



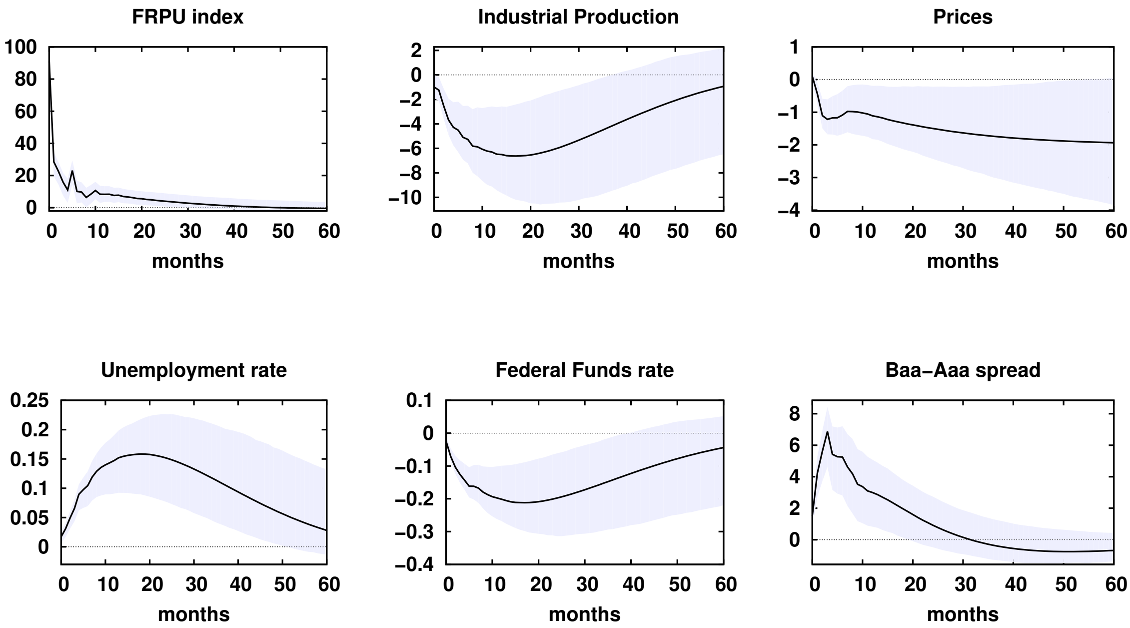
NOTES: The figure displays the evolution of U.S. financial regulation policy uncertainty, as measured by the index from Baker, Bloom and Davis (2013). Sample period: 1985:1-2012:10.

Figure 2: Uncertainty and Credit Spreads dynamics



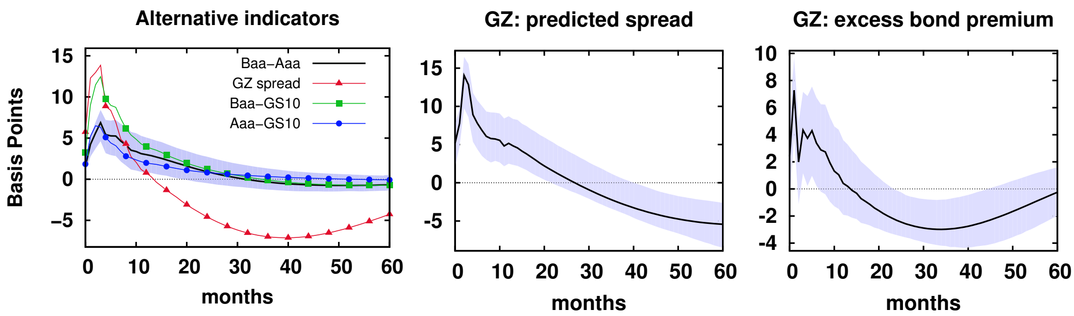
NOTES: The blue solid line depicts the spread between Baa–Aaa Moody's rated corporate bonds. The gray dashed line depicts the financial regulation policy uncertainty index (Baker et al., 2013). Sample period: 1985:1-2012:10. The shaded vertical bars are the NBER-dated recessions.

