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The benefits of using large high frequency financial datasets for empirical analyses: Two applied cases[1]

Massimo Ferrari, Catholic University of Milan and BIS,

Kristyna Ters, University of Basel and BIS

[1] This paper was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

The benefits of using large high frequency financial datasets for empirical analyses: Two applied cases

Massimo Minesso Ferrari§ and Kristyna Ters†

Case one: Market evaluation of monetary policy decisions: a simple approach using intraday data.

Massimo Minesso Ferrari§

Introduction

How do markets evaluate monetary policy announcements and how large are the shocks they convey? These are central questions for policy makers if they are interested in evaluating their decisions and quantitatively assess the outcomes of different and possibly alternative policies.

As we know, if markets were completely efficient and monetary policy was perfectly communicated by central banks, market agents should have already priced in the

§ Catholic University of Milan and BIS
† University of Basel and BIS Research Fellow
§ Catholic University of Milan and BIS

decision of the monetary authority at the time of the announcement. On the contrary, if the central banks are able to surprise the market, they might be able to generate real effects after their policies. In this short paper, that is based on the methodology applied in M. Ferrari, J. Kearns and A. Schrimpf "Monetary shocks at high-frequency and their changing FX transmission around the globe"[1], I will present a simple methodology to identify monetary policy shocks using high frequency financial data. When the precise moment of a shock is known, high frequency data allow us to pinpoint the exact moment of the event and, therefore, to correctly identify the reaction of market participants. This approach has the advantage to be fast and easily implementable but has some relevant caveats. They can be divided in two main groups: on one hand there are technical problems, connected to the size of the database used; on the other, especially for illiquid markets, the data reporting process may be inaccurate.

Why using high frequency data?

Monetary policy transmission is one of the main concern for policy makers. However, it is not always easy to understand how it works and, more interestingly, how large the shock delivered by each announcement[2] is.

Aggregate variables are reported, in the best case scenario, at monthly basis while firms data are update for listed corporations on a quarterly basis. In this setting it becomes therefore quite complicate to pinpoint exactly the effect of a single monetary policy announcement, to identify the effect of that announcement per se and to remove the impact of market overreactions or other shocks taking place in the same time interval.

[1] In that paper we looked at the market response to conventional and unconventional policies, measuring monetary policy surprises using bonds and overnight indexed swaps (OIS).

[2] The importance of this question is testified also by the huge amount of literature on the topics. Contributions are many and start from the early nineties, between them see (Bernanke & Gertler, 1995) and (Christiano, Eichenbaum, & Evans, 1999)

On financial markets, on the contrary, securities are traded daily with end-of-day quotes available on most data provider's platforms. This appears to be a solution for the previous problem reducing drastically the time interval of the analysis, and thus the number of possible overlapping shocks. However that is not entirely true. In fact, especially for the case of liquid markets such as the FX, observation at a daily basis can suffer for problems similar to those outlined before. Many authors have called for the necessity of a closer time interval to pinpoint exactly the impact of monetary policy decisions[3].

This approach has the clear advantage of focusing only on the exact moment of each monetary policy announcement and of evaluating how market reacted to that particular news. As follows from standard results of finance theory, a completely anticipated shock should be already priced when it actually takes place. With high frequency data researches can set a sufficiently narrow time window around each monetary policy announcement to check if markets are surprised or not by a specific news. Measuring the surprise on this limited time horizon allows to remove the noise deriving from other events that might influence the instrument's quote along the day and potential crowding-in or out effects. This is true not only for large economies, such as the U.S. or the euro area, but also for smaller countries. An example can clarify this point. On the 3rd of May 2016 the RBA announced a 25 bp cut in the target rate. The reaction of the Australian dollar is reported in Figure 1.

[3] See for example (Kearns & Manners, 2006), (Wright, 2012), (Rogers, Scotti, & Wright, 2015), (Gertler & Karadi, 2015) and (Ferrari, Kearns, & Schrimpf, 2016)

Figure 1: Market reaction to RBA decision of May 3 2016.

As it is clear from Figure 1 the monetary policy decision had an immediate and sharp impact on the exchange rate, evident from the sharp devaluation around 6:30 CET. However, if this policy shock is measured at the daily level, the result is quite different. The end of day quote, in fact, incorporates other events that in the day have affected the FX quote during the day leading to a much different and noisier measure of the FX change due to the monetary shock. This case is a clear example of how setting a too wide window around an event may lead to misperception of its size.

High frequency data to measure exchange rate reactions

The methodology outlined above was used in (Ferrari, Kearns, & Schrimpf, 2016). In this paper we look at the FX reaction to conventional and unconventional monetary policy decisions. In order to assess the impact of monetary policy on the exchange rate we used a minute tick database provided by Thomson Reuters. This dataset contains information on the FX, 2- and 10-year bonds and 1- and 6-month OIS for 7 countries of interest[4] from 2000 to 2015, for every calendar day. Data are reported by market

[4] Australia, Canada, euro area, Japan, Switzerland, UK and US.

participants, providing details from the number of trades to the bid/ask quote for each instrument at the minute frequency.

The dataset contains a huge amount of information regarding quotes, prices and liquidity of each instruments with hundreds of millions of entries. Between all those information we were interested in identifying the monetary policy shock related to each monetary policy decision and the reaction to that shock in the exchange rate.

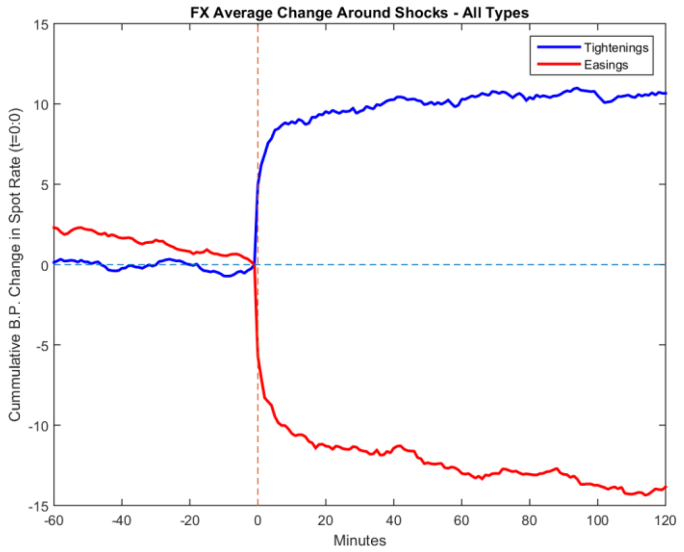

Figure 2: Cumulative basis point change around each monetary policy decision, averaged between events and countries. Source: (Ferrari, Kearns, & Schrimpf, 2016).

