# Regulation and Spillovers between Firms in the Corporate Bond and Stock Markets 

Renaud Beaupain ${ }^{\text {a,b,* }}$, Stephanie Heck ${ }^{\text {c }}$ and Quentin Jarret ${ }^{\text {a }}$<br>${ }^{\text {a }}$ IESEG School of Management<br>${ }^{\mathrm{b}}$ LEM-CNRS 9221<br>${ }^{\text {c }}$ Commission de Surveillance du Secteur Financier<br>*Corresponding author. Email: r.beaupain@ieseg.fr. Address: 3 Rue de la Digue, 59000 Lille, France.

December 2020


#### Abstract

In this paper we study return and return volatility spillover effects between firms in a market and we highlight economic and regulatory events as determinants of these spillovers. To this end, we consider a same sample of firms that have securities traded in the stock and corporate bond market. Our approach to capturing firm specific return and volatility time series in the corporate bond market is unique, as it is based on a repeat-sales index applied at the firm level. We first document the intensity with which firms transmit and receive shocks to other firms within a market. We show the predominance of financial firms as main transmitters and receivers of shocks. Second, we explain spikes and regime breaks in the spillover intensity within a market by a set of economic and regulatory shocks. We demonstrate that shock events such as the collapse of Lehman Brothers or the U.S. credit downgrade have had a positive impact on spillovers by increasing their intensity. We nevertheless highlight a differential impact in the stock and corporate bond market. We show that the Dodd-Frank Act and the Volcker Rule in particular have had a negative impact on spillovers in the corporate bond market, suggesting that the introduction of this regulation has been able to reduce the transmission of shocks from one firm to another.


JEL classification: E44, E58, G01, G28
Keywords: Financial crisis, Financial regulation, Volatility spillovers, Connectedness, Corporate bonds

## 1 Introduction

In a world of global financial markets, interconnectedness among financial entities represents a main source of concern for investors and policy makers. The global financial crisis of 20082010 has particularly pointed out the strong links between entities of the financial system and the fact that linkages can amplify shocks. It has also brought the discussion on the existence of systemic risk to the forefront, which is of high concern to policy makers. While securities regulators were very much focused on investor protection, there is now growing attention to the financial stability risks that arise from strong linkages. There are typically two distinct channels by which institutions or companies are considered as directly interconnected and which leads to systemic risk. The first channel are direct linkages in the system, when assets of one entity represent the liability of another. The second one are indirect connections that arise from overlapping holdings of some assets. In both cases, the situation becomes problematic in case of fire sales or massive asset liquidation leading eventually to price spirals. Fire sales can have adverse consequences for real activity when they undermine physical capital investment (Kiyotaki and Moore, 1997). In that sense, financial crises have important implications for the real economy because they raise the costs of intermediation and restrict credit, which in turn restrains the level of activity in the real sector and ultimately can lead to periods of low growth and recession (Allen and Gale, 2000).

We do not measure interconnectedness in the sense described above as we do not measure overlapping portfolio holdings nor do we look at direct exposures of firms to one another. We rather focus on the type of connectedness that arises when shocks from one firm spill over to another firm via the financial markets. This puts our study into the strand of spillover or interdependence analysis, sometimes also called contagion. According to Forbes and Rigobon (2002) however, contagion only occurs if cross-market comovements increase significantly after a shock, in other instances the word interdependence is preferred. We think that the terms of spillover or connectedness are appropriate terminology for our study and are in line with Diebold and Yilmaz (2012) and Diebold and Yilmaz (2014). We also argue that our spillover analysis can directly inform the systemic risk assessment that would arise from a direct connectedness analysis. We follow the methodology of Diebold and Yilmaz (2014), which is related to the network topology thinking and is appropriate for risk measurement and management.

In the literature, a number of papers has examined whether and how return and volatility shocks propagate across markets or across asset classes. In this paper, we take a different perspective. We center the analysis on the propagation of shocks within two markets, the equity market and the corporate bond market. Knowing that these two markets have distinctive features, we compare two things: i) the spillover effects between firms in a market, referred to as directional spillover and ii) the spillover intensity over time, which we refer to as spillover
index. ${ }^{1}$ Our analysis builds company-specific information from equity market data and from corporate bond market data. The corporate bond market is characterized by over-the-counter trading and by an irregular and in some instance low trading frequency. Furthermore, a firm will typically issue several corporate bonds, while it has only a single traded stock. For a given issuer, there is thus a possibly large number of price series. To aggregate the information by issuer we require a specific methodology and we rely on firm-specific repeat-sales indices. Beaupain and Heck (2016) show that the application of repeat-sales indices as developed by Case and Shiller (1987) for the real estate market can be used to represent the dynamics of the market for corporate bonds, and that such a method is superior to alternative measures that imply an averaging of prices. These issuer specific indexes form the basis for the spillover analysis within the corporate bond market, while the spillover analysis within the equity market is based on stock price data.

The first part of the paper is dedicated to the analysis of directional spillovers. We measure how much of a shock to a firm is transmitted to another firm and vice versa. This also encompasses the measurement of how much a firm transmits to others or receives from others. The transmission of shocks is measured on a firm's return series and its return volatility series. It is important for us to consider those two dimensions as they do not reflect the same type of information. While return series give a picture of the general price evolution and performance of the firm, the return volatility series are good indicators of risk or uncertainty related to the firm.

Our paper is not limited to a static spillover analysis. In the second part, we examine the evolution of the spillover intensity in each market over time and we relate it to the occurrence of a series of events. We look at two types of events. We first consider economic shocks. Due to their unanticipated nature, we expect such shocks to alter the spillover intensities in a direct and rather brutal manner. The collapse of Lehman Brothers on 15 September 2008 is one of such shocks. We also look at the impact of the downgrade of the issuer rating of the United States by Standard and Poor's, which lowered its rating from AAA to AA+ on 5 August 2011. This event marks the first time that the United States lost its AAA rating attributed by a rating agency. The taper tantrum episode is the last economic shock that we consider in this paper. The event arose from the quantitative easing policy implemented by the Federal Reserve during the Global Financial Crisis. Through this unconventional tool, the Federal Reserve purchased large amounts of U.S Treasury and mortgage-backed securities over an extended period of time. On 22 May 2013, Ben Bernanke however announced the intention of the Federal Reserve to taper the quantitative easing in a speech before the U.S. Congress. This unanticipated comment surprised market participants and gave rise to the socalled taper tantrum. The tapering finally started on 18 December 2013. Second, we consider the impact of a series of regulatory events. Unlike economic shocks, the implementation

[^0]of new regulations does not surprise market participants. The content of such regulations is typically gradually disseminated to market participants, when the rules are debated by authorities. We accordingly expect such regulations to alter the intensity of spillovers, in line with their objectives, yet in a more progressive manner. We look at the series of regulations that were adopted after the Global Financial Crisis. In the United States, the Dodd-Frank Wall Street Reform and Consumer Protection Act was passed into law by President Obama on 21 July 2010. The Dodd-Frank Act aims at protecting the interests of investors and taxpayers, notably by introducing reforms related to systemic risk and capital requirements for banks (Acharya et al., 2011). The Volcker Rule (Section 619 of the Dodd-Frank Act) further regulates proprietary trading. The Rule specifically forbids the banks, whose deposits are insured by the Federal Deposit Insurance Corporation (FDIC), to engage in proprietary trading. While the implementation of the Volcker Rule was delayed to 1 April 2014, Trebbi and Xiao (2019) and Bessembinder et al. (2018) discussed the close of proprietary trading desks by several major financial institutions, sometimes up to three years before its application. At an international level, the Basel II framework was also revised to better account for market risk (Basel II.5) and to enforce stronger capital requirements for banks (Basel III). The United States adopted the revised Basel II. 5 framework on 7 June 2012 and Basel III on 9 July 2013 (Getter, 2014). The capital requirements in the adopted text account for both the recommendations of the Basel Committee on Banking Supervision and those included in the Dodd-Frank Act (Getter, 2014), which makes those two regulations particularly related.

Our paper has two main parts of analysis and therefore also two main contributions. In the first part, we look at the intensity of spillovers, be it directional spillovers between firms or net spillovers of a specific firm. We further explore the determinants of the directional spillover values. We point to important transmitters and receivers of shocks. It also stands out that the location of a firm - whether a firm is based in the U.S. or not - can impact the intensity of its spillovers. The network visualization of the bilateral links between firms points to a predominance of financial and insurance companies in some cases and to 'intra'industry effects. The predominance of financial firms in the propagation of shocks is even more pronounced in the stock market than in the corporate bond market.

In the second part, we provide a temporal analysis of the market-wide connectedness within the corporate bond market and within the equity market by constructing a spillover index. We also identify specific market events that have impacted the propagation of shocks within a specific market. We highlight that three specific events, namely, the Collapse of Lehman Brothers (September 2008), the U.S. Credit Downgrade (August 2011) and the taper tantrum (May 2013) all had an impact on market-wide connectedness, which exhibits its highest value during the Global Financial Crisis. In all parts of the analysis, we dedicate attention to the comparison between the propagation of shocks in the two different financial markets. The connectedness analysis is undertaken within a market, however we compare the results that we obtain for one market to those obtained for the other market. We identify the following
notable differences. The reaction to the Fed tapering announcement of May 2013 is different in the two markets: connectedness within the corporate bond market increases, while it decreases within the stock market. Furthermore, quantitative easing has a negative impact on the connectedness in both markets. We thus find that a programme designed to inject liquidity into the market also reduces the propagation of shocks between firms, which might be a beneficial and desirable result. A break analysis confirms that different regimes are associated to the occurrence of an economic event. In the corporate bond market, our results also suggest that the intensity of spillovers decreased after the implementation of the Volcker Rule. Again this is not a surprising result as the Volcker Rule is directly targeting proprietary trading, which is an important component in the corporate bond market set up and not so much in the stock market.

The rest of this paper is structured as follows. We discuss the related literature in Section 2. We detail our methodology in Section 3. We report the results of the directional spillover analysis in Section 4 and of the spillover indices in Section 5. We finally conclude in Section 6.

## 2 Literature

Over the past few years, the literature on spillover and interdependence has been growing fast. Spillover effects have been investigated across a variety of markets and geographical locations and different methodologies have been applied. A review of econometric approaches to measure spillover effects is provided by Forbes (2012) and Diebold and Yilmaz (2015). In this paper, we rely on the methodology put forward by Diebold and Yilmaz (2014), who apply a variance decomposition of responses to shocks to track daily time-varying connectedness of major U.S. financial institutions. While the study of Diebold and Yilmaz (2014) is focused on stock return volatility spillovers, Bayoumi and Bui (2012), Belke and Dubova (2018) and De Santis and Zimic (2018) investigate return spillover effects within and/or across bond and equity markets. Belke and Dubova (2018) and Bayoumi and Bui (2012) consider international transmissions across bond and equity markets in the four largest global financial markets: the United States, the Euro area, Japan, and the United Kingdom. They find that asset prices react most strongly to international shocks within the same asset class, but that there are also substantial international spillovers across asset classes. Shocks in the U.S. market represent the strongest transmission, while inward spillovers to the U.S. from elsewhere are minimal. De Santis and Zimic (2018) find that U.S. and European sovereign debt markets are highly interconnected. However, as their results suggest, the total cross-border connectedness among sovereign yields declined steadily between October 2008 and December 2012, which the authors attribute to financial fragmentation. Ehrmann et al. (2011) add money markets and exchange rates to the analysis of financial transmission, which follows the structural model of Rigobon (2003). The focus is on return propagation across asset classes and within and
across geographical location. They find that asset prices react strongest to other domestic asset price shocks, but that there are also substantial international spillovers. They also find a predominance of U.S markets as a driver of financial markets. Such a result is also found by Finta et al. (2017), who capture contemporaneous volatility spillover effects between U.S. and U.K. equity markets, by Finta et al. (2019) who investigate contemporaneous and intraday spillover effects between oil and stock markets in the U.S. and Saudi Arabia or by Davidson (2020) who focuses on contagion episodes in Latin America. BenSaida (2019) make a distinction between the spillover intensity arising from good news and from bad news, finding that during the global financial crisis and the European sovereign debt crisis, the markets transmitted, on average, more bad volatility than good volatility. Collet and Ielpo (2018) specifically address the question of cross-sectoral spillovers in credit markets. Volatility spillovers of credit spreads are assessed across eight sectors and over the period 2001-2012. The authors find higher spillover effects during the financial crises of 2001 and 2008. The consumer non-cyclical and the insurance sectors are found to be the top-contributors to these volatility spillovers whereas capital goods is typically a sector that receives shocks rather than gives them.

As Collet and Ielpo (2018), part of our study considers spillover effects within the credit market. Thus a first notable difference to other related papers is that we examine the corporate bond market and not government bond yields. Second, we focus on the spillovers effects within an asset class (bond or equity) as opposed to spillovers across markets. We also analyse both spillovers between return series and spillovers between return volatility. While most studies focus on one or the other, we look at the differences in return spillovers and return volatility spillovers.

We dedicate an important part of our paper to examining the determinants of the spillover intensity over time. Economic shocks, as well as regulatory events might be typical determinants of an increase or decrease in the spillover intensity of a market. Yang and Zhou (2017) show that economic conditions have the ability to alter the propagation of volatility shocks across markets. The authors notably document the role played by the quantitative easing policy of the United States in driving volatility spillovers at an international scale. They specifically examine the spillovers of implied volatility across international stock and commodities markets. The unanticipated nature of economic shocks make their expected impact on spillovers both direct and possibly brutal. The adoption (or implementation) of new regulation, by contrast, is expected to alter the propagation of shocks in a smoother and more progressive manner. This is consistent with the rationale developed by Bao et al. (2018) and Bessembinder et al. (2018), who argue that it is, by nature, difficult to time precisely the impact of new regulations on market dynamics and therefore advocate for capturing their impact over a defined time frame. Among financial regulations, the Volcker Rule, which bans bank-affiliated dealers' proprietary trading, was seen as a potential source of impairment to market making activities. Thakor (2012) provides a critical assessment of this rule suggesting
that it has a negative impact on market making and that it also makes bank risk management less efficient. Dastarac (2020) also suggests that the latter regulation did not alleviate the problems related to proprietary trading. Bao et al. (2018) find that the Volcker Rule has had a significant adverse effect on market liquidity, approaching levels seen during the financial crisis period, even accounting for the extra liquidity provided by dealers not affected by the Volcker Rule. Dick-Nielsen and Rossi (2018) support the finding that, after the crisis, the costs of liquidity provision have significantly increased. In contrast, Trebbi and Xiao (2019) and Bessembinder et al. (2018) find that trading costs did not increase after the crisis and may even have improved. However, Bessembinder et al. (2018) point out that several measures of market quality, such as turnover, dealer's capital commitment, average trade size and block trade frequency, that were degraded during the financial crisis also failed to return to pre-crisis levels in more recent years.

## 3 Methodology and data

We want to compare spillovers in return and in return volatility series between firms in two distinct markets. Our stock market data is from the CRSP (The Center for Research in Security Prices) database and available through WRDS (Wharton Research Data Services). Our corporate bond market data comes from the TRACE database in which transaction-level data on corporate bond trades is reported. The available data contains the details of each corporate bond transaction executed in the U.S. market. ${ }^{2}$ We follow Dick-Nielsen (2014) to manually filter out error reports, cancellations, reversals and agency transactions in this dataset.