Figure 3: Macroeconomic implications of FRPU shocks



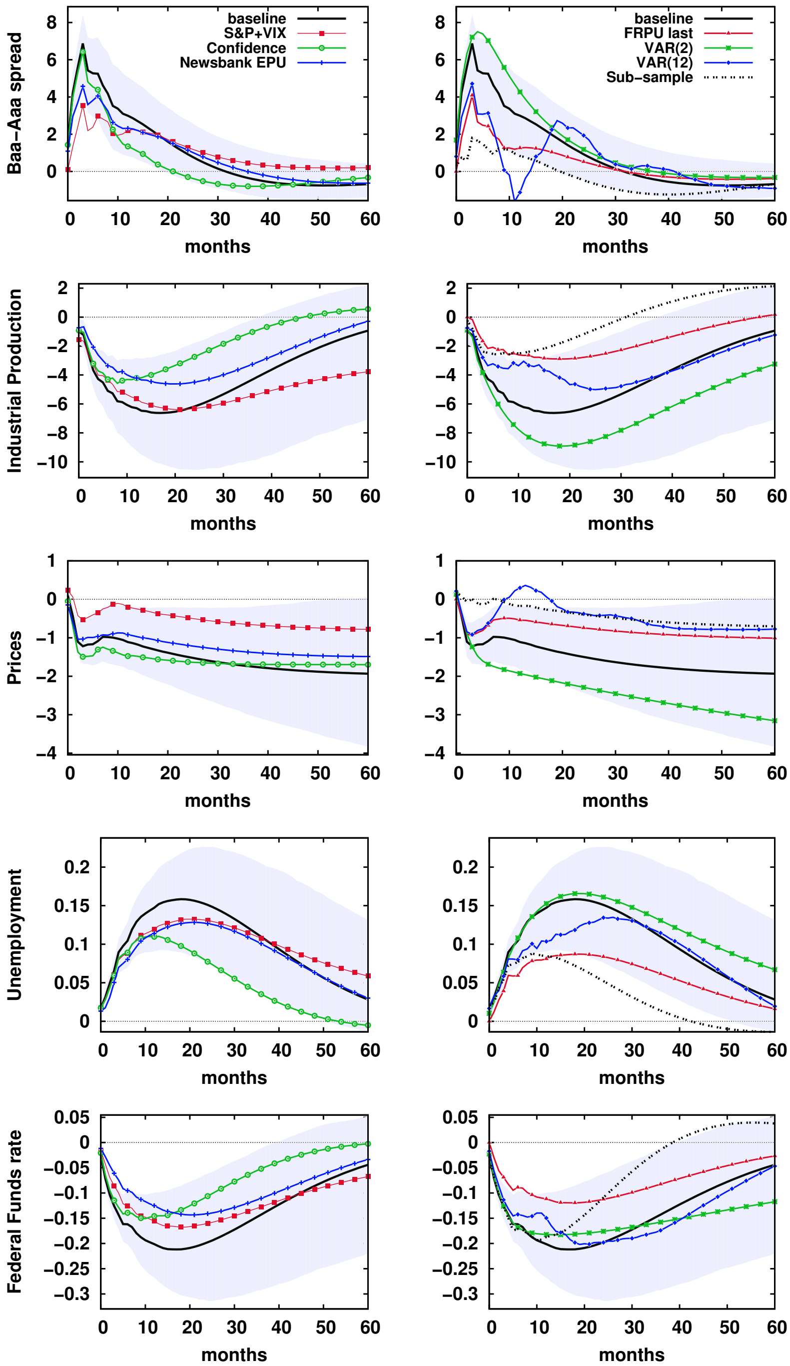
NOTES: Impulse responses to a one standard deviation orthogonalized shock to the financial regulation policy uncertainty index. Baseline VAR(6), where $\boldsymbol{x}_t = [frpu_t, \Delta y_t, \pi_t, u_t, i_t, s_t]'$. The responses of the industrial production growth and the inflation rate have been accumulated. Gray areas: 90% bootstrapped confidence intervals, calculated with the bootstrap-after-bootstrap procedure (Kilian, 1998), based on 2,000 replications.

Figure 4: Credit Spread Dynamics



NOTES: The figure shows the impulse response functions of different credit spread indicators to a one standard deviation orthogonalized shock to the FRPU index. All the responses are obtained by substituting, in turn, the Baa–Aaa benchmark measure with the alternative spread indicators in the baseline VAR specification.

Figure 5: Sensitivity Analysis



NOTES: Effects of a one standard deviation shock to the FRPU index: Robustness checks. The responses of industrial production growth and inflation rate have been accumulated. Gray areas: 90% bootstrapped confidence intervals, calculated with the bootstrap-after-bootstrap procedure (Kilian, 1998), based on 2,000 replications.