To do so we developed a simple procedure to select only the relevant information in the database and compute the change in each instrument's quote around each monetary policy decision. The time window we selected (20 minutes around each announcement) is tight enough to ensure that every variation within that amount of time is entirely related to the monetary policy shock itself. Therefore the measure we compute is the market perceived surprise of each move of central banks, free from the (possible) noise deriving from other events and bounds. This procedure has the advantage to be simple to implement, neat in the results and constrained only by data availability and computing power. In fact it is only necessary to know when an event takes place, to extract the data on the desired time interval around each event and to compute a measure of the shock.

There are, however, some caveats related to the nature of the dataset under consideration that will be tackled in the next section.

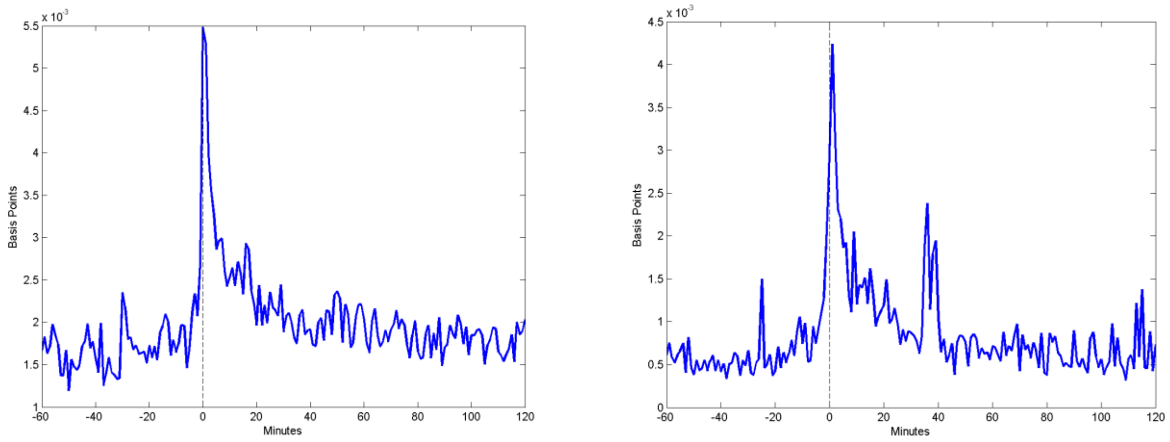

Figure 3: Intra minute absolute basis point change in 2-year bonds (left) and 1-month OIS (right), averaged across events and countries. Source: (Ferrari, Kearns, & Schrimpf, 2016).

Based on this methodology, we identify a strong response of the FX to monetary policy surprises and a sizable shock connected to each communication of central banks (see Table 1). We use these data to compute a target shock measure to the FX (using the 1-month OIS) and the change in the yield curve related to each announcement. By measuring monetary policy shocks in this way we are able to identify the impact of 1 bp monetary policy surprise on the exchange rate and how that the impact changes over time.

	Policy Rate	FX Spot	Target	Path
U.S.	7.8	17.4	1.0	2.2
Euro Area	5.5	12.6	0.9	1.1
Japan	0.0	10.3	0.2	0.3
U.K.	4.9	16.5	1.4	2.1
Australia	9.5	21.8	2.9	2.8
Switzerland	6.2	29.1	0.6	1.2
Canada	7.9	31.9	1.9	3.1

Table 1: Average absolute surprise by country. The second column reports the average absolute change in the policy rate at each monetary policy decision for each country, Column 3-5 report average absolute market surprise computed using a 20 minutes window around each shock. Source: (Ferrari, Kearns, & Schrimpf, 2016).

Problems specific to high frequency data

The procedure outlined before[5] has, as pointed out, the advantages of simplicity and clearness, delivering at the same time high precision identification of the variable of interest.

There are, however, two main sources of concerns related to its implementation.

The first problem, which is common to all big data exercises, is merely technical and related to the size of the used database. Data are double compressed in order to be easily downloadable and each part of the dataset contains the information of an entire month of trading, about 700 thousands cells (for each instrument) that are a mixture of strings and numbers. This huge amount of information makes it unfeasible to load and save the entire tick history and requires a relative high amount of time to access each element of the database. Additionally there are limitations on the platform we used (Matlab) to the amount of data of mixed type that can be saved without using complex saving methods and which take hours to run also on high spec machines. To circumvent these problems we developed an algorithm that interacts as little as possible with the database and divides data into smaller objects allowing to save and load them fasters. At the same time we implemented checks to identify missing observations or data errors.

The second order of problem is, on the contrary, deeply related to the type of data under consideration. Tick databases are compiled by data providers such as Thomson or Bloomberg using quotes reported by market participants. Data providers, however, update quotes only if a sufficient number of trades take place within the time interval (in this case the minute) and the market participant monitored. If there

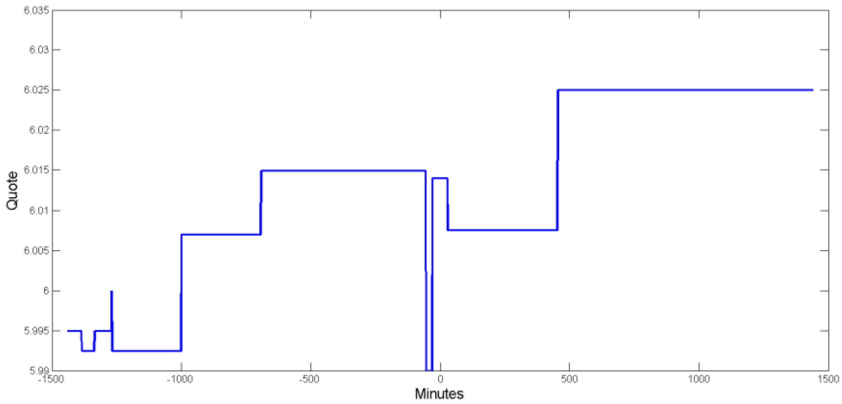

Figure 4: Example of sticky quotes from Australian 1-month OIS. Changes in one day interval around event (at time 0).