Our analysis requires us to select a sample of firms for which stock market and corporate bond market information are available. A firm is retained in the sample when, i) its equity shares trade publicly in the stock market and ii) it has a least one weekly transaction in one of its corporate bond issues over the entire sample period. Even though a firm may have a variety of corporate bond issues, the trading frequency can be very low. The latter condition of at least one transaction a week considerably limits our sample of firms. Our final sample is composed of 27 firms, with a total of 24,614 issues over the sample period. We have a total of 1,086,599 corporate bond transaction observations, with on average $40,244.4$ transactions recorded for an issuer (see Table 1). The number of issues ranges from 26 for Royal Dutch Shell PLC (RDS) to a maximum of 4,251 for JPMorgan Chase and Co. (JPM). To obtain a regularly timed dataset we use weekly data, the sample period from 23 June 2006 to 31 December 2014. ${ }^{3}$

[^1]Table 1 further describes the companies in the sample. While the sample is mainly composed of firms headquartered in the United States (21 firms), there are six international companies: Barclays PLC (BCS) and HSBC Holdings PLC (HSBC) from the United Kingdom, Toyota Motor Corp. (TM) from Japan, Royal Bank of Canada (RY) from Canada, Royal Dutch Shell PLC (RDS) from the Netherlands and Credit Suisse Group (CS) from Switzerland. Based upon NAICS industry classification, there are eight commercial banks in our sample: the Bank of New York Mellon Corp. (BK), Royal Bank of Canada (RY), Barclays PLC (BCS), Citigroup Inc. (C), Bank of America Corp. (BAC), Wells Fargo and Co. (WFC), JPMorgan Chase and Co. (JPM) and HSBC Holdings PLC (HSBC). There are also 4 other financial firms: Credit Suisse Group (CS), the Goldman Sachs Group Inc. (GS), Morgan Stanley (MS) and SLM Corp. (SLM). Importantly, with the exceptions of Royal Bank of Canada (RY) and SLM Corp. (SLM), all those financial firms have been identified as GlobalSystemically Important Financial Institutions (G-SIFIs) by the Financial Stability Board since November 2011. Prudential Financial Inc. (PRU), indentified as a Global-Systemically Important Insurer (G-SII) since July 2013, completes our sample of financial firms. Turning to non-financial corporations, our sample is composed of two automobile manufacturers (Ford Motor Co. - F - and Toyota Motor Co. - TM) and two telecommunication resellers (Verizon Communications Inc. - VZ - and AT\&T Inc. - T). The other (non-financial) firms each belong to a different industry. There are eighteen different industries represented overall.

To construct return and return volatility series for each firm and for each market we start from weekly price series. While a weekly stock price time series is readily available, the construction of similar series from bond market data requires a finer treatment. Transactions of multiple bond issues exist for a single firms. Moreover this transaction data is naturally unequally-spaced in time and timestamped to the actual time at which each transaction occurred. To address these issues, we construct a repeat-sales index for each bond issuer, that exploits the information contained in each transaction. This technique extends the methodology developed by Case and Shiller (1987), where a repeat-sales index is built for the real estate market. As evidence by Beaupain and Heck (2016) repeat-sales indices are able to better represent the dynamics of the corporate bond market than the traditional summary methods used by academics or practitioners. This encourages us to construct a single repeatsales index capturing the dynamics of all the corporate bonds issued by a single firm. We end up with a weekly corporate bond price index for each firm. ${ }^{4}$

For each firm and for each security type (bond or stock) we obtain return and volatility series. For stocks, the series are based on weekly share price data, while for bonds, the series are based on the repeat-sales price index. Volatility series are computed with a $\operatorname{GARCH}(1,1)$ model, to overcome some of the drawbacks of a historical volatility measure and thereby to account for the time-varying variance of financial data. We obtain 4 datasets that form the

[^2]basis of the spillover analysis: issuers' returns in the corporate bond market, issuers' returns in the stock market and issuers' volatilities in both markets. We follow Diebold and Yilmaz (2014) to measure total and directional spillovers. In a simple VAR (Vector Auto-regressive) setup, variance decompositions depend on the ordering of the variables. Therefore Diebold and Yilmaz (2012) rely on the framework introduced by Koop et al. (1996) and Pesaran and Shin (1998), to make variance decompositions invariant to ordering. The framework also improves the initial framework as it allows the measurement of total spillovers as spillovers from/to a specific asset/market to/from all others and of directional spillovers as the spillovers from/to a specific asset to/from another specific asset.

Any spillover measure is based on the decomposition of a forecast error variance associated to a $N$-variable VAR, where $N$ is the number of firms or entities in the sample. As argued by Diebold and Yilmaz (2014) a generalized variance decomposition is not sensitive to ordering and is therefore preferred over a Cholesky-based variance decomposition. The results of Wiesen et al. (2018) suggest that the generalized variance decomposition should be preferred for the type of analysis conducted in this paper, where we want to examine the network connection between firms as well as the evolution of the spillovers over time.

All connectedness measures - from simple pairwise to system-wide - are based on 'non-own' reactions, that is, they are measured 'across' entities, namely for $i \neq j$. They answer the questions: What fraction of the 1 -step-ahead error variance in forecasting $x_{i}$ is due to shocks to $x_{j}$ ? And similarly, what fraction of the 1-step-ahead error variance in forecasting $x_{j}$ is due to shocks to $x_{i}$ ?, where $x_{i}$ or $x_{j}$ typically represent return or volatility series. Individual connectedness measures are then aggregated in certain ways to build pairwise or system-wide spillover measures. We rely on the notation put forward in Diebold and Yilmaz (2014) and illustrate the main measures hereafter. ${ }^{5}$

The starting point is a connectedness table obtained as the variance decomposition matrix of a generalized VAR. Let's denote such a matrix by $D^{H}$ and its individual elements by $d_{i j}^{H}$. Individual elements represent the fraction of variable $i$ 's $H$-step forecast error variance due to shocks in variable $j$. The focus is on off-diagonal elements $d_{i j}^{H}$ such that $i, j=1, \ldots, N, \mathrm{i} \neq \mathrm{j}$. Several connectedness measures can be derived from this table:

Pairwise directional connectedness: This measure illustrates the spillover from $j$ to $i$ or from $i$ to $j$. It is given by element $d_{i j}^{H}$. We do not necessarily have $d_{i j}^{H}=d_{j i}^{H}$, as the shocks propagated from $j$ to $i$ are not necessarily equal to those propagated from $i$ to $j$. Let these pairwise directional connectedness measures be denoted $C_{i \leftarrow j}^{H}$ and $C_{j \leftarrow i}^{H}$.
Net pairwise directional connectedness: This measure is obtained as the difference between what ' $i$ transmits to $j$ ' and what ' $i$ receives from $j$ '. Let it be denoted by $C_{i j}^{H}$ and it is therefore equal to $C_{j \leftarrow i}^{H}-C_{i \leftarrow j}^{H}$.

[^3]These 'pairwise' measures can then be summed over rows or columns (always abstracting from considering diagonal elements) to obtain total directional connectedness measures.

Total directional connectedness from others to $i$ : This measure is obtained by summing all elements of a row (except the diagonal element). Hence it gives the share of the $H$-step forecast error variance of variable $i$ that is coming from shocks arising in other variables ('what variable $i$ receives from others').

$$
\begin{equation*}
C_{i \leftarrow \bullet}^{H}=\sum_{j=1 ; j \neq i}^{N} d_{i j}^{H} \tag{1}
\end{equation*}
$$

Total directional connectedness to others from $j$ : This measure is obtained by summing all elements of a column (except the diagonal element). Hence it gives the share of the $H$-step forecast error variance that are transmitted by shocks in variable $j$ to other variables ('what variable $j$ transmits to others').

$$
\begin{equation*}
C_{\bullet \leftarrow j}^{H}=\sum_{i=1 ; i \neq j}^{N} d_{i j}^{H} \tag{2}
\end{equation*}
$$

Net total directional connectedness: This measure is then easily obtained by subtracting one from the other, namely 'to others' - 'from others':

$$
\begin{equation*}
C_{\bullet \leftarrow i}^{H}-C_{i \leftarrow \bullet}^{H} \tag{3}
\end{equation*}
$$

There are thus $N$ net total directional connectedness measures.
Finally, the grand total of the sum of all 'from' measures and of all 'to' measures, or equivalently the sum of all off-diagonal elements measures total connectedness, is denoted by $C^{H}$ and is called 'system-wide' connectedness. It is scaled by $N$, so as to be expressed as an average per variable.

$$
\begin{equation*}
C^{H}=\frac{1}{N} \sum_{i, j=1 ; i \neq j}^{N} d_{i j}^{H} \tag{4}
\end{equation*}
$$

Our sample contains 27 issuers, such that we rely on a 27 -variable VAR. We keep it simple to a VAR of order 1 and estimate spillovers for a 2 -week, 10 -week and 26 -week ahead forecast horizon. ${ }^{6}$ This allows us to compare results for a rather short time horizon to those for a longer horizon of up to half a year. For each issuer, and for both its return and volatility series, we obtain a directional spillover: 'how much do innovations from company $j$ contribute to the forecast error variance of company $i$ ' or 'how much of the forecast error variance of company $j$ is received from innovations to the return or volatility series of company $i$ '. Results are provided in a table format such that one can easily obtain the average forecast error

[^4]variance of an issuer coming from all other companies, by averaging over a row, or the average forecast error variance transmitted from one company to other companies, by averaging over a column. Finally, a net spillover measure is obtained as the difference between 'transmission' and 'reception', that is, 'to others' minus 'from others', such that positive values represent a net shock transmitter and negative values a net shock receiver. The total connectedness is defined as the sum of all variance decompositions, either to or from others. A index of total connectedness is obtained by rolling over a window of one year at weekly steps. We refer to it as rolling total connectedness or as spillover index.

## 4 Directional spillover analysis

We report the results of directional spillover analysis in this section. In contrast to a large body of the existing literature (see, e.g., the work of BenSaida 2019, Belke and Dubova 2018 or Bayoumi and Bui 2012), we do not examine the propagation of return and volatility shocks between markets. Instead, we consider how such shocks propagate inside a given market, that is, from one firm to another. We start by examining whether and how return and volatility shocks propagate in the market for corporate bonds and we subsequently compare it to the case of the stock market. We then explore the network structures that emerge from the identified propagation patterns.

### 4.1 Corporate Bond Market Spillovers

Tables 2 and 3 present the spillover results for the return series, with a forecast horizon of 2 weeks (table 2) and 10 weeks (table 3). The tables illustrate pairwise directional connectedness values between firms. It first stands out that both tables, although obtained at different forecast horizons have very similar values. Looking at the diagonal elements of Table 2, hence at the strength of shocks that a firm transmits to itself, those can be of varying magnitudes. For HSBC Holdings PLC (HSBC), Caterpillar Inc. (CAT), Comcast Corp. (CMSA), General Electric Co.(GE) or AT\&T Inc. (T), the 'own' connectedness is rather low, at around 11 to $13 \%$. For other firms, such as Royal Bank of Canada (RY) or Barclays BLC (BCS), it is however much higher, at a level slightly above $40 \%$. Looking at the off-diagonal elements, hence at the pairwise directional connectedness (i.e., $d_{i, j}^{H}$ for $i \neq j$ ), we notice the following. The highest pairwise directional connectedness is from Prudential Financial Inc. (PRU) to HSBC Holdings PLC (HSBC) and reaches $12.4 \%$. It is closely followed by the connectedness from Goldman Sachs (GS) to Morgan Stanley (MS) at $11.8 \%$. We then identify several connectedness values at around 10 to $11 \%$ : from Prudential Financial Inc. (PRU) to Bank of America Corp. (BAC) at $11.5 \%$, from Walmart Inc. (WMT) to Royal Dutch Shell PLC (RDS) at $11.2 \%$, from Wells Fargo and Co. (WFC) to Royal Bank of Canada (RY) at 10.8 \%, from Verizon Communications Inc. (VZ) to AT\&T Inc. (T) at 10.6\%, from AT\&T Inc. (T) to Verizon Communications Inc. (VZ) at $10.5 \%$, from Bank of America Corp. (BAC)
to Prudential Financial Inc (PRU) at $10.3 \%$ and from General Electric Co. (GE) to HSBC Holdings PLC (HSBC) at 10.0\%. These results suggest that financial firms seem to be major players in the transmission of shocks. There also appears to be some intra industry effect, as the directional connectedness values that we point out are often between two firms of the same industry (financials or telecommunications). Finally it also appears that Prudential Financial Inc (PRU), an insurer, is an important shock transmitter. This result can be related to the findings in Collet and Ielpo (2018), who show that the insurance sector is a top contributor to volatility spillovers. Furthermore the strong connectedness between the Goldman Sachs Group Inc. (GS) and Morgan Stanley (MS) - in both directions - had already been pointed out for the stock market by Diebold and Yilmaz (2014). Connectedness results obtained from a longer forecast horizon ( 10 weeks) as illustrated in Table 3 are very similar, in fact of almost identical intensity. It therefore suggests that return spillovers as measured from forecast error variance are insensitive to the forecast horizon. Hence short term and medium term return spillovers are similar.

Turning to the analysis of volatility spillovers reported in Tables 4 (2-week horizon) and 5 (10-week horizon), we observe the following. First, among all firms, Barclays PLC (BCS) is the largest self-receiver of volatility shocks over a 2 -week forecast period - its level stands at $59.5 \%$-, then followed by Royal Bank of Canada (RY) at $34.7 \%$, Amgen Inc. (AMGN) at $33.5 \%$, Royal Dutch Shell PLC (RDS) at $31.5 \%$ and Wells Fargo and Co. (WFC) at $28.6 \%$. In contrast, JP Morgan Chase and Co. (JPM), Comcast Corp. (CMCSA) and the Goldman Sachs Group Inc. (GS) are the firms which receive the smallest share of their own shocks and therefore most of the volatility shocks that they receive are from other firms. Second, pairwise directional connectedness is strongest from General Electric Co. (GE) to HSBC Holdings PLC (HSBC) at 12.7\%, Comcast Corp. (CMCSA) to Royal Dutch Shell PLC (RDS) at $11.7 \%$, from Wells Fargo and Co. (WFC) to Royal Bank of Canada (RY) at $11.3 \%$, from the Goldman Sachs Group Inc. (GS) to Citigroup Inc. (C) at $10.7 \%$ and from Prudential Financial Inc (PRU) to General Electric Co. (GE) at 10.6\%. Subsequent pairwise directional connectedness measures are all under the $10.5 \%$ level. Similar to the case of return spillovers, this further supports the finding that financial institutions play a significant role in the propagation of volatility shocks in the market for corporate bonds. In contrast to the analysis of return spillovers reported above, we however notice a different pattern according to the time horizon considered. The results reported in Table 5 for a 10week forecast horizon suggest that volatility spillovers between firms might be sensitive to the chosen forecast period. In fact, the 'own' transmission, measured in the diagonal elements of the Tables is usually higher at the 2 -week forecast horizon than at the 10 -week forecast horizon, while the directional transmissions seem lower. This finding is very interesting and highlights the fact that volatility spillovers take a bit more time than return spillovers. ${ }^{7}$

[^5]To further identify potential spillover patterns in the corporate bond market, we run a series of regressions. The dependent variable is the intensity of the spillover from firm $j$ to firm $i$, that is, $C_{i \leftarrow j}^{H}$. We adopt the following baseline model specification, which defines Model 1 :

$$
\begin{equation*}
C_{i \leftarrow j}^{H}=\alpha+\beta D_{i=j}+\varepsilon_{i j} \tag{5}
\end{equation*}
$$

where $D_{i=j}$ is a dummy variable that is one for shocks that a firm transmits to itself (i.e., when $i=j$ ), and is 0 otherwise. We then test alternative model specifications, where we extend the list of explanatory variables. First, we include a dummy variable that is one when both the sender and the receiver of the shocks are from the same industry, and is 0 otherwise. This is Model 2. Second, in Model 3, we extend Model 2 with a dummy variable that is 1 when the headquarters of the receiver and of the sender are located in the same country, and is 0 otherwise. Finally, in Model 4, we further explore the role played by the location of the sender relative to the location of the receiver. Importantly, in the definition of the additional dummy variables used in Models 2 to 4, the case where the sender and the receiver are the same firm is always excluded. The corresponding case has a value of 0 , as it is already captured in $D_{i=j}$. The general specification of Models 2 to 4 is accordingly:

$$
\begin{equation*}
C_{i \leftarrow j}^{H}=\alpha+\beta D_{i=j}+\gamma Z+\varepsilon_{i j} \tag{6}
\end{equation*}
$$

where $Z$ represents the additional regressors used in Models 2 to 4 .
The results are reported in Table 6 for return (Panel A) and for volatility (Panel B) spillovers. Among all pairs of companies, the average intensity of the spillovers of return shocks at a 2 week forecast horizon is 3.05 . This nevertheless increases significantly in the case of shocks that a firm transmits to itself. The regression coefficient of $D_{i=j}$ is 17.73 , which corresponds to an increase of $17.73 \%$ for the spillover from a firm to itself. Model 2 suggests that shocks are stronger between firms of the same industry ( $+1.18 \%$ on average). This is consistent with our initial observations. Model 3 further hints at the significant role played by the location: spillovers are $1.23 \%$ stronger when the sender and the receiver are located in the same country. In Model 4, the baseline case is the case of shocks sent by a non-U.S.-based sender to a non-U.S.-based receiver. Our results suggest that shocks sent by U.S.-based senders are correspondingly stronger: the increase is on average $2.01 \%$ for shocks sent to U.S.-based receivers and it is $1.59 \%$ when sent to companies located outside of the U.S. region. In contrast, shocks sent by non-U.S.-based senders are statistically similar whether they are sent to firms located inside or outside of the U.S. market. The coefficient of the dummy variable that captures the shocks sent from other countries to the U.S. is indeed not statistically significant. Importantly, our findings are not altered by the length of the forecast period: the results are qualitatively similar at a 10 -week horizon. The picture is generally also unchanged in the case of volatility spillovers, both in terms of the size of the corresponding coefficients and of their statistical significance. However, the most notable difference is that
the industry fails to explain the strength of volatility spillovers. The reported evidence is rather mixed at the 2-week forecast horizon (the industry is a significant determinant only in Model 3). For a longer forecast period ( 10 weeks), it is never significant.