[5] It can be summarized in three steps: identify the exact timing of each shock, extract the data related to the interval around each shock and compute the shock.

are not enough trades, the quote is not updated as if there were no trades at all. This is a potential downfall for the entire methodology. In that case in fact the change in the instrument is computed as zero, while, on the contrary, there is a non-zero monetary policy shock. This issue is particularly relevant for relatively illiquid markets (such as that in Figure 4), that are populated by few and possibly smaller players.

To implement our methodology correctly it is crucial to separate those events for which monetary policy decisions are already priced in from those in which quotes are simply not updated. In the first case the observation needs to be included in the sample, because it conveys relevant policy information; on the contrary, in the second case we want to treat that observation as a missing datapoint to not dilute the sample.

In order to distinguish between the two cases we construct a secondary dataset using daily data from an alternative provider (Bloomberg Analytics). This dataset has open and close quotes at daily frequency, computed independently from Thomson Reuters. In this way it is possible to compare open and close quotes based on Bloomberg data with our own dataset. If the shock is computed we check the daily change and compare it with the Bloomberg's daily change. If the change computed out of our data is zero, while Bloomberg's is positive, we consider the observation as a missing data. In this way we are sure to minimize the impact of sticky quotes in our sample, reducing them to a negligible number of data points.

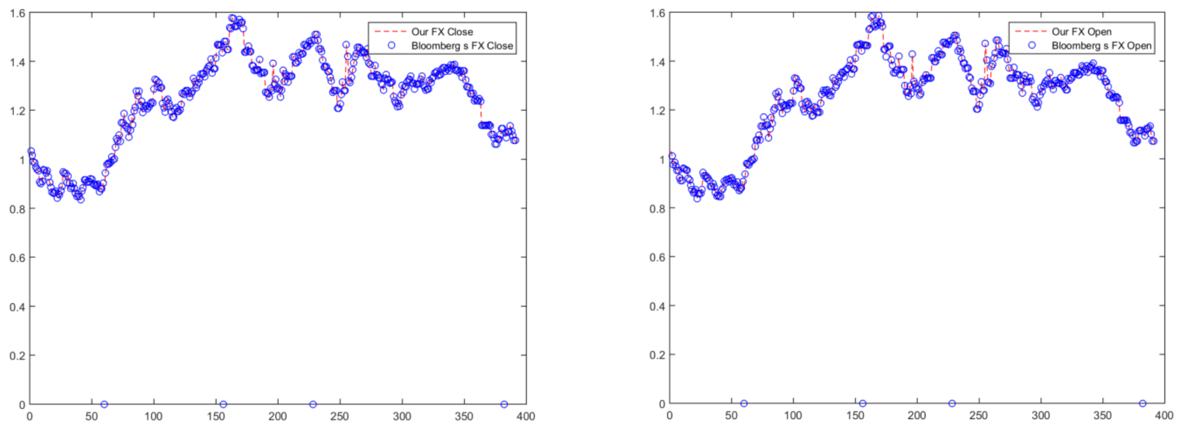

Figure 5: Daily open and close quotes from Bloomberg's data and Thomson intraday database for Euro/Dollar exchange rate. Data points overlap if measurements coincide. Source: (Ferrari, Kearns, & Schrimpf, 2016).

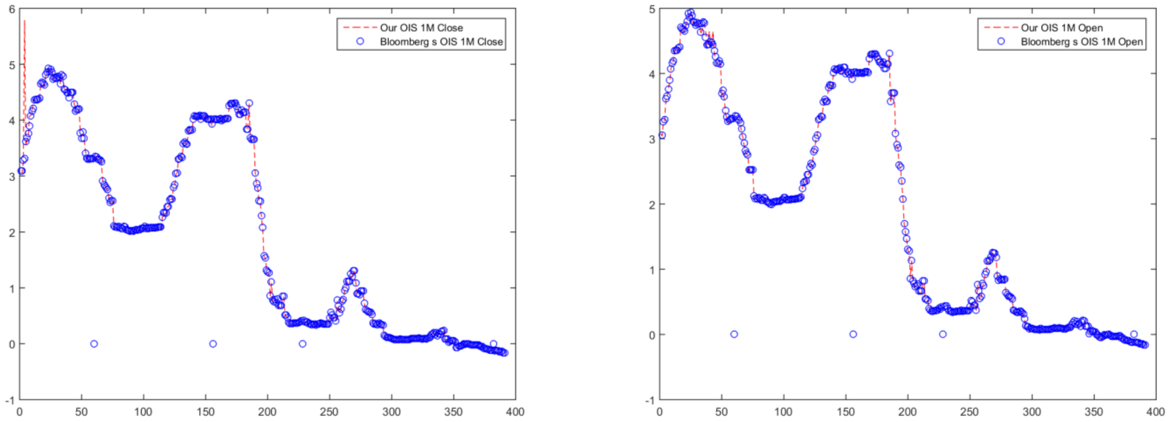

Figure 6: Daily open and close quotes from Bloomberg's data and Thomson intraday database for Euro Area 1-month OIS. Data points overlap if measurements coincide. Source: (Ferrari, Kearns, & Schrimpf, 2016).

Conclusions

High frequency data allow researchers to easily identify the impact of precisely timed shocks on market quotes. Shocks identified in this way can be used to easily assess the impact of monetary policy on market quotes.

This approach shares some of the main problems related to big data concerning mainly memory space and computing power but presents also issues that are specific to the type of data under consideration. In this setting, in fact, it is critical to understand if a shock measured as zero is generated by the reporting mechanism or if it is indeed in the data.

In the page above we have outlined a possible way to check the data quality against an independent source, in order to minimize the impact of data errors on the final estimation. With this methodology, in (Ferrari, Kearns, & Schrimpf, 2016), we were able to identify monetary policy shocks, to show the impact of monetary policy surprise on the exchange rate and how the sensitivity of markets to monetary policy increases trough time.

Case two: Intraday dynamics of euro area sovereign credit risk contagion

Kristyna Ters[†]

Introduction

We analyse euro area sovereign credit risk contagion effects in GIIPS[6] countries plus France and Germany from January 2008 to end-December 2011, which we split into a pre-crisis and crisis period. The use of intraday CDS and bond data lets us estimate credit risk contagion effects with substantially more accuracy than existing studies on sovereign credit markets have done. In addition, little is yet known about the transmission channels of credit risk contagion through the CDS and the bond market, and their relative importance in the euro area sovereign debt crisis. As we have data for both the CDS market and the bond market, we are able to assess the contagion impacts conditioned on the credit channel. The use of intraday data allows us to capture the intraday patterns of credit risk contagion. Indeed, shocks that may seem to affect several countries simultaneously when viewed at a daily or lower data frequency are revealed, through the lens of intraday data, to have possible origins in one particular country with clear contagion effects on other countries. Via the use of intraday data we are able to estimate the dynamics of sovereign credit risk much more accurately than in existing studies as no other empirical work so far has tested the intraday patterns of sovereign CDS and bond market credit spreads.

Our findings suggest that, prior to the crisis, the CDS and bond markets were similarly important in the transmission of sovereign risk contagion, but that the importance of

[†] University of Basel and BIS Research Fellow

[6] Greece, Ireland, Italy, Portugal and Spain.

the bond market waned during the crisis. We find flight-to-safety effects during the crisis in the German bond market that are not present in the pre-crisis sample. Our estimated sovereign risk contagion was greater during the crisis, with an average timeline of one to two hours in GIIPS countries. By using an exogenous macroeconomic news shock, we can show that, during the crisis period, increased credit risk was not related to economic fundamentals. Further, we find that central European countries were not affected by sovereign credit risk contagion, independent of their debt level and currency.

Data

The core data we use in our empirical analysis consists of USD-denominated five-year maturity intraday quotes on CDS contracts and government bonds for France, Germany, Greece, Ireland, Italy, Portugal and Spain. We choose this group of countries as it includes the countries most affected by the euro sovereign debt crisis, as well as Germany, which serves as the near-risk-free reference country, and France, which we consider as a low-risk control country. According to (Gyntelberg, Hoerdahl, Ters, & Urban, 2013) when one considers the number of quotes of CDS contracts at the peak of the sovereign debt crisis in 2010, the five-year segment is the most liquid. The use of intraday data in our empirical analysis enables us to obtain much sharper estimates and clearer results with respect to market mechanisms as also shown in (Gyntelberg, Hoerdahl, Ters, & Urban, 2013). Further, (Gyntelberg, Hoerdahl, Ters, & Urban, 2013) show that sovereign credit risk dynamics follow an intraday pattern. Our sovereign bond price data is provided by MTS (Mercato Telematico dei Titoli di Stato[7]). The MTS data comprise both actual transaction prices and binding bid-offer quotes. The number of transactions of sovereign bonds on the MTS platform is, however, insufficient to allow us to undertake any meaningful intraday analysis. Therefore, we

[7] The Italian secondary market for sovereign bonds, created by the Ministry of Treasury in 1988 and privatized in 1997.

use the trading book from the respective domestic MTS markets. The MTS market is open from 8:15 to 17:30 local Milan time, preceded by a pre-market phase (7.30 to 8.00) and an offer-market phase (8:00 to 8:15). We use data from 8:30 to 17:30. The CDS data consist of price quotes provided by CMA (Credit Market Analysis Ltd.) Datavision. CMA continuously gathers information on executable and indicative CDS prices directly from the largest and most active credit investors. After cleaning and checking the individual quotes, CMA applies a time- and liquidity-weighted aggregation so that each reported bid and offer price is based on the most recent and liquid quotes. The CDS market, which is an OTC market, is open 24 hours a day. However, most of the activity in the CMA database is concentrated between around 7:00 and 17:00 London time. As we want to match the CDS data with the bond market data, we restrict our attention to the period from 8:30 to 17:30 CET (CEST during summer). We construct our intraday data on a 30-minute sampling frequency on our data set, which spans from January 2008 to end-December 2011. The available number of indicative quotes for CDS does not allow a data frequency higher than 30 minutes. The euro area sovereign CDS markets were very thin prior to 2008, which makes any type of intraday analysis before 2008 impossible. Microstructural noise effects may come into play when high frequency data is used. However, this does not apply to our data based on a 30-minute sampling frequency because we average the reported quotes over each 30-minute interval as shown in Figure 6 (for tests, robustness checks and for a more detailed discussion please refer to (Gyntelberg, Hoerdahl, Ters, & Urban, 2013)).