In Table 7, we report the total spillover that each firm sends to (in the 'To' column) and receives from (in the 'From' column) the other firms of the sample. In the case of return spillovers, with a 2-week forecast horizon, Citigroup Inc. (C) is the largest sender and HSBC Holdings PLC (HSBC) is the largest receiver. The top senders and top receivers are almost the same at a 10-week forecast horizon. Interestingly, some firms are among both top senders and top receivers. This is for example the case of Caterpillar Inc. (CAT), which sends $110.9 \%$ to others and receives $86.6 \%$ from them. We finally consider the net directional connectedness of the firms included in our sample, which, for each firm, is measured as the difference between what it sends to other firms and what it receives from them. Whereas positive values point to net senders, negative values correspond to net receivers. The results are reported in the 'Net' column of Table 7. For return spillovers, 15 firms are net receivers and 12 firms are net senders. The largest net senders include Citigroup Inc. (C), Prudential Financial Inc (PRU), the Goldman Sachs Group Inc. (GS), Caterpillar Inc. (CAT) and Bank of America Corp. (BAC). In contrast, Toyota Motor Corp. (TM), Royal Bank of Canada (RY), Barclays PLC (BCS), HP Inc. (HPQ) and Amgen Inc. (AMGN) are the largest net receivers. This picture is the same whatever the forecast horizon considered. Volatility spillovers behave somewhat differently however. First, the largest senders and largest receivers of volatility spillovers are mostly different from the return spillovers. Second, changing the forecast horizon alters markedly the ranking of the firms among top senders and receivers. Third, the total directional connectedness as well as the net directional connectedness are generally stronger with a 10 -week forecast horizon. These results further suggest that volatility spillovers are more heterogeneous over time than return spillovers and that the former are stronger as the forecast horizon increases, as we already pointed out in the directional analysis.

### 4.2 Stock Market Spillovers

We now turn to an examination of return and volatility spillovers in the stock market. This analysis will allow us to gain further insights into the relative dynamics of the stock and corporate bond markets, and specifically examine whether the two markets have the same driving firms in the shock propagation. Return spillovers are reported in Tables 8 (2-week forecast) and 9 (10-week forecast). The Tables contain several striking features. First, among all firms included in our sample, financial companies have the lowest 'own' contributions to shocks. The contribution stands at $9.8 \%$ for Bank of America Corp. (BAC), 10.3\% for Prudential Financial Inc (PRU) and for the Goldman Sachs Group Inc. (GS) and is $10.5 \%$ for JP Morgan Chase and Co. (JPM) and for Credit Suisse Group AG (CS). This differs markedly from the largest receivers of 'own' shocks, which, in contrast, are all non-financial firms, including Amgen Inc. (AMGN at 36.1\%), Walmart Inc. (WMT at 28.1\%), HP Inc.
(HPQ at 20.4\%), Verizon Communications Inc. (VZ at $18.2 \%$ ) and Toyota Motor Corp. (TM at $17.7 \%$ ). This split between financial and non-financial 'own' contributors is more clearly cut in the equity market than in the corporate bond market. Second, when compared to its level in the corporate bond market, the intensity of our directional connectedness measures is generally lower in the equity market. Interestingly, the pair composed of AT\&T Inc. (T) and Verizon Communications Inc. (VZ) leads our directional connectedness measures, with a level of $10.2 \%$ from T to VZ, and $9.4 \%$ from VZ to T. All other directional connectedness levels are, for the sample of firms examined in this paper, markedly lower. Third, our findings suggest that directional connectedness is generally stronger between firms of the same sector. It is notably the case of the directional connectedness between AT\&T Inc. (T) and Verizon Communications Inc. (VZ), which is followed by directional connectedness between financial firms (from Bank of America Corp. - BAC - to Wells Fargo and Co. - WFC - from JP Morgan Chase and Co. - JPM - to Wells Fargo and Co. - WFC -, among others). Those results are importantly unchanged with a 10 -week forecast horizon period (see the results reported in Table 9) and are also qualitatively similar in the case of the spillovers of volatility shocks reported in Tables 10 (2-week forecast) and 11 ( 10 -week forecast). This is in contrast to the findings in the corporate bond market were we highlighted a distinct behaviour between the propagation of return shocks and volatility shocks.

Table 1: General Information and Descriptive Statistics. This Table contains general information and descriptive statistics for the sample of companies examined in this paper. NAICS industries are from WRDS and follow the classification of the U.S. Census Bureau. Country and City correspond to the locations of the headquarters of the firm and are from the Compustat service available through WRDS. Number of Issues is the number of bonds issued by the firm. Number of trades is the total number of transactions recorded for the different bonds issued by the firm over our sample period. Avg Trades per Issue is the average number of transactions recorded per bond issued by the firm.

Table 2: Return Spillovers in the Corporate Bond Market - 2-Week-ahead Forecast. This table represents the full sample connectedness of corporate bond returns over the period from March 2006 to December 2014. The forecast horizon is 2 weeks. Each $i j$ entry of the table represents pairwise directional connectedness, i.e., the percent of the 2 -week-ahead forecast error variance of the returns of firm $i$ due to shocks from firm $j$.

Table 3: Return Spillovers in the Corporate Bond Market - 10-Week-ahead Forecast. This table represents the full sample connectedness of corporate bond returns over the period from March 2006 to December 2014. The forecast horizon is 10 weeks. Each $i j$ entry of the
 due to shocks from firm $j$.

Table 4: Volatility Spillovers in the Corporate Bond Market - 2-Week-ahead Forecast. This table represents the full sample connectedness of corporate bond volatility over the period from March 2006 to December 2014. The forecast horizon is 2 weeks. Each $i j$ entry of the table represents pairwise directional connectedness, i.e., the percent of 2-week-ahead forecast error variance of the return volatility of firm $i$ due to shocks from firm $j$.

hess of corporate bond volatility over the period from March 2006 to December 2014. The forecast horizon is 10 weeks. Each $i j$ entry of the table represents pairwise directional connectedness, i.e., the percent of 10 -week-ahead forecast error variance of the return volatility of firm $i$ due to shocks from firm $j$.


Table 6: Analysis of Spillovers in the Corporate Bond Market. This Table examines the role played by the industry and by the location in the transmission of shocks in returns (Panel A) and in volatility (Panel B) for the corporate bond market. The dependent variable is the intensity of the shock sent from firm $i$ to firm $j$. To Itself is a dummy variable that is 1 for shocks that a firm transmits to itself and is 0 otherwise. Same Industry is 1 when the NAICS industry of the sender is the same as the industry of the receiver and is 0 otherwise. Same Country is 1 when the country of the sender is the same as the country of the receiver and is 0 otherwise. From U.S. to U.S., From U.S. to Other and From Other to U.S. are dummy variables that are 1 when a shock is sent by a U.S.-based firm to a U.S.-based firm, by a U.S.-based firm to a non-U.S.-based firm and by a non-U.S.-based firm to a U.S.-based firm, respectively. They are 0 otherwise. The transmission of own shocks is excluded from Same Industry, Same Country, From U.S. to U.S., From U.S. to Other and From Other to U.S. Standard errors are reported in the parentheses. ${ }^{* * *}$, ${ }^{* *}$ and ${ }^{*}$ denote statistical significance at the $1 \%, 5 \%$ and $10 \%$ levels, respectively.

Panel A - Return Spillovers

|  | 2-Week Forecast Horizon |  |  |  | 10-Week Forecast Horizon |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Model 1 | Model 2 | Model 3 | Model 4 | Model 1 | Model 2 | Model 3 | Model 4 |
| Intercept | $\begin{array}{r} \hline 3.05^{* * *} \\ (0.10) \end{array}$ | $\begin{gathered} 2.95^{* * *} \\ (0.11) \end{gathered}$ | $\begin{array}{r} \hline 2.18^{* * *} \\ (0.17) \end{array}$ | $\begin{array}{r} 1.50^{* * *} \\ (0.49) \end{array}$ | $\begin{gathered} \hline 3.06^{* * *} \\ (0.10) \end{gathered}$ | $\begin{array}{r} \hline 2.96^{* * *} \\ (0.11) \end{array}$ | $\begin{array}{r} \hline 2.19^{* * *} \\ (0.17) \end{array}$ | $\begin{array}{r} 1.51^{* * *} \\ (0.49) \end{array}$ |
| To Itself | $\begin{array}{r} 17.73^{* * *} \\ (0.54) \end{array}$ | $\begin{array}{r} 17.83^{* * *} \\ (0.54) \end{array}$ | $\begin{array}{r} 18.59^{* * *} \\ (0.54) \end{array}$ | $\begin{array}{r} 19.28^{* * *} \\ (0.71) \end{array}$ | $\begin{array}{r} 17.49^{* * *} \\ (0.54) \end{array}$ | $\begin{array}{r} 17.59^{* * *} \\ (0.54) \end{array}$ | $\begin{array}{r} 18.35^{* * *} \\ (0.54) \end{array}$ | $\begin{array}{r} 19.04^{* * *} \\ (0.71) \end{array}$ |
| Same Industry |  | $\begin{array}{r} 1.18^{* * *} \\ (0.37) \end{array}$ | $\begin{array}{r} 1.45^{* * *} \\ (0.37) \end{array}$ |  |  | $\begin{array}{r} 1.17^{* * *} \\ (0.37) \end{array}$ | $\begin{array}{r} 1.44^{* * *} \\ (0.36) \end{array}$ |  |
| Same Country |  |  | $\begin{array}{r} 1.23^{* * *} \\ (0.21) \end{array}$ |  |  |  | $\begin{array}{r} 1.23^{* * *} \\ (0.21) \end{array}$ |  |
| From U.S. to U.S. |  |  |  | $\begin{array}{r} 2.01^{* * *} \\ (0.51) \end{array}$ |  |  |  | $\begin{array}{r} 2.01^{* * *} \\ (0.50) \end{array}$ |
| From U.S. to Other |  |  |  | $\begin{array}{r} 1.59^{* * *} \\ (0.55) \end{array}$ |  |  |  | $\begin{array}{r} 1.59^{* * *} \\ (0.54) \end{array}$ |
| From Other to U.S. |  |  |  | $\begin{array}{r} 0.35 \\ (0.55) \\ \hline \end{array}$ |  |  |  | $\begin{array}{r} 0.34 \\ (0.54) \\ \hline \end{array}$ |
| Adjusted R-Squared | 0.59 | 0.60 | 0.62 | 0.62 | 0.59 | 0.60 | 0.61 | 0.61 |
| Observations | 729 | 729 | 729 | 729 | 729 | 729 | 729 | 729 |

Panel B - Volatility Spillovers

|  | 2-Week Forecast Horizon |  |  |  | 10-Week Forecast Horizon |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Model 1 | Model 2 | Model 3 | Model 4 | Model 1 | Model 2 | Model 3 | Model 4 |
| Intercept | $\begin{array}{r} \hline 3.03^{* * *} \\ (0.12) \end{array}$ | $\begin{array}{r} 2.98^{* * *} \\ (0.12) \end{array}$ | $\begin{array}{r} 2.32^{* * *} \\ (0.19) \end{array}$ | $\begin{gathered} 1.30^{* *} \\ (0.56) \end{gathered}$ | $\begin{array}{r} 3.31^{* * *} \\ (0.11) \end{array}$ | $\begin{gathered} 3.29^{* * *} \\ (0.11) \end{gathered}$ | $\begin{array}{r} 2.78^{* * *} \\ (0.17) \end{array}$ | $\begin{array}{r} 2.11^{* * *} \\ (0.51) \end{array}$ |
| To Itself | $\begin{array}{r} 18.08^{* * *} \\ (0.61) \end{array}$ | $\begin{array}{r} 18.14^{* * *} \\ (0.61) \end{array}$ | $\begin{array}{r} 18.79^{* * *} \\ (0.62) \end{array}$ | $\begin{array}{r} 19.81^{* * *} \\ (0.81) \end{array}$ | $\begin{array}{r} 10.68^{* * *} \\ (0.55) \end{array}$ | $\begin{array}{r} 10.70^{* * *} \\ (0.55) \end{array}$ | $\begin{array}{r} 11.21^{* * *} \\ (0.56) \end{array}$ | $\begin{array}{r} 11.87^{* * *} \\ (0.74) \end{array}$ |
| Same Industry |  | $\begin{array}{r} 0.69 \\ (0.42) \end{array}$ | $\begin{gathered} 0.92^{* *} \\ (0.42) \end{gathered}$ |  |  | $\begin{array}{r} 0.25 \\ (0.38) \end{array}$ | $\begin{array}{r} 0.43 \\ (0.38) \end{array}$ |  |
| Same Country |  |  | $\begin{array}{r} 1.06^{* * *} \\ (0.24) \end{array}$ |  |  |  | $\begin{gathered} 0.82^{* * *} \\ (0.22) \end{gathered}$ |  |
| From U.S. to U.S. |  |  |  | $\begin{array}{r} 2.14^{* * *} \\ (0.58) \end{array}$ |  |  |  | $\begin{array}{r} 1.52^{* * *} \\ (0.53) \end{array}$ |
| From U.S. to Other |  |  |  | $\begin{array}{r} 1.72^{* * *} \\ (0.62) \end{array}$ |  |  |  | $\begin{array}{r} 1.19^{* *} \\ (0.57) \end{array}$ |
| From Other to U.S. |  |  |  | $\begin{array}{r} 0.81 \\ (0.62) \\ \hline \end{array}$ |  |  |  | $\begin{array}{r} 0.41 \\ (0.57) \\ \hline \end{array}$ |
| Adjusted R-Squared | 0.55 | 0.55 | 0.56 | 0.56 | 0.34 | 0.34 | 0.35 | 0.35 |
| Observations | 729 | 729 | 729 | 729 | 729 | 729 | 729 | 729 |