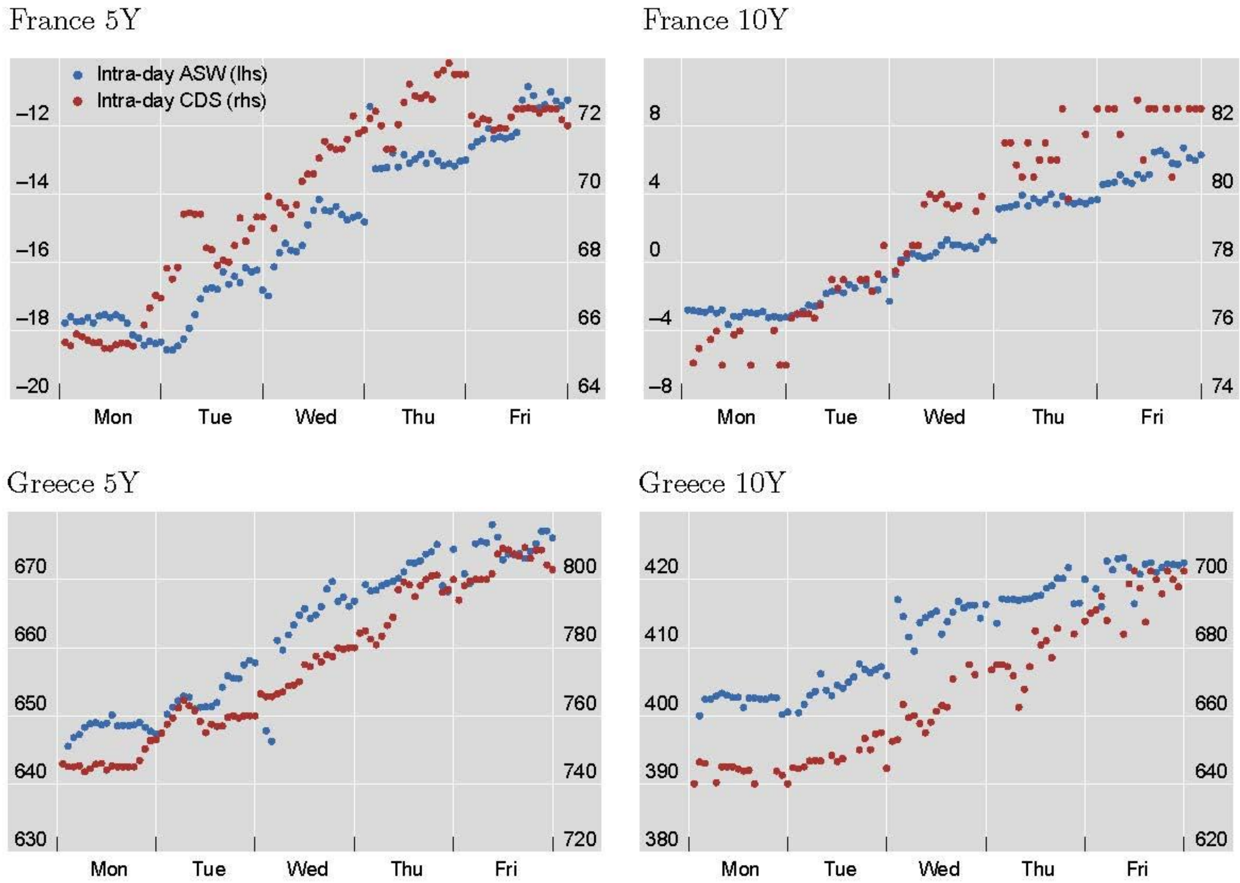

Figure 6: Sample of intraday CDS and ASW spreads. Intraday movements of CDS (right-hand axis) and ASW (left-hand axis) spreads in basis points for an arbitrary sampling period (Monday 9 August to Friday 13 August 2010). The figures show data for a 30 minutes sampling frequency, i.e. 18 time intervals per trading day.

When implementing our analysis we split the data into two subsamples. The first covers the period January 2008 to 19 October 2009 and, as such, represents the period prior to the euro area sovereign debt crisis. While this period includes the most severe phase of the financial crisis, including the default of Lehman Brothers, it is relatively unaffected by market distortions stemming from concerns about the sustainability of public finances in view of rising government deficits and therefore represents the pre-sovereign debt crisis period. The second subsample covers the euro area sovereign debt crisis period and runs from 20 October 2009 to end-December 2011. As the beginning of the crisis period, we designate 20 October 2009, when the new Greek government announced that official statistics on Greek debt had previously been fabricated. Instead of a public deficit estimated at 6% of GDP for 2009, the government now expected a figure at least twice as high. We employ CDS and bond data in our analysis in order to be able to differentiate between the transmission of sovereign risk contagion according to the credit risk channel from one country to another. Based on the no arbitrage theory the CDS and the bond yield spread both price the same default of a given reference entity, their price should be equal if markets are perfect and frictionless. Thus, in a perfect market, due to arbitrage, the CDS spread equals the bond yield over the risk-free rate. However, for this parity to hold, a number of specific conditions must be met, including that markets are perfect and frictionless, that bonds can be shorted without restrictions or cost and that there are no tax effects, etc. A further complication linked to the use of fixed-rate or plain vanilla bonds as substitutes is that it is unlikely that the maturity of these instruments exactly matches that of standard CDS contracts. To ensure proper comparability with CDS, (Gyntelberg, Hoerdahl, Ters, & Urban, 2013) employ synthetic par asset swap spreads (ASW) for the bond leg of the basis. The use of ASW is in line with the practice used in commercial banks when trading the CDS-bond basis. By calculating ASW for our empirical analysis, we ensure an accurate cash flow matching, as opposed to studies that use simple "constant maturity" yield differences for credit risk. An asset swap is a financial instrument that exchanges the cash flows from a given security - e.g. a particular government bond - for a floating market rate. This floating rate is typically a reference rate such as Euribor for a given maturity plus a fixed spread, the ASW. This spread is determined such that the net value of the transaction is zero at inception. The ASW allows the investor to maintain the original credit exposure to the fixed rate bond without being exposed to interest rate risk. Hence, an asset swap on a credit risky bond is similar to a floating rate note with identical credit exposure, and the ASW is similar to the floating-rate spread that theoretically should be equivalent to a corresponding CDS spread on the same reference entity. Specifically, the ASW is the fixed value A required for the following equation to hold:

$$\underbrace{100 - P}_{\substack{\text{Upfront payment for bond} \\ \text{asset in return for par}}} \quad \overbrace{+ C \cdot \underbrace{\sum_{i=1}^{N_{\text{fixed}}} d(t_i)}_{\text{Fixed payments}} = \underbrace{\sum_{i=1}^{N_{\text{float}}} \left(L_i + A\right) \cdot d(t_i)}_{\text{Floating payments}}}^{\text{Interest rate swap}}, \tag{1}$$

where P is the full (dirty) price of the bond, C is the bond coupon, Li is the floating reference rate (e.g. Euribor) at time ti and d(ti) is the discount factor applicable to the corresponding cash flow at time ti. In order to compute the ASW A, several observations and simplifications have to be made. First, in practice it is almost impossible to find bonds outstanding with maturities that exactly match those of the CDS contracts and second, the cash-flows of the bonds and the CDS will not coincide. To overcome these issues, in what follows we use synthetic asset swap spreads based on estimated intraday zero-coupon sovereign bond prices. Specifically, for each interval and each country, we estimate a zero-coupon curve based on all available bond price quotes during that time interval using the Nelson and Siegel method. With this procedure, we are able to price synthetic bonds with maturities that exactly match those of the CDS contracts, and we can use these bond prices to back out the corresponding ASW. As this results in zero coupon bond prices, we can set C in Equation (1) to zero. A CDS contract with a maturity of m years for country j in time interval k of day t, denoted as Sj (tk, m), has a corresponding ASW Aj (tk, m):

$$100 - P_j(t_k, m) = \sum_{i=1}^{N_m} \left(L_i(t_k) + A_j(t_k, m)\right) \cdot d(t_k, t_i), \tag{2}$$

with Pj (tk, m) as our synthetic zero coupon bond price. For the reference rate Li in Equation (2), we use the 3-month Euribor forward curve to match as accurately as possible the quarterly cash flows of sovereign CDS contracts. We construct the forward curve using forward rate agreements (FRAs) and euro interest rate swaps. We collect the FRA and swap data from Bloomberg, which provides daily (end-of-day) data. 3-month FRAs are available with quarterly settlement dates up to 21 months ahead, i.e. up to 21 × 24. From two years onwards, we bootstrap zero-coupon swap rates from swap interest rates available on Bloomberg and back out the corresponding implied forward rates. Because the swaps have annual maturities, we use a cubic spline to generate the full implied forward curve, thereby enabling us to obtain the quarterly forward rates needed in Equation (2). Given our interest in intraday dynamics, we follow (Gyntelberg, Hoerdahl, Ters, & Urban, 2013) and generate estimated intraday Euribor forward rates by assuming that the intraday movements of the Euribor forward curve are proportional to the intraday movements of the German government forward curve. To be precise, for each day, we calculate the difference between our Euribor forward curve and the forward curve implied by the end-of-day Nelson-Siegel curve for Germany. We then keep this difference across the entire curve fixed throughout that same day and add it to the estimated intraday forward curves for Germany earlier on that day to generate the approximate intraday Euribor forward curves. This approach makes the, in our view, reasonable assumption that the intraday variability in Euribor forward rates will largely mirror movements in corresponding German forward rates.

Finally, we need to specify the discount rates $d(t_k, t_i)$ in Equation (2). The market has increasingly moved to essentially risk-free discounting using the overnight index swap (OIS) curve. We therefore take $d(t_k, t_i)$ to be the euro OIS discount curve, which is constructed in a way similar to the Euribor forward curve. For OIS contracts with maturities longer than one year, we bootstrap out zero-coupon OIS rates from interest rates on long-term OIS contracts. Thereafter, we construct the entire OIS curve using a cubic spline. We use the same technique as described above to generate approximate intraday OIS discount curves based on the intraday movements of the German government curve. To gauge the potential impact of this assumption on our empirical results, we reestimate our model using an alternative assumption that the Euribor and OIS curves are fixed throughout the day at their observed end-of-day values. Under this alternative assumption, we obviously fail to capture any movements in money market rates within the day when we price our synthetic asset swaps. Our results remain robust. Please refer to (Gyntelberg, Hoerdahl, Ters, & Urban, 2013) for an in-depth discussion of the construction of our intraday ASW. According to different panel unit root tests (see Appendix C in (Komarek, Ters, & Urban, 2016)) our CDS and ASW price data (displayed in Figure 7) is I(1). Therefore, we estimate our subsequent models (panel VAR and panel VARX) in first differences. For in depth results and tests please refer to (Komarek, Ters, & Urban, 2016).

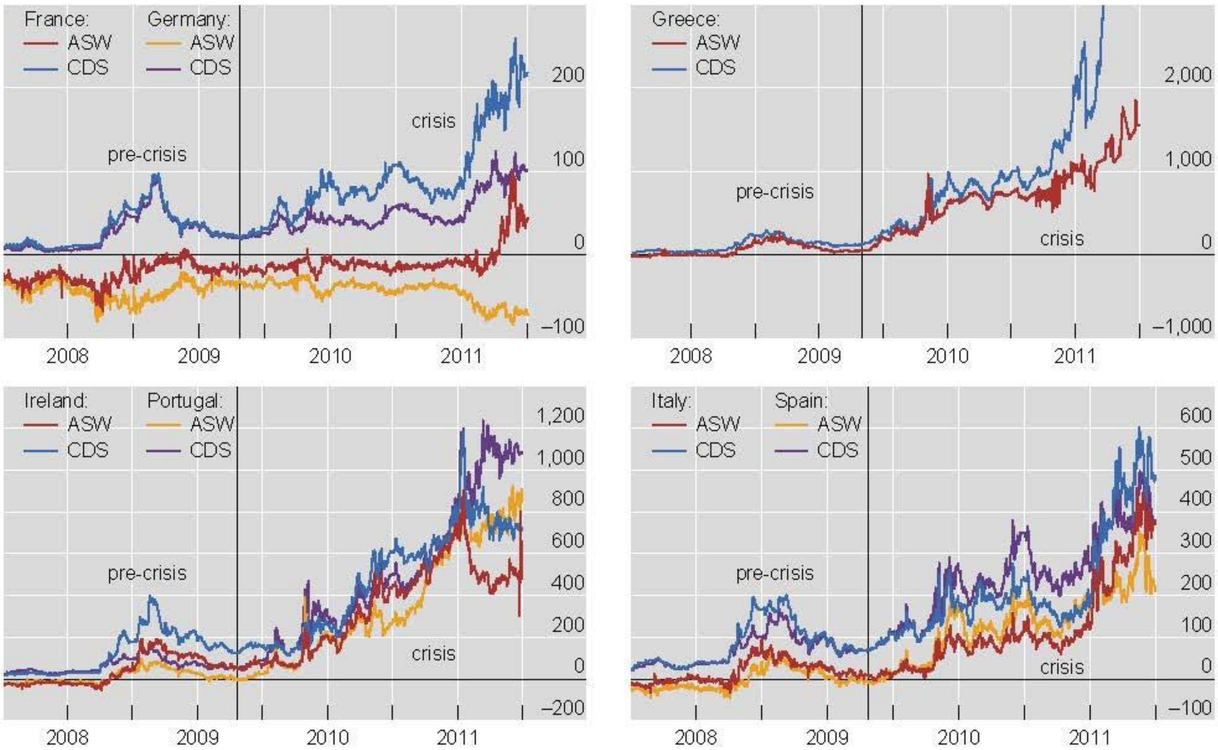

Figure 7: The figure is based on a 30-minute sampling frequency. Our split into the pre- and the crisis period is indicated by the vertical line in each figure. Due to the Greek debt restructuring the data for Greece ends in September 2011.

Our empirical analysis of the intraday CDS and bond spread dynamics will be based on a panel and time-series methodology, which means that we need to construct equally-spaced time series of spreads. After extensive initial analysis of the amount and distribution of our intraday quotes, both for sovereign CDS and bonds, we conclude that a 30-minute time interval gives us a satisfactory trade-off between data frequency and the occurrence of missing observations. In practice, this means that we use the average of the mid-quotes reported for both bonds and CDS within each half-hour interval. Figure A.2 shows that using a 30-minute sampling frequency, between 75% and 90% of the half hour intervals contain a price for 5-year CDS from 2009 onwards. The proportion of non-empty intervals is somewhat lower for the 10-year contracts, in particular towards the end of the sample. Figure 8 shows that using a 30-minute sampling interval for bonds we have in almost all cases more than 90% non-empty time intervals.