Table 7: Net Spillovers in the Corporate Bond Market. This table represents various full sample connectedness measures of corporate bond returns and volatility over the period from March 2006 to December 2014. Results are shown for a forecast horizon of 2 weeks and 10 weeks. The column 'To', represents the total directional connectedness to others from $j$. The column 'From' represents the total directional connectedness from others to $i$. The column 'Net' is the net directional connectedness obtained as the difference of the two.

|  |  | Returns |  |  |  |  |  | Volatility |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 2 Weeks |  |  | 10 Weeks |  |  | 2 Weeks |  |  | 10 Weeks |  |  |
|  |  | To | From | Net | To | From | Net | To | From | Net | To | From | Net |
| American Express Co. | AXP | 53.6 | 72.1 | -18.5 | 54.3 | 72.8 | -18.5 | 51.0 | 77.8 | -26.7 | 72.7 | 89.8 | -17.1 |
| The Bank of New York Mellon Corp. | BK | 90.6 | 85.5 | 5.2 | 90.8 | 85.7 | 5.2 | 136.7 | 85.7 | 51.0 | 163.2 | 88.4 | 74.8 |
| Caterpillar Inc. | CAT | 110.9 | 86.6 | 24.2 | 112.5 | 86.7 | 25.7 | 143.3 | 86.4 | 56.9 | 159.9 | 88.1 | 71.8 |
| Deere and Co. | DE | 61.4 | 81.9 | -20.4 | 61.5 | 82.2 | -20.8 | 49.3 | 81.8 | -32.5 | 30.6 | 92.3 | -61.7 |
| Ford Motor Co. | F | 55.8 | 70.0 | -14.3 | 57.7 | 70.3 | -12.6 | 36.1 | 80.7 | -44.7 | 52.3 | 93.4 | -41.1 |
| General Electric Co. | GE | 107.5 | 86.2 | 21.4 | 106.3 | 86.3 | 20.0 | 122.2 | 85.0 | 37.3 | 146.7 | 87.6 | 59.2 |
| International Business Machines Corp. | IBM | 65.8 | 79.4 | -13.5 | 65.9 | 79.5 | -13.6 | 40.0 | 72.7 | -32.7 | 32.5 | 86.7 | -54.2 |
| Toyota Motor Corp. | TM | 28.7 | 76.0 | -47.4 | 29.9 | 76.3 | -46.4 | 62.6 | 80.5 | -17.9 | 68.2 | 90.3 | -22.0 |
| Walmart Inc. | WMT | 80.3 | 82.4 | -2.0 | 79.9 | 82.4 | -2.5 | 56.9 | 77.3 | -20.4 | 40.7 | 88.2 | -47.5 |
| Royal Bank of Canada | RY | 16.5 | 57.7 | -41.2 | 16.8 | 58.2 | -41.4 | 21.3 | 65.3 | -44.1 | 19.7 | 84.0 | -64.3 |
| Amgen Inc. | AMGN | 51.0 | 75.8 | -24.8 | 51.3 | 75.9 | -24.6 | 45.6 | 66.5 | -20.9 | 72.1 | 73.2 | -1.1 |
| HP Inc. | HPQ | 47.8 | 75.6 | -27.8 | 47.8 | 75.9 | -28.1 | 37.4 | 73.0 | -35.6 | 51.8 | 80.9 | -29.1 |
| Barclays PLC | BCS | 26.9 | 57.0 | -30.1 | 27.0 | 57.6 | -30.6 | 16.8 | 40.5 | -23.8 | 42.3 | 50.6 | -8.2 |
| Citigroup Inc. | C | 135.4 | 85.7 | 49.6 | 137.4 | 85.8 | 51.5 | 118.0 | 86.6 | 31.4 | 132.7 | 91.1 | 41.7 |
| The Goldman Sachs Group Inc. | GS | 125.3 | 85.7 | 39.6 | 125.2 | 85.8 | 39.3 | 149.4 | 87.4 | 62.0 | 170.4 | 89.8 | 80.6 |
| Bank of America Corp. | BAC | 105.5 | 81.4 | 24.1 | 104.8 | 81.9 | 22.9 | 110.0 | 83.0 | 26.9 | 113.7 | 87.6 | 26.1 |
| Wells Fargo and Co. | WFC | 68.1 | 73.5 | -5.4 | 67.5 | 73.6 | -6.2 | 61.0 | 71.4 | -10.4 | 68.0 | 75.2 | -7.1 |
| JP Morgan Chase and Co. | JPM | 98.2 | 83.6 | 14.7 | 98.6 | 83.7 | 14.9 | 115.3 | 88.0 | 27.3 | 114.1 | 91.9 | 22.3 |
| Verizon Communications Inc. | VZ | 107.9 | 85.5 | 22.4 | 107.9 | 85.5 | 22.3 | 78.0 | 84.9 | -6.9 | 51.1 | 93.1 | -42.0 |
| Prudential Financial Inc. | PRU | 124.0 | 83.4 | 40.6 | 124.9 | 83.7 | 41.2 | 133.8 | 84.6 | 49.2 | 147.0 | 88.1 | 58.9 |
| SLM Corp. | SLM | 77.3 | 79.8 | -2.5 | 78.7 | 80.1 | -1.4 | 93.0 | 77.5 | 15.5 | 125.9 | 81.9 | 44.1 |
| Comcast Corp. | CMCSA | 106.8 | 86.5 | 20.3 | 106.9 | 86.6 | 20.4 | 93.2 | 87.6 | 5.6 | 67.1 | 94.1 | -27.0 |
| Morgan Stanley | MS | 91.4 | 79.2 | 12.2 | 91.8 | 79.4 | 12.4 | 88.9 | 85.1 | 3.8 | 94.0 | 88.3 | 5.7 |
| HSBC Holdings PLC | HSBC | 71.4 | 87.9 | -16.5 | 70.9 | 88.4 | -17.5 | 70.4 | 85.2 | -14.8 | 67.3 | 89.1 | -21.7 |
| AT\&T Inc. | T | 96.8 | 85.8 | 11.0 | 96.4 | 85.9 | 10.5 | 66.5 | 87.2 | -20.6 | 34.8 | 94.2 | -59.5 |
| Royal Dutch Shell PLC | RDS | 61.9 | 77.1 | -15.2 | 61.6 | 77.1 | -15.5 | 35.2 | 68.5 | -33.4 | 30.4 | 82.8 | -52.4 |
| Credit Suisse Group AG | CS | 72.4 | 78.1 | -5.7 | 71.7 | 78.3 | -6.6 | 98.4 | 79.8 | 18.6 | 153.3 | 82.3 | 71.0 |

Table 8: Return Spillovers in the Equity Market - 2-Week-ahead Forecast. This table represents the full sample connectedness of stock returns over the period from March 2006 to December 2014. The forecast horizon is 2 weeks. Each $i j$ entry of the table represents pairwise directional connectedness, i.e., the percent of the 2 -week-ahead forecast error variance of the returns of firm $i$ due to shocks from firm $j$.


Table 10: Volatility Spillovers in the Equity Market - 2-Week-ahead Forecast. This table represents the full sample connectedness of equity volatility over the period from March 2006 to December 2014. The forecast horizon is 2 weeks. Each $i j$ entry of the table represents pairwise directional connectedness, i.e., the percent of 2 -week-ahead forecast error variance of the return volatility of firm $i$ due to shocks from firm $j$.

[^6]Table 11: Volatility Spillovers in the Equity Market - 10-Week-ahead Forecast. This table represents the full sample connectedness of equity volatility over the period from March 2006 to December 2014. The forecast horizon is 10 weeks. Each $i j$ entry of the table represents pairwise directional connectedness, i.e., the percent of 10 -week-ahead forecast error variance of the return volatility of firm $i$ due to shocks from firm $j$.

[^7]Similar to the case of the corporate bond market, we run a series of regressions to explore the presence of potential spillover patterns in the stock market. The results are reported in Table 12. The return spillovers for the stock market reported in Panel A share some similarities with the patterns identified in the corporate bond market. At a 2-week forecast horizon, they are on average $3.28 \%$ and increase by $11.46 \%$ in the case of own shock (i.e. a firm transmits to itself). Return spillovers are also stronger between firms from the same industry: in Model 2, the coefficient of the dummy variable capturing the same industry between the sender and the receiver stands at $1.93 \%$ and is strongly significant. However, in contrast to the case of bonds, our results also suggest that equity return spillovers are affected differently by the location of the sender relative to the location of the receiver. We report mixed evidence. Our Model 3 first suggests that the average intensity of return spillovers between firms located in the same country is comparable to what is observed between firms based in different countries. By contrast, in Model 4, the average intensity is systematically lower when the receiver of the shock or its sender (or both) are based in the U.S. market. The results are unchanged with a 10 -week forecast horizon. In contrast, volatility spillovers are generally weaker across firms but the self-propagation of shocks is correspondingly stronger. The average across firms stands at $2.98 \%$ and increases by $19.43 \%$ in the case of 'own' shocks. Apart from this notable difference, return and volatility shocks in the stock market behave in a similar way.

The net directional spillovers for the stock market are reported in Table 13. It is first interesting to note that, in the stock market, financial firms are both among the largest senders and among the largest receivers of return shocks. The top senders include Prudential Financial Inc (PRU, 116.9\%), Bank of America Corp. (BAC, 115.9\%), JP Morgan Chase and Co. (JPM, 112.2\%), Credit Suisse Group AG (CS, 111.0\%) and the Goldman Sachs Group Inc. (GS, 110.7\%). The list of largest receivers is similarly composed of Bank of America Corp. (BAC, 90.2\%), Prudential Financial Inc. (PRU, 89.8\%), the Goldman Sachs Group Inc. (GS, $89.7 \%$ ), JP Morgan Chase and Co. (JPM, 89.6\%) and Credit Suisse Group AG (CS, $89.5 \%$ ). Although ranked differently, our results accordingly suggest that the same financial firms are both the largest senders and the largest receivers of shocks in equity returns. This interestingly highlights the systemic importance of the financial firms in the equity market in general, but also the specific role played by a subset of these firms. Given that, by design of our sample, these firms are also among the largest issuers of corporate bonds, this latter finding takes even larger importance for policymakers. Second, we observe that those financial firms are overall the largest net senders of return shocks in the equity market. Their net directional spillovers stand at $27.2 \%$ for PRU, $25.7 \%$ for BAC, $22.7 \%$ for JPM, $21.5 \%$ for CS and $21.0 \%$ for GS. In contrast, the overall net receivers of return shocks are non-financial firms, notably including Amgen Inc. (AMGN at $-38.7 \%$ ), Walmart Inc. (WMT at $-35.5 \%$ ), HP Inc. (HPQ at $-28.0 \%$ ), SLM Corp. (SLM at $-26.5 \%$ ) and Toyota Motor Corp. (TM at $-17.9 \%)$. Those results are importantly unaltered by the length of the forecast horizon. For the propagation of volatility shocks, financial firms similarly dominate the firms from other

Table 12: Analysis of Spillovers in the Equity Market. This Table examines the role played by the industry and by the location in the transmission of shocks in returns (Panel A) and in volatility (Panel B) for the equity market. The dependent variable is the intensity of the shock sent from firm $i$ to firm $j$. To Itself is a dummy variable that is 1 for shocks that a firm transmits to itself and is 0 otherwise. Same Industry is 1 when the NAICS industry of the sender is the same as the industry of the receiver and is 0 otherwise. Same Country is 1 when the country of the sender is the same as the country of the receiver and is 0 otherwise. From U.S. to U.S., From U.S. to Other and From Other to U.S. are dummy variables that are 1 when a shock is sent by a U.S.-based firm to a U.S.-based firm, by a U.S.-based firm to a non-U.S.-based firm and by a non-U.S.-based firm to a U.S.-based firm, respectively. They are 0 otherwise. The transmission of own shocks is excluded from Same Industry, Same Country, From U.S. to U.S., From U.S. to Other and From Other to U.S.. Standard errors are reported in the parentheses. ${ }^{* * *},{ }^{* *}$ and ${ }^{*}$ denote statistical significance at the $1 \%, 5 \%$ and $10 \%$ levels, respectively.

|  | 2-Week Forecast Horizon |  |  |  | 10-Week Forecast Horizon |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Model 1 | Model 2 | Model 3 | Model 4 | Model 1 | Model 2 | Model 3 | Model 4 |
| Intercept | $\begin{array}{r} 3.28^{* * *} \\ (0.07) \end{array}$ | $\begin{gathered} 3.11^{* * *} \\ (0.07) \end{gathered}$ | $\begin{gathered} 3.08^{* * *} \\ (0.11) \end{gathered}$ | $\begin{gathered} 4.09^{* * *} \\ (0.32) \end{gathered}$ | $\begin{gathered} 3.28^{* * *} \\ (0.07) \end{gathered}$ | $\begin{gathered} 3.11^{* * *} \\ (0.07) \end{gathered}$ | $\begin{array}{r} 3.08^{* * *} \\ (0.11) \end{array}$ | $\begin{array}{r} 4.09^{* * *} \\ (0.32) \end{array}$ |
| To Itself | $\begin{array}{r} 11.46^{* * *} \\ (0.35) \end{array}$ | $\begin{array}{r} 11.63^{* * *} \\ (0.33) \end{array}$ | $\begin{array}{r} 11.66^{* * *} \\ (0.34) \end{array}$ | $\begin{array}{r} 10.65^{* * *} \\ (0.47) \end{array}$ | $\begin{array}{r} 11.45^{* * *} \\ (0.35) \end{array}$ | $\begin{array}{r} 11.62^{* * *} \\ (0.33) \end{array}$ | $\begin{array}{r} 11.65^{* * *} \\ (0.34) \end{array}$ | $\begin{array}{r} 10.64^{* * *} \\ (0.47) \end{array}$ |
| Same Industry |  | $\begin{array}{r} 1.93^{* * *} \\ (0.23) \end{array}$ | $\begin{array}{r} 1.94^{* * *} \\ (0.23) \end{array}$ |  |  | $\begin{array}{r} 1.93^{* * *} \\ (0.23) \end{array}$ | $\begin{array}{r} 1.94^{* * *} \\ (0.23) \end{array}$ |  |
| Same Country |  |  | $\begin{array}{r} 0.05 \\ (0.13) \end{array}$ |  |  |  | $\begin{array}{r} 0.05 \\ (0.13) \end{array}$ |  |
| From U.S. to U.S. |  |  |  | $\begin{array}{r} -0.86^{* *} \\ (0.33) \end{array}$ |  |  |  | $\begin{array}{r} -0.86^{* *} \\ (0.33) \end{array}$ |
| From U.S. to Other |  |  |  | $\begin{array}{r} -0.93^{* * *} \\ (0.36) \end{array}$ |  |  |  | $\begin{array}{r} -0.93^{* * *} \\ (0.36) \end{array}$ |
| From Other to U.S. |  |  |  | $\begin{array}{r} -0.73^{* *} \\ (0.36) \\ \hline \end{array}$ |  |  |  | $\begin{array}{r} -0.73^{* *} \\ (0.36) \\ \hline \end{array}$ |
| Adjusted R-Squared | 0.60 | 0.63 | 0.63 | 0.60 | 0.60 | 0.63 | 0.63 | 0.60 |
| Observations | 729 | 729 | 729 | 729 | 729 | 729 | 729 | 729 |
| Panel B - Volatility Spillovers |  |  |  |  |  |  |  |  |
|  | 2-Week Forecast Horizon |  |  |  | 10-Week Forecast Horizon |  |  |  |
|  | Model 1 | Model 2 | Model 3 | Model 4 | Model 1 | Model 2 | Model 3 | Model 4 |
| Intercept | $\begin{gathered} 2.98^{* * *} \\ (0.11) \end{gathered}$ | $\begin{array}{r} \hline 2.85^{* * *} \\ (0.11) \end{array}$ | $\begin{gathered} \hline 2.90^{* * *} \\ (0.17) \end{gathered}$ | $\begin{gathered} \hline 3.79^{* * *} \\ (0.52) \end{gathered}$ | $\begin{gathered} 3.28^{* * *} \\ (0.08) \end{gathered}$ | $\begin{array}{r} 3.18^{* * *} \\ (0.08) \end{array}$ | $\begin{array}{r} 3.31^{* * *} \\ (0.13) \end{array}$ | $\begin{array}{r} 4.04^{* * *} \\ (0.38) \end{array}$ |
| To Itself | $\begin{array}{r} 19.43^{* * *} \\ (0.56) \end{array}$ | $\begin{array}{r} 19.57^{* * *} \\ (0.55) \end{array}$ | $\begin{array}{r} 19.51^{* * *} \\ (0.57) \end{array}$ | $\begin{array}{r} 18.62^{* * *} \\ (0.75) \end{array}$ | $\begin{array}{r} 11.51^{* * *} \\ (0.41) \end{array}$ | $\begin{array}{r} 11.61^{* * *} \\ (0.40) \end{array}$ | $\begin{array}{r} 11.48^{* * *} \\ (0.42) \end{array}$ | $\begin{array}{r} 10.75^{* * *} \\ (0.55) \end{array}$ |
| Same Industry |  | $\begin{array}{r} 1.63^{* * *} \\ (0.38) \end{array}$ | $\begin{array}{r} 1.61^{* * *} \\ (0.38) \end{array}$ |  |  | $\begin{array}{r} 1.18^{* * *} \\ (0.28) \end{array}$ | $\begin{array}{r} 1.13^{* * *} \\ (0.28) \end{array}$ |  |
| Same Country |  |  | $\begin{aligned} & -0.09 \\ & (0.22) \end{aligned}$ |  |  |  | $\begin{aligned} & -0.21 \\ & (0.16) \end{aligned}$ |  |
| From U.S. to U.S. |  |  |  | $\begin{array}{r} -0.89^{*} \\ (0.54) \end{array}$ |  |  |  | $\begin{array}{r} -0.88^{* *} \\ (0.39) \end{array}$ |
| From U.S. to Other |  |  |  | $\begin{aligned} & -0.85 \\ & (0.58) \end{aligned}$ |  |  |  | $\begin{array}{r} -0.83^{* *} \\ (0.42) \end{array}$ |
| From Other to U.S. |  |  |  | $\begin{array}{r} -0.69 \\ (0.58) \\ \hline \end{array}$ |  |  |  | $\begin{array}{r} -0.47 \\ (0.42) \\ \hline \end{array}$ |
| Adjusted R-Squared | 0.63 | 0.63 | 0.63 | 0.63 | 0.52 | 0.53 | 0.53 | 0.53 |
| Observations | 729 | 729 | 729 | 729 | 729 | 729 | 729 | 729 |