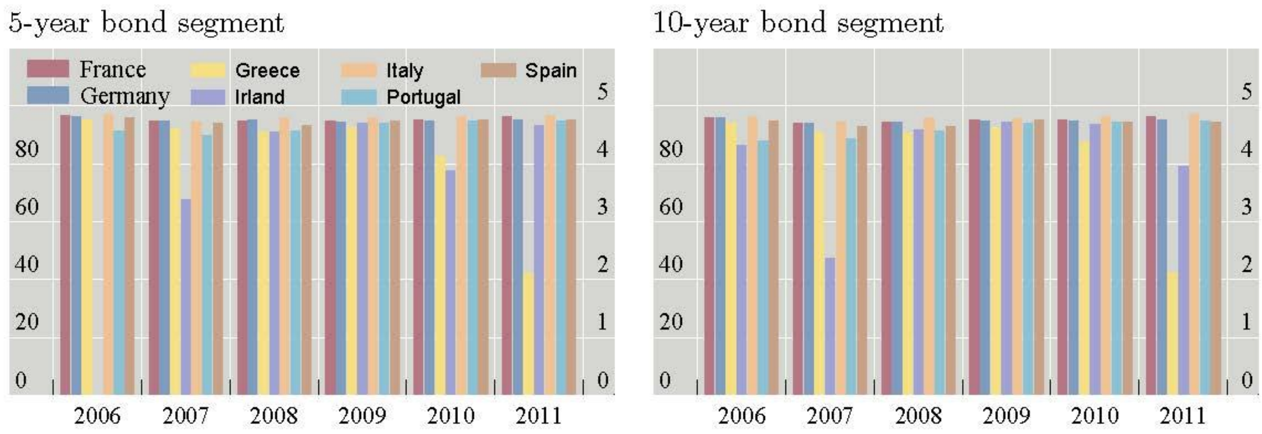

Figure 8: The figure is based on a 30-minute sampling frequency. Our split into the pre- and the crisis period is indicated by the vertical line in each figure. Due to the Greek debt restructuring the data for Greece ends in September 2011.

Conclusions

The CDS market was the main venue for the transmission of sovereign credit risk contagion during the euro area sovereign debt crisis. In contrast, we find that, prior to the crisis, the two markets (CDS and bond) were similarly important in the transmission of financial contagion, while the importance of the bond market decreased relative to the CDS market during the crisis period. We find evidence for sovereign credit risk contagion during the euro area sovereign debt crisis period, as our results show more drastic reactions to shocks in terms of magnitude and absorption compared to the pre-crisis period. Thus, our results on the responses to sovereign credit risk shocks during the crisis period confirm the contagion across euro area countries, as they result from extreme negative, systemic effects and are much larger in magnitude compared to the pre-crisis period, a fact which cannot be explained by macroeconomic fundamentals.

We find comovement effects rather than contagion during the pre-crisis period, as markets react rationally to economic fundamentals, while the responses to sovereign credit risk shocks remain moderate in magnitude. The use of intraday data substantially increases the precision of the results, as we find average timelines of financial shock contagion of one to two hours during the crisis period and 30 minutes to one hour prior to the crisis. We find a flight to safety during the crisis period in the German bond market. This is not present prior to the crisis and, interestingly, is also not visible in the French bond market. The flight-to-safety effect can be explained by market participants' lack of belief in the future path of public finances (a self-fulfilling crisis), which cannot be explained by macroeconomic news. Our results using an unexpected exogenous macroeconomic news shock suggest that, during the pre-crisis period, markets for sovereign credit risk were driven by macroeconomic news. Positive news led to a decrease in credit spreads and negative news to an increase. Using the same experiment for the euro area sovereign debt crisis period, our results show that movements in sovereign credit spreads did not respond to macroeconomic news but were rather driven by either monetary policy or exaggerations in financial markets due to lack of belief (a self-fulfilling crisis). We find that central European countries were practically unaffected by sovereign risk contagion during the crisis. Our model further indicates no difference in the responses to shocks according to debt levels or whether the country belongs to the monetary union or not. This implies that, in general, countries that lie geographically outside of the crisis region were much less affected by sovereign risk contagion. As stated by (Gyntelberg, Hoerdahl, Ters, & Urban, 2013), the fact that CDS premia are more responsive to new information may reflect the fact that the market participants in these markets on average are more highly leveraged, are more aggressive in taking positions and hence respond more quickly to new information. Thus it is crucial for policy makers and regulators to understand the dynamics in the market for sovereign credit risk, especially in the derivative market, where contagion effects are more severe during our analysed crisis sample.

In our empirical paper (Komarek, Ters, & Urban, 2016) we make use of intraday data which allows us to capture the intraday patterns of credit risk contagion. Indeed, shocks that may seem to affect several countries simultaneously when viewed at a daily or lower data frequency are revealed, through the lens of intraday data, to have possible origins in one particular country with clear contagion effects on other countries. Also, (Gyntelberg, Hoerdahl, Ters, & Urban, 2013) discuss the advantages of using intraday data due to the higher accuracy of the results as compared with lower-frequency data. (Gyntelberg, Hoerdahl, Ters, & Urban, 2013) report that the use of daily data yields mixed results with no clear evidence in contrast to the use of intraday data. They state that they find a drastic decrease in the precision of their results with very wide confidence bands the lower the sampling frequency gets.

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Eighth IFC Conference on *"Statistical implications of the new financial landscape"*

Basel, 8–9 September 2016

The benefits of using large high frequency financial datasets for empirical analyses: Two applied cases[1]

Massimo Ferrari, Catholic University of Milan and BIS,

Kristyna Ters, University of Basel and BIS

[1] This presentation was prepared for the meeting. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

High frequency financial datasets for empirical analyses: two applied cases

Massimo Ferrari [1,2]   Kristyna Ters [1,3]

[1]Bank for International Settlements

[2]Catholic University of Milan   [3]Basel University

Basel, 9 September 2016
Bank for International Settlements

Disclaimer: The views presented are those of the authors
and do not necessarily reflect those of the BIS.

Market evaluation of monetary policy decisions: a simple approach using intraday data.

Based on the findings of *Ferrari, M., Kearns, J. and Schrimpf, A. (2016)*: **Monetary shocks at high-frequency and their changing FX transmission around the globe**.

Why High Frequency Data?

- Monetary policy transmission is one of the main concern for policy makers.
- However, aggregate variables are reported, in the best case scenario, at **monthly base**: the impact of a single announcement is captured with significant **noise**.
- Using market daily quotes is not a solution, as liquid instruments (such as the FX) present similar issues.
- With intraminute data it is possible to select the **exact moment** of a specific event and **isolate** the market response to it.