sectors. There are four financial firms among the five largest senders of volatility shocks and all the five largest receivers of those shocks are financial firms. Similarly, four of the five overall largest net senders are financial companies, whereas the largest overall net receivers are mainly non-financial corporations.

### 4.3 Network Analysis

We explore the network structure that emerges from the return and volatility spillovers discussed above. To this end, we examine the largest spillover relations: we specifically consider the directional connectedness values that are greater than or equal to the $90^{t h}$ percentile among all directional connectedness values. To this end, we exclude the spillover that a firm sends to itself, that is, we only retain the off-diagonal elements of the spillover tables, from which we isolate the largest connectedness values. This therefore leaves us with the most important network connections. The network structure associated with the return spillovers at a 2-week forecast horizon is reported in Figure 1, where Panel A depicts the corporate bond market and the stock market is in Panel B. In the Figure, we group the firms by industry and we use the following color codes. Commercial banks are depicted in blue and the other financial companies are colored in green. Prudential Financial Inc (PRU), the only insurance company in our sample, appears in orange. The telecommunication resellers are in red and the automobile manufacturers are in purple. The other, grey-colored, firms correspond to single representatives of other industries. Under this grouping, the upper part of each network graph essentially corresponds to financial companies and the lower part is composed of non-financial firms. In the network, each node corresponds to a single firm, with in-coming and out-coming edges, which show what the firm receives and sends to the other firms of the network. Each node is composed of two rings. The width of the inner colored ring shows the number of in-coming edges for the node, that is, the in-degree of the node. Correspondingly, the outer colored ring shows the number of out-coming edges of the node, that is, its out-degree. Thicker rings therefore denote higher in-coming (inner ring) or out-coming (outer ring) activity for the node. Moreover, we weigh the edges differently according to the intensity of the spillover between the source node and its target. Thicker edges correspond to stronger spillover intensities between the two corresponding nodes. The arrow shows the direction of the network relation.

In the corporate bond market, there are two distinct clusters of network relations. There is a first cluster of bilateral relations between financial firms. In particular, the commercial banks (in blue) are well connected among each other, but also with the other financial firms (in green). The propagation of return shocks also goes in the opposite direction. The other financial firms propagate return shocks among themselves, as well as to the commercial banks. The second cluster is composed of the relations between telecommunication companies (in red) and the firms from the other industries (in grey). Interestingly, the relations between financial and non-financial firms (i.e., between the upper and the lower part of the network
graph) are generally very weak, with the notable exception of Prudential Financial Inc (PRU, in orange), which propagates return shocks across (financial and non-financial) industries. This latter finding confirms the systemic importance of the insurer, which was identified as a Global-Systemically Important Insurer by the Financial Stability Board from July 2013. The network structure of the stock market depicted in Panel B of Figure 1 is markedly different. In this market, the strongest relations are clearly between the financial firms. More precisely, the connections between commercial banks (in blue) dominate the network structure. Bank of America Corp. (BAC) and JP Morgan Chase and Co. (JPM) are both strong senders and strong receivers of return shocks in this market. Interestingly, while Citigroup Inc. (C) was a top sender in the corporate bond market, it is a top receiver in the stock market. Similar to the corporate bond market, our results suggest that Prudential Financial Inc (PRU) plays a particular role in the propagation of return shocks. The connections between firms from non-financial industries are markedly weaker or even non-existent (Toyota Motor Corp. TM - and Amgen Inc. - AMGN - have no in-coming nor out-coming connections at this percentile level). Those findings are essentially unchanged when we consider a longer forecast horizon (10 weeks), as depicted in Figure 2. Apart from few stronger node connections, the network structures are remarkably similar at this forecast horizon.


Figure 1: Network Structure of Return Spillovers at a 2-Week Forecast Horizon
We report a series of statistics for the network structures in Table 14. We specifically examine the relations between financial and non-financial firms. In Panel A, we measure the proportion of network relations across those groups. This confirms our initial observations. First, in the corporate bond market (at a 2-week forecast horizon), $42.25 \%$ of all relations are between financial firms and $43.66 \%$ are between non-financial firms. The relations across those groups are markedly lower: $8.45 \%$ from financial to non-financial firms, and $5.63 \%$ from non-financial


Figure 2: Network Structure of Return Spillovers at a 10-Week Forecast Horizon
to financial companies. Second, in the stock market, the bulk of the network relations (68.49\%) is between financial firms. The relations between the other classes are remarkably lower: $13.70 \%$ between non-financial firms and $13.70 \%$ ( $4.11 \%$ ) from financial to non-financial (from non-financial to financial) companies. In Panel B, we report the corresponding intensities of the relations, that is, the sum of the connectedness values associated with the corresponding network edges. Those are consistent with the observations made from Panel A. The statistics are qualitatively similar with a 10 -week forecast period.

Figure 3 shows the network structures that emerge from the propagation of volatility shocks in the corporate bond market (Panel A) and in the stock market (Panel B). In the Figure, a forecast horizon of 2 weeks is used. The associated network statistics are provided in Table 15. Similar to the case of returns, there are also strong spillovers of volatility shocks among the financial firms ( $38.03 \%$ ), as well as among the non-financial companies ( $30.99 \%$ ) in the market for corporate bonds. In the stock market, the connections are essentially among the financial firms: they stand at $50.70 \%$ of all connections. In contrast to return shocks however, there are, in both markets, more connections between the upper and the lower parts of the network structures: there is therefore a stronger propagation of volatility shocks across financial and non-financial firms. In the corporate bond market, $22.54 \%$ of all connections are from financial to non-financial companies. In the stock market, $14.08 \%$ of the relations are from non-financial to financial companies and $12.68 \%$ are from financial to non-financial firms. At a 10 -week forecast horizon, the pictures change markedly, as reported in Figure 4. First, at this longer horizon, it appears that the financial firms (i.e., the commercial banks in blue, the insurer in orange and the other financial firms in green) now clearly dominate
the network structure, with connections to both financial and non-financial industries. In the corporate bond (stock) market, $32.39 \%$ ( $38.89 \%$ ) of the relations are between financial firms and $42.25 \%(22.22 \%)$ are from financial to non-financial companies. Second, the non-financial firms in the lower part of the network structure correspondingly play a somewhat weaker role in the propagation of the volatility shocks at this forecast horizon. However, the connections across those firms still represent $25.00 \%$ of all relations in the stock market.


Figure 3: Network Structure of Volatility Spillovers at a 2-Week Forecast Horizon


Figure 4: Network Structure of Volatility Spillovers at a 10-Week Forecast Horizon

## 5 Spillover Indices

We conclude our analysis with an examination of the evolution of the spillover intensity over time. Specifically, we proceed to a rolling estimation of the total connectedness described in equation 4. The chosen duration of the rolling window used in our estimations is set at 52 weeks (i.e., one full calendar year of return or volatility observations). Each estimation gives the total connectedness, that is, the $C^{H}$ value, for the corresponding rolling window. We then repeat the estimation by rolling the window by one week, until the end of our sample period. This generates a time series of spillover intensity, commonly referred to as a rolling total connectedness or as spillover index, which takes the form of a time series of $C_{t}^{H}$ values, where $t$ is the time index. Such indices show how the spillover intensity varies over time, under the influence of internal or external factors. The indices cover the period from 22 June 2007 to 31 December 2014, which represents a total of 394 weekly observations. ${ }^{8}$

### 5.1 Spillover Dynamics over Time

We start with the market for corporate bonds. The spillover indices for the return series are reported in Figure 5, where the full line shows the index obtained with a 2-week forecast horizon and the dotted line corresponds to a 10 -week horizon. In the Figure, the occurrence of economic shocks is depicted by the vertical black lines. The vertical blue lines correspondingly identify the (adoption or implementation) dates of the financial regulation. As the Figure first suggests, the intensity of the return spillovers in this market changes over time. Detailed statistics on the intensity are reported in Table 16. At a 2 -week forecast horizon, the index of the propagation of return shocks stands at an average of $84.73 \%$ and it fluctuates between $77.83 \%$ during the week of 27 July 2007 and $93.88 \%$ on 19 September 2008. At a 10 -week forecast horizon, the index is on average higher, but it shares similar dynamics over our sample period. Interestingly, both indices peak around the same periods. The two series first react markedly to the collapse of Lehman Brothers: they both increase and they both remain at a higher level for an extended period of time. This is when the 2 -week spillover index reaches its highest value. In contrast, after peaking following the credit downgrade of the United States' debt by Standard and Poor's from AAA to AA+ in August 2011, the two spillover indices rapidly return to their pre-event levels. It is also around this date that we observe the highest value of the 10 -week index. Finally, the two indices react in a similar way to the announcement of the tapering intentions by the Federal Reserve in May 2013. The indices first increase markedly following the announcement and the spillover intensities remain stronger for several periods.

Figure 6 reports the indices for the volatility spillovers in the corporate bond market, with two forecast horizons ( 2 weeks depicted by the full line and 10 weeks by the dotted line). We

[^8]

Figure 5: Rolling Total Connectedness of Corporate Bond Returns. The rolling estimation window is 52 weeks and the forecast horizon for the variance decomposition is 2 weeks (full line) and 10 weeks (dotted line). Fed Tapering (A) denotes the announcement of the tapering intentions in May 2013 and Fed Tapering (E) marks the start of the tapering in December 2013.
note the following. First, as in the case of returns, the intensity of volatility spillovers varies similarly over time. Over our sample period, the indices stand at an average of $82.46 \%$ (2-week forecast horizon) and $89.51 \%$ ( 10 -week horizon). Second, the 10 -week index is systematically above its 2 -week equivalent. Third, the two indices also react to the intensification of the Global Financial Crisis, especially following the collapse of Lehman Brothers in September 2008. They both reach their maximum values in the aftermath of this particularly stressful period. The 2-week index is maximum at $94.86 \%$ on 26 September 2008 and the 10 -week series peaks at $96.54 \%$ on 6 March 2009. By contrast, the credit downgrade of August 2011 has a longer-lasting impact on the indices: they both increase following the downgrade and maintain a higher level over several periods. Spillover intensities are also stronger during the tapering episode of the Federal Reserve, starting in May 2013. Fourth, at the 10-week forecast horizon, the index is markedly less dispersed than its 2 -week equivalent.

The spillover indices for the stock market are provided in Figures 7 (return spillovers) and 8 (volatility spillovers), where the full lines represent the indices obtained with a 2 -week forecast horizon and the dotted lines corresponds to the 10 -week forecast horizon. The corresponding descriptive statistics are provided in Table 17. The spillover indices for the stock market fluctuate around levels comparable to those observed in the market for corporate bonds. At a 2-week forecast horizon, the index stands at an average of $86.49 \%$ for return shocks and at $82.42 \%$ for volatility shocks. It is interesting to see that the forecast horizon essentially makes a difference in the volatility spillover, while the return spillover intensity is relatively similar whether the forecast horizon is 2 or 10 weeks. Compared to the market for corporate bonds, the spillover indices of the stock market also react to the same events. The intensity of the


Figure 6: Rolling Total Connectedness of Corporate Bond Return Volatility. The rolling estimation window is 52 weeks and the forecast horizon for the variance decomposition is 2 weeks (full line) and 10 weeks (dotted line). Fed Tapering (A) denotes the announcement of the tapering intentions in May 2013 and Fed Tapering (E) marks the start of the tapering in December 2013.
stock market spillovers also increases markedly following the intensification of the financial crisis in 2008. It is also during this period that 3 of our 4 series reach their highest values. Compared to the corporate bond market, the indices for the stock market however react with lag of three weeks. Such a finding suggests the credit market is a leader over the stock market and could be in line with the predictive power of credit markets for future economic activity, that is evidenced by Gilchrist et al. (2009) for instance. Whereas the spillovers indices of the corporate bond market jump during the week of the collapse of Lehman Brothers, it is only during the week of 10 October 2008 that stock market spillover indices start increasing. This specifically corresponds to the week when the U.S. stock market plunged significantly following the intensification of fears related to the financial crisis. Stock market spillovers also intensified during the downgrade episode of August 2011. The increase is however much less marked than in the market for corporate bonds. Finally, the most notable divergence between the corporate bond market and the stock market is observed during the Federal Reserve tapering period. Whereas the corporate bond spillovers increased over this period, their intensity decreased markedly in the stock market. For both return and volatility series, the tapering episode corresponds to a notable period of lower spillover intensities in the stock market.

### 5.2 Multiple Break Analysis

The above analysis suggests that the occurrence of specific events may alter the intensity of spillovers in both markets. In this Section, we further examine the periods during which the mean value of the spillover indices changed and we relate those changes to the occurrence


Figure 7: Rolling Total Connectedness of Stock Returns. The rolling estimation window is 52 weeks and the forecast horizon for the variance decomposition is 2 weeks (full line) and 10 weeks (dotted line). Fed Tapering (A) denotes the announcement of tapering intentions in May 2013 and Fed Tapering (E) marks the start of the tapering in December 2013.
of unexpected economic shocks as well as to the adoption of financial regulations. To this end, we adopt the framework developed in Trebbi and Xiao (2019). Specifically, we conduct a series of tests for the identification of breaks in the spillover series. We use the methodology of Bai and Perron $(1998,2003)$ for the identification of multiple breaks in each series. We use a significance level of $5 \%$ and we allow a maximum of five break dates for each series. We allow heterogeneous error distributions across the regimes determined by the identified break dates. ${ }^{9}$ In each case, we identify four break dates.

We report the results for the series of return spillovers in Figure 9 (for the corporate bond market) and in Figure 10 (for the stock market). The identified break dates are provided in Panel A of Table 18, where we also report the mean value of the spillover series in each corresponding regime. As our results suggest, the collapse of Lehman Brothers on 15 September 2008 triggered a first break in both markets. After this event, the intensity of return spillovers increased in both markets. At a 2 -week forecast horizon, the mean spillover intensity increased from $82.54 \%$ to $88.31 \%$ in the corporate bond market and from $83.94 \%$ to $90.05 \%$ in the stock market. There is another break identified in the corporate bond market that can be directly related to the taper tantrum episode that followed the surprise tapering announcement made by Ben Bernanke in May 2013. Spillover intensities increased markedly in the period after this event, which triggered a break in the mean series. It is by contrast more difficult to attribute the other break dates to the occurrence of other significant events. However, in both markets, we observe that a break is identified before the U.S. downgrade of August 2011. Similarly, we observe that the adoption of the different financial regulations fall in separate regimes, which is consistent with the expectation of a more progressive impact

[^9]

Figure 8: Rolling Total Connectedness of Stock Return Volatility. The rolling estimation window is 52 weeks and the forecast horizon for the variance decomposition is 2 weeks (full line) and 10 weeks (dotted line). Fed Tapering (A) denotes the announcement of tapering intentions in May 2013 and Fed Tapering (E) marks the start of the tapering in December 2013.
of such events on the dynamics of financial markets. This is particularly the case for the adoption of the Dodd-Frank Act in July 2010 as well as of the Basel II. 5 framework in June 2012.

The results for the volatility series of the corporate bond market are provided in Figure 11. Panel B of Table 18 shows the identified break dates and the mean of the spillover series in the corresponding regimes. In this market, the intensity of volatility spillovers changed markedly following three events. First, similar to the case of returns, the intensity of volatility spillovers increased after the collapse of Lehman Brothers. At a 2-week forecast horizon, the mean intensity jumps from $78.38 \%$ before the occurrence of this event to $89.66 \%$ in the period thereafter. Second, volatility spillovers also intensified following the rating downgrade of the United States by Standard and Poor's: their mean value (at a 2 -week forecast horizon) increased from $77.77 \%$ to $82.50 \%$. Third, the taper tantrum also triggered a break in the series, which increased after the tapering announcement of May 2013. As was the case for return spillovers, the financial regulations all fall inside an identified regime, but there is no break directly associated with their adoption dates. We report the results for the stock market in Figure 12, where the series similarly appear reactive to the collapse of Lehman Brothers as well as to the U.S. downgrade event. Unlike corporate bonds however, no break can be directly associated with the taper tantrum.

Two main findings emerge from this analysis. First, spillovers intensify markedly following the occurrence of economic shocks. Our results suggest that unanticipated events led to stronger spillover intensities. This is particularly clear in the case of volatility spillover in the corporate bond market, which increased following the collapse of Lehman Brothers in September 2008,
after the U.S. downgrade of August 2011 as well as during the taper tantrum episode triggered by the surprise tapering announcement of May 2013. Second, while financial regulations do not trigger a break in the spillover series on their adoption (or implementation) dates, our results suggest that they nevertheless impact market dynamics, yet in a more progressive manner.

(a) 2-Week Forecast Horizon

(b) 10-Week Forecast Horizon

Figure 9: Breaks in the Rolling Total Connectedness of Corporate Bond Returns. Breaks are first identified sequentially based on the methodology in Bai and Perron (1998, 2003). The repartition technique of Bai (1997) is used in a second step to re-estimate each break date. We use a significance level of $5 \%$ and a maximum of 5 breaks for each series. The white and grey colored areas denote the regimes determined by the identified break dates.

### 5.3 Spillover Determinants

We complete this section with an examination of the potential drivers of the observed spillovers dynamics. Our dependent variables are the spillovers indices of each market. We build our first model (Model 1) with the economic drivers identified in the literature. As in Yang and Zhou (2017), we first look at the influence of the quantitative easing measures taken by the Federal Reserve in the aftermath of the Global Financial Crisis, as well as at the evolution of economic conditions. We follow the authors and we define quantitative easing as the total amount of U.S. Treasury, Federal agency debt and mortgage-backed securities on the balance of the Federal Reserve. The data is available on the Wednesday of each week. Economic conditions are measured through the default spread, the term spread and the TED spread. We follow Fama and French (1989), and we interpret the default spread as an indicator of


Figure 10: Breaks in the Rolling Total Connectedness of Stock Returns. Breaks are first identified sequentially based on the methodology in Bai and Perron (1998, 2003). The repartition technique of Bai (1997) is used in a second step to re-estimate each break date. We use a significance level of $5 \%$ and a maximum of 5 breaks for each series. The white and grey colored areas denote the regimes determined by the identified break dates.
business conditions. Similarly the term spread denotes the evolution of short-term business cycles. The TED spread is traditionally seen as a measure of funding illiquidity arising from counterparty risk (see, e.g., Brennan et al. (2012)). The default spread is the difference between the yield of the Moody's Baa corporate bond index and the yield of the U.S. 10 year Treasury bond. The term spread is the difference between the yield of the U.S. 10-year Treasury bond and the yield of the U.S. 3-month Treasury bill. The TED spread is the difference between the yield of the 3-month USD LIBOR and the yield of the U.S. 3-month Treasury bill. We also include the economic policy uncertainty index of Baker et al. (2016) for the United States. We retrieve the Friday values of those indicators. All data is from the FRED database provided by the Federal Reserve Bank of Saint Louis. We also consider two alternative specifications. In Model 2, we augment the specification of Model 1, by including a series of dummy variables capturing the impact of financial regulation and economic events. More specifically, we add the following dummy variables. For financial regulation: DoddFrank is 1 for the period after 21 July 2010, Basel II. 5 is 1 for the period after 7 June 2012, Basel III is 1 for the period after 9 July 2013, and Volcker Rule is 1 for the period after 1 April 2014. Regarding economic events: Lehman Brothers is 1 for the period after 15 September 2008, U.S. Downgrade is 1 for the period after 5 August 2011, Fed Tapering Announcement

(a) 2-Week Forecast Horizon

(b) 10-Week Forecast Horizon

Figure 11: Breaks in the Rolling Total Connectedness of Corporate Bond Return Volatility. Breaks are first identified sequentially based on the methodology in Bai and Perron (1998, 2003). The repartition technique of Bai (1997) is used in a second step to re-estimate each break date. We use a significance level of $5 \%$ and a maximum of 5 breaks for each series. The white and grey colored areas denote the regimes determined by the identified break dates.
is 1 for the period after 22 May 2013, and Start of Fed Tapering is 1 for the period after 18 December 2013. They are all 0 otherwise. Finally, we also consider Model 3, where we further explore the spillover connections between the 2 markets. We hypothesize that the intensity of spillovers in one market will likely alter its intensity in the other market. Specifically, for the corporate bond (stock) market, we add to the specification of Model 2 the intensity of the spillover index of the stock (corporate bond) market. ${ }^{10}$

We start our analysis with an examination of the stationarity of our variables, both dependent and independant. In the corporate bond market, all spillover indices are stationary. In the stock market, the series are either stationary (10-week volatility) or trend-stationary (2week volatility and 10 -week returns). The index of return spillovers at a 2 -week forecast horizon is the only non-stationary series. For the trend stationary variables, we consider the alternative specification where the dependent variable is detrended. The results are robust. For comparability purposes, we however systematically report the results for the dependent variable in levels. Among the explanatory variables, the term spread and the economic policy

[^10]
(a) 2-Week Forecast Horizon

(b) 10-Week Forecast Horizon

Figure 12: Breaks in the Rolling Total Connectedness of Stock Return Volatility. Breaks are first identified sequentially based on the methodology in Bai and Perron (1998, 2003). The repartition technique of Bai (1997) is used in a second step to re-estimate each break date. We use a significance level of $5 \%$ and a maximum of 5 breaks for each series. The white and grey colored areas denote the regimes determined by the identified break dates.
uncertainty index are both stationary. As quantitative easing and the TED spread are both trend-stationary, we use an adjusted version of those variables in our models, from which we remove the corresponding time trend. The default spread is the only non-stationary variable and we therefore use its first difference in our models.

We report the results for the determinants of the indices of return spillovers in Table 19. We first observe that, the intensity of return spillovers is negatively related to quantitative easing. The result holds for both corporate bonds and for stocks. By contrast, economic conditions affect the two markets differently: whereas the stock market spillovers react positively to the term spread, corporate bond spillovers are more sensitive to funding illiquidity (approximated by the TED spread). It confirms our expectation that funding illiquidity is of more importance to the corporate bond market than to the stock market. Second, we observe that financial regulation lowered the intensity of return spillovers. In particular, the adoption of the Basel II. 5 framework led to significantly lower return spillovers in both market. The corporate bond market also reacted to the Dodd-Frank Act and to the implementation of its Volcker Rule. The adoption of Basel III altered the return spillovers in the stock market. Our results also confirm the sensitivity of return spillovers to the occurrence of economic events. Return
spillovers increased in the stock market following the U.S. downgrade by Standard and Poor's. In the corporate bond market, spillovers reacted positively to the start of the tapering by the Federal Reserve. Interestingly, the taper tantrum that followed the tapering announcement by Ben Bernanke in May 2013 affected the two markets differently: while this event led to more intense return spillovers in the corporate bond market, it decreased their intensity in the stock market. Finally, the results of Model 3 confirm a positive and significant relation between the spillovers within the two markets.

The results for the determinants of volatility spillovers are reported in Table 20. Similar to the determinants of return spillovers, quantitative easing appears to affect negatively the intensity of volatility spillovers in both markets (its overall significance is nevertheless weaker in the case of the market for corporate bonds). While the TED spread retains some explanatory power for corporate bond spillovers, the default spread is here the most significant driver related to economic conditions. The impact of financial regulation is more homogenous across markets in the case of volatility spillovers: the passage of the Dodd-Frank Act into law as well as the adoption of the Basel II. 5 framework have negatively impacted the spillover intensities in both markets. As in the case of return spillovers, the impact of the Volcker Rule remains limited to the market for corporate bonds. The reaction of volatility spillovers to the occurrence of economic shocks is also more homogeneous across markets. The collapse of Lehman Brothers, the U.S. credit downgrade and the start of the tapering by the Federal Reserve in December 2013 led to stronger spillovers in both markets. By contrast, similar to the case of return spillovers, the two markets reacted differently to the surprise tapering announcement of May 2013: spillover intensities increased in the market for corporate bonds over the period of the taper tantrum, and they decreased in the stock market. Finally, our results confirm the positive and significant relation between the volatility spillovers of those markets (Model 3).

## 6 Conclusion

This paper undertakes an in-depth study of spillovers between firms in the corporate bond market and in the stock market. It stands out from different papers, as the focus is on the spillovers between individual firms rather than on spillovers between markets. We furthermore study how firms propagate shocks in each market from two perspectives: the spillovers in returns, which reflect performance, and the spillovers in return volatility, which is an important risk indicator. We provide a distinct analysis for the two markets and discuss differences and similarities that arise. Our approach to aggregate trade information into a firm specific price index for the corporate bond market is completely new in the context of a spillover analysis, as we construct a repeat-sales index for each issuer in the corporate bond market. As shown by Beaupain and Heck (2016) this methodology is very well suited to aggregate information provided by transactions on many different bonds, issued by the same issuer, into a single
price index. The methodology to derive spillover measures of returns and return volatilities then follows Diebold and Yilmaz (2014). Several interesting findings arise from this analysis. We first assess the intensity of directional spillovers. In the corporate bond market we find an important role of financial and insurance companies as main actors of shock transmissions as well as intra-industry effects. The dominance of financial firms is even more pronounced in the stock market. We find that volatility spillovers might be a bit slower than return spillovers, as they react with some lag. Furthermore, some individual firms stand out as being important transmitters and receivers of shocks. The location of the firm and in particular whether it is located in the U.S. or not also have an impact on the spillover intensity in the corporate bond market. Graphical illustrations of the spillovers between firms give a visual insight into the differences between the two markets. We highlight that, while in the corporate bond market the spillovers are mostly bilateral and within industry, for the stock market there is a clear dominance of spillovers between financial firms. In contrast to return shocks, volatility shock spillovers show more links between the two big segments which are financial vs. non-financial firms.

The second part of the empirical study is dedicated to a temporal analysis of spillover effects. This allows us to identify periods of increased connectedness and to relate them to market events. We find that spillover effects were particularly strong following the collapse of Lehman Brothers in September 2008, following the U.S. credit downgrade in August 2011 and following the Fed Tapering announcement in May 2013. The spillover intensity is however slightly lower in the stock market and this difference is particularly evident during the Fed tapering period. We also provide some evidence that important decisions taken in the area of banking regulation have affected the spillover intensity over time, although in a more gradual way. The Dodd-Frank Act, as well as the adoption of Basel II. 5 display a negative impact on volatility spillovers in both markets, suggesting that such events might have lowered the uncertainty spread out in a given market. In the corporate bond market, spillover intensities decreased after the implementation of the Volcker Rule. This result holds for both return spillovers and volatility spillovers. The Rule is associated to a ban in proprietary trading by banks, such that banks have reduced their active market making in the corporate bond market. This could thus explain why the information propagation between firms, be it in terms of return shocks or volatility shocks has been reduced.