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An example: the RBA decision of May the 3^{rd} 2016

Methodology

We use a database of 7 economies, 5 instruments (FX, 2 & 10 year bonds, 1 & 6 month OIS) with *minute* data from 2000 to 2015. With this dataset we are able to analyze the market surprise around each central bank announcement using the following methodology:

- Collect the exact date, time and type of monetary policy announcements.
- Define a tight window (20 minutes) around each monetary policy announcement.
- Measure the market (perceived) surprise using the trade data in that window.
- **Analyze:**: market response to monetary policy decisions (MPD), MPD vs UMP, time-varying impact of monetary policy, spillovers
- **Advantages:** easy to implement, neat in the results, constrained only by computing power. **Issues:** database size, high frequency specific problems.

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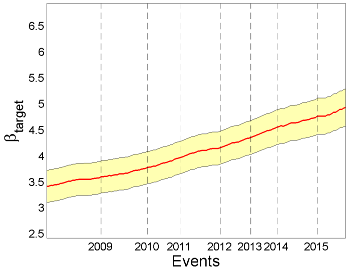
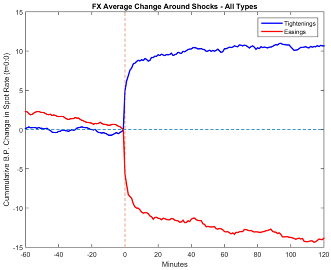
Results

- Country specific estimate of MPDs and UMPs impact on the exchange rate after target, path, expectations and time premium shocks.
- Increasing sensitivity over time of the exchange rate to monetary policy (left panel top: sensitivity to a *target shock* of *EUR/USD* exchange rate).
- Spillover between advanced economies.





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Methodological issues

This methodology is straight forward to implement but presents some specific problems: technical issues (same as in any big data analysis); data providers **do not** update ticks if the number of trade is not large enought (it is possible to **wrongly consider a missing update for a totally anticipated shock**); significant outliers may arise.

Our solutions:

- We developed an algorithm that axcess efficiently the database ($>$ 55 millions of entries).
- Constructed a parallel database with end-of-day quotes from an alternative provider to check against our data.
- Identify and treat as missing observations the cases with no update.

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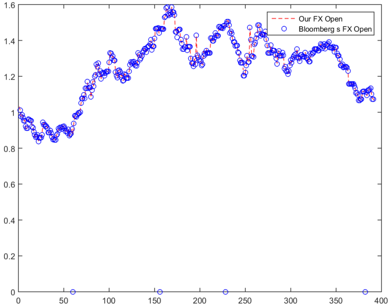
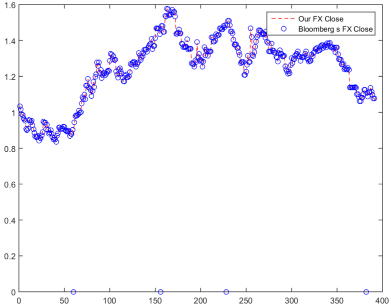
Cross check algorithm output

Euro-Dollar exchange rate output





Open quotes: primary vs secondary database

Close quotes: primary vs secondary database

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Intraday dynamics of euro area sovereign credit risk contagion.

Based on the findings of *Komarek, L., Ters, K. and Urban, J. (2016)*: **Intraday dynamics of euro area sovereign credit risk contagion**.

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The advantage of using intraday data

- We analyse credit risk contagion effects in GIIPS countries during and before the euro area sovereign debt crisis
- The use of intraday data leads to **substantially higher accuracy** than existing studies on sovereign credit markets
- We are able to capture **intraday patterns**: shocks that may seem to affect several countries simultaneously on a daily level are revealed, when using intraday data, to have origins in one particular country with clear contagion dynamics on other countries

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Data

- Greece, Ireland, Italy, Portugal, Spain (GIIPS)
- Germany as risk free and France as near risk free entities
- 5- and 10-year maturity intraday quotes from CMA DataVision (time-stamped quotes) for CDS
- Sovereign plain vanilla bond price data from MTS (inter-dealer market)
- Construction of intraday data on a **30-minute sampling frequency**
- We focus on the sovereign debt crisis and split the data into a pre-sovereign debt crisis (2008 - 19 Oct 2009) and a crisis period (20 Oct 2009 - 2011)

Synthetic Asset Swap Spreads (ASW)

dirty price coupon discount factor reference rate

$$\underbrace{100 - P}_{\text{Upfront payment for bond asset in return for par}} \overbrace{+ C \underbrace{\sum_{i=1}^{N_{\text{fixed}}} d(t_i)}_{\text{Fixed payments}} = \underbrace{\sum_{i=1}^{N_{\text{float}}} (L_i + A) d(t_i)}_{\text{Floating payments}}}^{\text{Interest rate swap}},$$

ASW

- To compare 5-year ASW with 5-year CDS with an identical cash flow structure, we estimate zero-coupon bond prices for each 30-minute time interval according to Nelson-Siegel (1999)
- For L we use the Euribor and for d we follow the market standard for riskfree discounting using the euro OIS
- Our CDS and ASW are I(1), estimation in first differences

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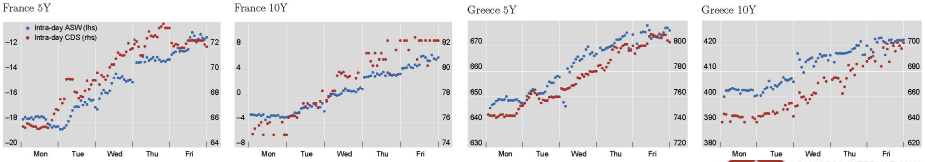
Microstructural noise

- intraday data is subject to market microstructural noise as traders tend to place orders in the morning following new information overnight, and before closing
- typically we see volatility smirks and/or smiles in intraday data
- as we calculate prices for each equidistant 30 minute interval by averaging over all available 5-minutes quotes, we do not detect volatility smirks or smiles in our data on 30 minutes or lower data frequency



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Conclusion

- In contrast to existing studies we find sovereign risk contagion dynamics at an intraday speed (2 - 3 hours)
- CDS have been more responsive during the euro area sovereign debt crisis to new information compared to the bond market
- CDS market participants respond more quickly to new information as they are highly leveraged and more agressive in taking positions
- Intraday data dramatically increases the precision of our estimates