Interconnectedness between firms and between markets has been largely documented. In our paper we provide important findings on the intensity of connectedness between firms within a market and on its temporal evolution. It is important as we show that the transmission of shocks is affected by economic and regulatory events and that this impact differs between markets. Our results can thus also inform policy making on the relation between economic events and interconnectedness and on whether given events increase or decrease spillover effects. However whether there is an optimal level of connectednes in the market and what this level would be remains an open question.
Table 13: Net Spillovers in the Equity Market. This table represents various full sample connectedness measures of stock returns and volatility over the period from March 2006 to December 2014. Results are shown for a forecast horizon of 2 weeks and 10 weeks. The column 'To', represents the total directional connectedness to others from $j$. The column 'From' represents the total directional connectedness from others to $i$. The column 'Net' is the net directional connectedness obtained as the difference of the two.

|  |  | Returns |  |  |  |  |  | Volatility |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 2 Weeks |  |  | 10 Weeks |  |  | 2 Weeks |  |  | 10 Weeks |  |  |
|  |  | To | From | Net | To | From | Net | To | From | Net | To | From | Net |
| American Express Co. | AXP | 107.5 | 89.2 | 18.3 | 107.5 | 89.2 | 18.3 | 118.2 | 84.2 | 34.1 | 115.0 | 89.6 | 25.4 |
| The Bank of New York Mellon Corp. | BK | 101.6 | 88.7 | 12.9 | 101.6 | 88.8 | 12.9 | 86.5 | 80.4 | 6.0 | 121.7 | 87.4 | 34.3 |
| Caterpillar Inc. | CAT | 93.4 | 87.5 | 6.0 | 93.4 | 87.5 | 5.9 | 82.4 | 79.9 | 2.5 | 84.1 | 85.1 | -1.0 |
| Deere and Co. | DE | 69.8 | 84.3 | -14.5 | 69.8 | 84.4 | -14.6 | 18.6 | 33.6 | -15.0 | 45.5 | 65.6 | -20.1 |
| Ford Motor Co. | F | 85.7 | 86.7 | -1.0 | 85.8 | 86.7 | -0.9 | 93.9 | 86.7 | 7.2 | 91.1 | 92.1 | -1.0 |
| General Electric Co. | GE | 105.1 | 89.1 | 16.0 | 105.1 | 89.1 | 15.9 | 82.7 | 82.1 | 0.6 | 82.7 | 88.5 | -5.8 |
| International Business Machines Corp. | IBM | 72.3 | 84.1 | -11.8 | 72.2 | 84.1 | -11.9 | 88.3 | 76.4 | 11.9 | 100.6 | 78.0 | 22.6 |
| Toyota Motor Corp. | TM | 64.5 | 82.3 | -17.9 | 64.5 | 82.3 | -17.8 | 53.6 | 77.0 | -23.3 | 48.0 | 83.9 | -35.9 |
| Walmart Inc. | WMT | 36.4 | 71.9 | -35.5 | 36.4 | 72.0 | -35.6 | 57.3 | 76.6 | -19.3 | 64.0 | 85.4 | -21.4 |
| Royal Bank of Canada | RY | 105.8 | 88.7 | 17.1 | 105.8 | 88.7 | 17.1 | 113.4 | 86.4 | 27.0 | 117.3 | 90.8 | 26.5 |
| Amgen Inc. | AMGN | 25.3 | 63.9 | -38.7 | 25.3 | 64.0 | -38.7 | 40.9 | 68.4 | -27.6 | 72.3 | 77.6 | -5.3 |
| HP Inc. | HPQ | 51.6 | 79.6 | -28.0 | 51.7 | 79.7 | -27.9 | 34.2 | 66.9 | -32.8 | 31.6 | 85.7 | -54.2 |
| Barclays PLC | BCS | 83.1 | 86.7 | -3.6 | 83.1 | 86.7 | -3.6 | 58.2 | 72.2 | -14.0 | 109.7 | 83.6 | 26.1 |
| Citigroup Inc. | C | 102.0 | 89.0 | 13.0 | 102.0 | 89.0 | 13.0 | 81.2 | 84.9 | -3.6 | 68.9 | 91.4 | -22.5 |
| The Goldman Sachs Group Inc. | GS | 110.7 | 89.7 | 21.0 | 110.7 | 89.7 | 21.0 | 124.3 | 87.8 | 36.5 | 137.3 | 90.5 | 46.8 |
| Bank of America Corp. | BAC | 115.9 | 90.2 | 25.7 | 115.9 | 90.2 | 25.7 | 105.3 | 87.4 | 17.9 | 95.5 | 91.0 | 4.5 |
| Wells Fargo and Co. | WFC | 90.3 | 87.7 | 2.7 | 90.4 | 87.7 | 2.7 | 48.8 | 73.2 | -24.4 | 41.5 | 80.3 | -38.8 |
| JP Morgan Chase and Co. | JPM | 112.2 | 89.6 | 22.7 | 112.2 | 89.6 | 22.7 | 89.2 | 81.4 | 7.8 | 89.1 | 89.1 | 0.0 |
| Verizon Communications Inc. | VZ | 67.1 | 81.9 | -14.8 | 67.2 | 81.9 | -14.7 | 74.5 | 81.3 | -6.8 | 64.3 | 88.2 | -23.9 |
| Prudential Financial Inc. | PRU | 116.9 | 89.8 | 27.2 | 116.9 | 89.7 | 27.2 | 112.9 | 85.8 | 27.1 | 103.3 | 90.1 | 13.3 |
| SLM Corp. | SLM | 56.1 | 82.6 | -26.5 | 56.1 | 82.6 | -26.5 | 29.4 | 60.3 | -30.9 | 39.1 | 72.3 | -33.2 |
| Comcast Corp. | CMCSA | 66.3 | 83.6 | -17.2 | 66.3 | 83.6 | -17.3 | 36.1 | 63.9 | -27.8 | 42.7 | 75.8 | -33.1 |
| Morgan Stanley | MS | 98.4 | 88.8 | 9.6 | 98.3 | 88.8 | 9.6 | 100.7 | 88.6 | 12.1 | 141.6 | 89.7 | 51.9 |
| HSBC Holdings PLC | HSBC | 102.4 | 88.6 | 13.9 | 102.4 | 88.6 | 13.9 | 73.0 | 80.2 | -7.2 | 59.2 | 91.1 | -31.8 |
| AT\&T Inc. | T | 70.9 | 83.2 | -12.3 | 71.0 | 83.2 | -12.3 | 84.6 | 80.3 | 4.2 | 97.9 | 82.3 | 15.7 |
| Royal Dutch Shell PLC | RDS | 79.7 | 85.3 | -5.6 | 79.7 | 85.3 | -5.5 | 96.4 | 81.5 | 14.9 | 135.3 | 85.1 | 50.2 |
| Credit Suisse Group AG | CS | 111.0 | 89.5 | 21.5 | 111.0 | 89.5 | 21.5 | 110.5 | 87.7 | 22.8 | 101.4 | 90.6 | 10.8 |

Table 14: Network Statistics for Return Spillovers
Panel A - Proportion of Network Relations

|  |  | 2-Week |  | Horizon | 10-Week Horizon |  |
| :--- | :--- | ---: | ---: | ---: | ---: | :---: |
| From | To | Bonds | Stocks | Bonds | Stocks |  |
| Financial | Financial | 42.25 | 68.49 | 40.28 | 68.49 |  |
|  | Non-Financial | 8.45 | 13.70 | 8.33 | 13.70 |  |
| Non-Financial | Financial | 5.63 | 4.11 | 6.94 | 4.11 |  |
|  | Non-Financial | 43.66 | 13.70 | 44.44 | 13.70 |  |

Panel B - Sum of Network Weights

|  |  | 2-Week |  | Horizon | 10-Week Horizon |  |
| :--- | :--- | ---: | ---: | ---: | ---: | :---: |
| From | To | Bonds | Stocks | Bonds | Stocks |  |
| Financial | Financial | 246.32 | 292.69 | 239.19 | 292.62 |  |
|  | Non-Financial | 46.93 | 53.87 | 47.12 | 53.87 |  |
| Non-Financial | Financial | 31.96 | 15.59 | 37.83 | 15.59 |  |
|  | Non-Financial | 259.00 | 65.01 | 264.70 | 65.00 |  |

Table 15: Network Statistics for Volatility Spillovers
Panel A - Proportion of Network Relations

|  |  | 2-Week Horizon |  | 10-Week Horizon |  |
| :--- | :--- | ---: | ---: | ---: | ---: |
| From | To | Bonds | Stocks | Bonds | Stocks |
| Financial | Financial | 38.03 | 50.70 | 32.39 | 38.89 |
|  | Non-Financial | 22.54 | 12.68 | 42.25 | 22.22 |
| Non-Financial | Financial | 8.45 | 14.08 | 11.27 | 13.89 |
|  | Non-Financial | 30.99 | 22.54 | 14.08 | 25.00 |

Panel B - Sum of Network Weights

|  |  | 2-Week |  | Horizon | 10-Week Horizon |  |
| :--- | :--- | ---: | ---: | ---: | ---: | :---: |
| From | To | Bonds | Stocks | Bonds | Stocks |  |
| Financial | Financial | 225.29 | 243.25 | 185.14 | 176.91 |  |
|  | Non-Financial | 125.36 | 59.28 | 232.09 | 98.79 |  |
| Non-Financial | Financial | 53.08 | 59.01 | 66.81 | 59.81 |  |
|  | Non-Financial | 186.32 | 103.14 | 77.38 | 117.61 |  |

Table 16: Descriptive Statistics for the Rolling Total Connectedness of the Corporate Bond Market.

|  | Returns |  |  | Volatility |  |
| :--- | :--- | :---: | :---: | :---: | :---: |
|  | 2 Weeks | 10 Weeks | 2 Weeks | 10 Weeks |  |
| Average | 84.73 | 86.82 | 82.46 | 89.51 |  |
| Median | 84.10 | 86.35 | 81.04 | 89.42 |  |
| Standard Deviation | 3.15 | 3.07 | 5.07 | 3.17 |  |
| Maximum | Value | 93.88 | 96.29 | 94.86 | 96.54 |
|  | Date | $19 / 09 / 2008$ | $12 / 08 / 2011$ | $26 / 09 / 2008$ | $06 / 03 / 2009$ |
| Minimum | Value | 77.83 | 80.53 | 74.62 | 84.12 |
|  | Date | $27 / 07 / 2007$ | $20 / 07 / 2007$ | $18 / 06 / 2010$ | $18 / 06 / 2010$ |
| Observations |  | 394 | 394 | 394 | 394 |

Table 17: Descriptive Statistics for the Rolling Total Connectedness of the Stock Market.

|  | Returns |  | Volatility |  |
| :---: | :---: | :---: | :---: | :---: |
|  | 2 Weeks | 10 Weeks | 2 Weeks | 10 Weeks |
| Average | 86.49 | 87.83 | 82.42 | 89.26 |
| Median | 87.25 | 88.28 | 82.16 | 88.86 |
| Standard Deviation | 3.61 | 3.14 | 4.03 | 2.95 |
| Maximum Value | 92.74 | 95.50 | 93.74 | 96.48 |
| Date | 18/05/2012 | 10/10/2008 | 17/10/2008 | 24/10/2008 |
| Minimum Value | 77.42 | 80.29 | 73.10 | 82.42 |
| Date | 15/11/2013 | 15/11/2013 | 14/06/2013 | 14/06/2013 |
| Observations | 394 | 394 | 394 | 394 |

Table 18: Break Periods in the Rolling Total Connectedness. This Table reports the break dates identified in the multiple break analysis. Breaks are first identified sequentially based on the methodology proposed in Bai and Perron (1998, 2003). The repartition technique of Bai (1997) is used in a second step to re-estimate each break date. We use a significance level of $5 \%$ and a maximum of 5 breaks for each series. Mean is the average value of the spillover index in the corresponding period. Date is the break date, hence the start date of each regime.

|  | Corporate Bonds |  |  |  | Stocks |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 2-Week |  | 10-Week |  | 2-Week |  | 10-Week |  |
|  | Date | Mean | Date | Mean | Date | Mean | Date | Mean |
| Sample Start | 22/06/2007 | 82.54 | 22/06/2007 | 84.80 | 22/06/2007 | 83.94 | 22/06/2007 | 85.86 |
| Break 1 | 19/09/2008 | 88.31 | 19/09/2008 | 91.02 | 08/08/2008 | 90.05 | 08/08/2008 | 91.36 |
| Break 2 | 15/01/2010 | 82.03 | 15/01/2010 | 84.23 | 09/10/2009 | 87.00 | 09/10/2009 | 88.11 |
| Break 3 | 01/04/2011 | 83.24 | 01/04/2011 | 85.36 | 26/11/2010 | 89.44 | 26/11/2010 | 90.10 |
| Break 4 | 21/06/2013 | 87.67 | 07/06/2013 | 88.86 | 30/11/2012 | 82.78 | 23/11/2012 | 86.66 |

Panel B - Breaks in the Volatility Spillovers

|  | Corporate Bonds |  |  |  | Stocks |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 2-Week |  | 10-Week |  | 2-Week |  | 10-Week |  |
|  | Date | Mean | Date | Mean | Date | Mean | Date | Mean |
| Sample Start | 22/06/2007 | 78.38 | 22/06/2007 | 88.47 | 22/06/2007 | 82.07 | 22/06/2007 | 89.82 |
| Break 1 | 26/09/2008 | 89.66 | 26/09/2008 | 93.90 | 26/09/2008 | 88.72 | 10/10/2008 | 93.37 |
| Break 2 | 18/12/2009 | 77.77 | 15/01/2010 | 86.30 | 13/11/2009 | 81.99 | 27/11/2009 | 87.98 |
| Break 3 | 12/08/2011 | 82.50 | 12/08/2011 | 89.13 | 30/09/2011 | 84.96 | 19/08/2011 | 90.71 |
| Break 4 | 28/06/2013 | 85.04 | 28/06/2013 | 90.41 | 21/12/2012 | 78.04 | 11/09/2012 | 86.97 |

Table 19: Determinants of the Rolling Total Connectedness of Returns. Quantitative Easing is the total amount of U.S. Treasury, Federal agency debt and mortgage-backed securities. The spreads are the difference in yield between Moody's Baa corporate bond index and the 10-year Treasury bonds (Default Spread), between the 10-year Treasury bonds and the 3-month Treasury bill (Term Spread) and between the 3-month USD LIBOR and the 3-month Treasury bill (TED Spread). Quantitative Easing and TED Spread are detrended. Default Spread is in first difference. Economic Uncertainty is the economic policy uncertainty index of Baker et al. (2016), divided by 100. Dummy variables are 1 for the period after 21 July 2010 (Dodd-Frank), after 7 June 2012 (Basel II.5), after 9 July 2013 (Basel III), after 1 April 2014 (Volcker Rule), after 15 September 2008 (Lehman Brothers), after 5 August 2011 (U.S. Downgrade), after 22 May 2013 (Fed Tapering Announcement), and after 18 December 2013 (Start of Fed Tapering). They are 0 otherwise. The Newey and West (1987) heteroskedasticity- and autocorrelation-consistent standard errors are provided in the parentheses. ${ }^{* * *},{ }^{* *}$ and $*$ denote statistical significance at the $1 \%, 5 \%$ and $10 \%$ levels, respectively.

|  | Corporate Bonds |  |  |  |  |  | Stocks |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 2-Week Horizon |  |  | 10-Week Horizon |  |  | 2-Week Horizon |  |  | 10-Week Horizon |  |  |
|  | Model 1 | Model 2 | Model 3 | Model 1 | Model 2 | Model 3 | Model 1 | Model 2 | Model 3 | Model 1 | Model 2 | Model 3 |
| Intercept | $\begin{array}{r} 80.35^{* * *} \\ (0.73) \end{array}$ | $\begin{array}{r} 81.21^{* * *} \\ (0.74) \end{array}$ | $\begin{array}{r} 54.58^{* * *} \\ (8.67) \end{array}$ | $\begin{array}{r} 82.22^{* * *} \\ (0.70) \end{array}$ | $\begin{array}{r} 84.17^{* * *} \\ (0.69) \end{array}$ | $\begin{array}{r} 52.51^{* * *} \\ (7.64) \end{array}$ | $\begin{array}{r} 81.59^{* * *} \\ (0.88) \end{array}$ | $\begin{array}{r} 82.70^{* * *} \\ (0.83) \end{array}$ | $\begin{array}{r} 56.85^{* * *} \\ (6.97) \end{array}$ | $\begin{array}{r} 83.41^{* * *} \\ (0.76) \end{array}$ | $\begin{array}{r} 84.80^{* * *} \\ (0.75) \end{array}$ | $\begin{array}{r} 54.79^{* * *} \\ (6.82) \end{array}$ |
| Quantitative Easing | $\begin{aligned} & -1.22 \\ & (1.02) \end{aligned}$ | $\begin{array}{r} -3.98^{* * *} \\ (1.08) \end{array}$ | $\begin{array}{r} -2.35^{* * *} \\ (0.84) \end{array}$ | $\begin{aligned} & -1.68 \\ & (1.15) \end{aligned}$ | $\begin{array}{r} -4.52^{* * *} \\ (1.01) \end{array}$ | $\begin{array}{r} -2.88^{* * *} \\ (0.79) \end{array}$ | $\underset{(1.08)}{-5.00^{* * *}}$ | $\begin{array}{r} -5.06^{* * *} \\ (0.92) \end{array}$ | $\begin{array}{r} -3.79^{* * *} \\ (0.93) \end{array}$ | $\begin{array}{r} -4.01^{* * *} \\ (0.97) \end{array}$ | $\begin{array}{r} -4.40^{* * *} \\ (0.85) \end{array}$ | $\begin{array}{r} -2.79^{* * *} \\ (0.89) \end{array}$ |
| Default Spread | $\begin{array}{r} -5.42^{* *} \\ (2.26) \end{array}$ | $\begin{aligned} & -2.99 \\ & (1.90) \end{aligned}$ | $\begin{array}{r} -3.06^{*} \\ (1.80) \end{array}$ | $\begin{aligned} & -3.10 \\ & (2.22) \end{aligned}$ | $\begin{aligned} & -1.38 \\ & (1.71) \end{aligned}$ | $\begin{aligned} & -1.67 \\ & (1.58) \end{aligned}$ | $\begin{array}{r} 2.63 \\ (1.75) \end{array}$ | $\begin{array}{r} 0.22 \\ (1.19) \end{array}$ | $\begin{array}{r} 1.17 \\ (1.18) \end{array}$ | $\begin{gathered} 2.80^{*} \\ (1.64) \end{gathered}$ | $\begin{array}{r} 0.78 \\ (1.15) \end{array}$ | $\begin{array}{r} 1.27 \\ (1.07) \end{array}$ |
| Term Spread | $\begin{array}{r} 1.99^{* * *} \\ (0.34) \end{array}$ | $\begin{gathered} 0.89^{* *} \\ (0.41) \end{gathered}$ | $\begin{array}{r} 0.49 \\ (0.42) \end{array}$ | $\begin{array}{r} 1.90^{* * *} \\ (0.30) \end{array}$ | $\begin{array}{r} 0.28 \\ (0.37) \end{array}$ | $\begin{aligned} & -0.06 \\ & (0.36) \end{aligned}$ | $\begin{array}{r} 1.21^{* * *} \\ (0.35) \end{array}$ | $\begin{array}{r} 1.24^{* * *} \\ (0.39) \end{array}$ | $\begin{array}{r} 0.96^{* * *} \\ (0.35) \end{array}$ | $\begin{array}{r} 1.10^{* * *} \\ (0.31) \end{array}$ | $\begin{gathered} 0.92^{* *} \\ (0.36) \end{gathered}$ | $\begin{gathered} 0.82^{* *} \\ (0.33) \end{gathered}$ |
| TED Spread | $\begin{array}{r} 2.44^{* * *} \\ (0.65) \end{array}$ | $\begin{array}{r} 0.41 \\ (0.41) \end{array}$ | $\begin{gathered} 0.63^{*} \\ (0.37) \end{gathered}$ | $\begin{array}{r} 2.75^{* * *} \\ (0.58) \end{array}$ | $\begin{array}{r} 0.99^{* * *} \\ (0.35) \end{array}$ | $\begin{array}{r} 1.02^{* * *} \\ (0.32) \end{array}$ | $\begin{array}{r} -2.05^{* * *} \\ (0.67) \end{array}$ | $\begin{aligned} & -0.68 \\ & (0.45) \end{aligned}$ | $\begin{array}{r} -0.81^{*} \\ (0.42) \end{array}$ | $\begin{array}{r} -1.07^{*} \\ (0.60) \end{array}$ | $\begin{aligned} & -0.08 \\ & (0.43) \end{aligned}$ | $\begin{aligned} & -0.43 \\ & (0.41) \end{aligned}$ |
| Economic Uncertainty | $\begin{aligned} & -0.30 \\ & (0.35) \end{aligned}$ | $\begin{array}{r} 0.48 \\ (0.32) \end{array}$ | $\begin{array}{r} 0.35 \\ (0.31) \end{array}$ | $\begin{gathered} 0.04 \\ (0.34) \end{gathered}$ | $\begin{gathered} 0.52^{*} \\ (0.31) \end{gathered}$ | $\begin{array}{r} 0.36 \\ (0.29) \end{array}$ | $\begin{array}{r} 1.61^{* * *} \\ (0.31) \end{array}$ | $\begin{array}{r} 0.40 \\ (0.26) \end{array}$ | $\begin{array}{r} 0.25 \\ (0.26) \end{array}$ | $\begin{array}{r} 1.43^{* * *} \\ (0.29) \end{array}$ | $\begin{gathered} 0.43^{*} \\ (0.24) \end{gathered}$ | $\begin{array}{r} 0.25 \\ (0.23) \end{array}$ |
| Financial Regulations |  |  |  |  |  |  |  |  |  |  |  |  |
| Dodd-Frank |  | $\begin{array}{r} -2.28^{* * *} \\ (0.87) \end{array}$ | $\begin{array}{r} -2.51^{* * *} \\ (0.73) \end{array}$ |  | $\begin{array}{r} -2.90^{* * *} \\ (0.75) \end{array}$ | $\begin{array}{r} -2.91^{* * *} \\ (0.61) \end{array}$ |  | $\begin{array}{r} 0.70 \\ (0.57) \end{array}$ | $\begin{array}{r} 1.42^{* * *} \\ (0.40) \end{array}$ |  | $\begin{array}{r} 0.02 \\ (0.52) \end{array}$ | $\begin{array}{r} 1.06^{* * *} \\ (0.41) \end{array}$ |
| Basel II. 5 |  | $\begin{array}{r} -3.17^{* * *} \\ (0.68) \end{array}$ | $\begin{array}{r} -1.76^{* * *} \\ (0.65) \end{array}$ |  | $\begin{array}{r} -4.35^{* * *} \\ (0.74) \end{array}$ | $\begin{array}{r} -2.77^{* * *} \\ (0.60) \end{array}$ |  | $\begin{array}{r} -4.39^{* * *} \\ (1.10) \end{array}$ | $\begin{array}{r} -3.38^{* * *} \\ (1.13) \end{array}$ |  | $\begin{array}{r} -4.23^{* * *} \\ (0.94) \end{array}$ | $\begin{array}{r} -2.68^{* * *} \\ (1.00) \end{array}$ |
| Basel III |  | $\begin{array}{r} 3.41^{* * *} \\ (0.91) \end{array}$ | $\begin{array}{r} 4.22^{* * *} \\ (1.14) \end{array}$ |  | $\begin{array}{r} 1.55 \\ (0.96) \end{array}$ | $\begin{gathered} 2.24^{* *} \\ (1.07) \end{gathered}$ |  | $\begin{array}{r} -2.50^{* * *} \\ (0.93) \end{array}$ | $\begin{array}{r} -3.59^{* * *} \\ (1.13) \end{array}$ |  | $\begin{array}{r} -1.86^{* * *} \\ (0.69) \end{array}$ | $\begin{array}{r} -2.42^{* * *} \\ (0.85) \end{array}$ |
| Volcker Rule |  | $\begin{array}{r} -3.35^{* * *} \\ (0.71) \end{array}$ | $\begin{array}{r} -3.60^{* * *} \\ (0.77) \end{array}$ |  | $\begin{array}{r} -2.87^{* * *} \\ (0.57) \end{array}$ | $\begin{array}{r} -3.19^{* * *} \\ (0.65) \end{array}$ |  | $\begin{array}{r} 0.75 \\ (1.11) \end{array}$ | $\begin{array}{r} 1.82 \\ (1.14) \end{array}$ |  | $\begin{array}{r} 0.86 \\ (0.94) \end{array}$ | $\begin{aligned} & 1.89^{*} \\ & (0.96) \end{aligned}$ |
| Economic Events |  |  |  |  |  |  |  |  |  |  |  |  |
| Lehman Brothers |  | $\begin{array}{r} 1.38 \\ (1.07) \end{array}$ | $\begin{array}{r} 0.97 \\ (0.99) \end{array}$ |  | $\begin{array}{r} 2.97^{* * *} \\ (0.98) \end{array}$ | $\begin{gathered} 2.41^{* *} \\ (0.94) \end{gathered}$ |  | $\begin{array}{r} 1.26 \\ (0.92) \end{array}$ | $\begin{array}{r} 0.82 \\ (0.83) \end{array}$ |  | $\begin{gathered} 1.50^{*} \\ (0.90) \end{gathered}$ | $\begin{array}{r} 0.44 \\ (0.88) \end{array}$ |
| U.S. Downgrade |  | $\begin{gathered} 1.46^{*} \\ (0.88) \end{gathered}$ | $\begin{array}{r} 0.75 \\ (0.86) \end{array}$ |  | $\begin{array}{r} 1.32 \\ (0.88) \end{array}$ | $\begin{array}{r} 0.58 \\ (0.81) \end{array}$ |  | $\begin{array}{r} 2.20^{* * *} \\ (0.59) \end{array}$ | $\begin{array}{r} 1.74^{* * *} \\ (0.53) \end{array}$ |  | $\begin{array}{r} 1.97^{* * *} \\ (0.54) \end{array}$ | $\begin{array}{r} 1.50^{* * *} \\ (0.48) \end{array}$ |
| Fed Tapering Announcement |  | $\begin{array}{r} 3.65^{* * *} \\ (0.95) \end{array}$ | $\begin{array}{r} 4.33^{* * *} \\ (1.06) \end{array}$ |  | $\begin{array}{r} 5.38^{* * *} \\ (1.02) \end{array}$ | $\begin{array}{r} 5.99^{* * *} \\ (1.07) \end{array}$ |  | $\begin{array}{r} -2.12^{* *} \\ (1.01) \end{array}$ | $\begin{array}{r} -3.29^{* * *} \\ (1.11) \end{array}$ |  | $\begin{array}{r} -1.65^{*} \\ (0.85) \end{array}$ | $\begin{array}{r} -3.56^{* * *} \\ (1.05) \end{array}$ |
| Start of Fed Tapering |  | $\begin{array}{r} 2.15^{* * *} \\ (0.52) \end{array}$ | $\begin{array}{r} 1.63^{* * *} \\ (0.63) \end{array}$ |  | $\begin{array}{r} 1.95^{* * *} \\ (0.43) \end{array}$ | $\begin{array}{r} 1.38^{* * *} \\ (0.50) \end{array}$ |  | $\begin{array}{r} 1.63 \\ (1.28) \end{array}$ | $\begin{array}{r} 0.95 \\ (1.31) \end{array}$ |  | $\begin{array}{r} 1.52 \\ (1.03) \end{array}$ | $\begin{array}{r} 0.82 \\ (1.03) \end{array}$ |
| Stock Spillovers |  |  | $\begin{array}{r} 0.32^{* * *} \\ (0.11) \end{array}$ |  |  | $\begin{array}{r} 0.37^{* * *} \\ (0.09) \end{array}$ |  |  |  |  |  |  |
| Corporate Bond Spillovers |  |  |  |  |  |  |  |  | $\begin{array}{r} 0.32^{* * *} \\ (0.09) \\ \hline \end{array}$ |  |  | $\begin{array}{r} 0.36^{* * *} \\ (0.08) \\ \hline \end{array}$ |
| Adjusted R-Squared | 0.33 | 0.62 | 0.66 | 0.38 | 0.66 | 0.71 | 0.39 | 0.71 | 0.74 | 0.36 | 0.69 | 0.73 |
| Observations | 393 | 393 | 393 | 393 | 393 | 393 | 393 | 393 | 393 | 393 | 393 | 393 |

Table 20: Determinants of the Rolling Total Connectedness of Volatility. Quantitative Easing is the total amount of U.S. Treasury, Federal agency debt and mortgage backed securities. The spreads are the difference in yield between Moody's Baa corporate bond index and the 10-year Treasury bonds (Default Spread), between the 10-year Treasury bonds and the 3-month Treasury bill (Term Spread) and between the 3-month USD LIBOR and the 3-month Treasury bill (TED Spread). Quantitative Easing and TED Spread are detrended. Default Spread is in first difference. Economic Uncertainty is the economic policy uncertainty index of Baker et al. (2016), divided by 100. Dummy variables are 1 for the period after 21 July 2010 (Dodd-Frank), after 7 June 2012 (Basel II.5), after 9 July 2013 (Basel III), after 1 April 2014 (Volcker Rule), after 18 September 2008 (Lehman Brothers), after 5 August 2011 (U.S. Downgrade), after 22 May 2013 (Fed Tapering Announcement), and after 18 December 2013 (Start of Fed Tapering). They are 0 otherwise. The Newey and West (1987) heteroskedasticity- and autocorrelation-consistent standard errors are provided in the parentheses. ${ }^{* * *},{ }^{* *}$ and $*$ denote statistical significance at the $1 \%, 5 \%$ and $10 \%$ levels, respectively.

|  | Corporate Bonds |  |  |  |  |  | Stocks |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 2-Week Horizon |  |  | 10-Week Horizon |  |  | 2-Week Horizon |  |  | 10-Week Horizon |  |  |
|  | Model 1 | Model 2 | Model 3 | Model 1 | Model 2 | Model 3 | Model 1 | Model 2 | Model 3 | Model 1 | Model 2 | Model 3 |
| Intercept | $\begin{array}{r} 77.49^{* * *} \\ (1.56) \end{array}$ | $\begin{array}{r} 80.47^{* * *} \\ (1.12) \end{array}$ | $\begin{array}{r} 36.68^{* * *} \\ (9.39) \end{array}$ | $\begin{array}{r} 87.37^{* * *} \\ (1.11) \end{array}$ | $\begin{array}{r} 89.99^{* * *} \\ (0.92) \end{array}$ | $\begin{array}{r} 51.59^{* * *} \\ (7.50) \end{array}$ | $\begin{array}{r} 79.28^{* * *} \\ (1.13) \end{array}$ | $\begin{array}{r} 83.73^{* * *} \\ (1.05) \end{array}$ | $\begin{array}{r} 57.85^{* * *} \\ (4.76) \end{array}$ | $\begin{array}{r} 88.36^{* * *} \\ (0.79) \end{array}$ | $\begin{gathered} 91.46^{* * *} \\ (0.60) \end{gathered}$ | $\begin{array}{r} 59.91^{* * *} \\ (4.85) \end{array}$ |
| Quantitative Easing | $\begin{aligned} & -2.22 \\ & (2.14) \end{aligned}$ | $\begin{array}{r} -5.29^{* * *} \\ (1.54) \end{array}$ | $\begin{array}{r} -2.46^{* *} \\ (1.22) \end{array}$ | $\begin{aligned} & -0.90 \\ & (1.33) \end{aligned}$ | $\begin{array}{r} -2.72^{* *} \\ (1.09) \end{array}$ | $\begin{aligned} & -1.18 \\ & (0.81) \end{aligned}$ | $\begin{array}{r} -4.26^{* * *} \\ (1.56) \end{array}$ | $\begin{array}{r} -5.41^{* * *} \\ (1.03) \end{array}$ | $\begin{array}{r} -3.71^{* * *} \\ (0.96) \end{array}$ | $\begin{array}{r} -1.92^{*} \\ (1.13) \end{array}$ | $\begin{array}{r} -3.65^{* * *} \\ (0.84) \end{array}$ | $\begin{array}{r} -2.61^{* * *} \\ (0.66) \end{array}$ |
| Default Spread | $\begin{array}{r} -10.01^{* *} \\ (3.95) \end{array}$ | $\begin{array}{r} -7.19^{* * *} \\ (2.46) \end{array}$ | $\begin{array}{r} -4.44^{* *} \\ (1.90) \end{array}$ | $\begin{array}{r} -4.21^{*} \\ (2.42) \end{array}$ | $\begin{array}{r} -3.15^{* *} \\ (1.52) \end{array}$ | $\begin{aligned} & -1.18 \\ & (1.28) \end{aligned}$ | $\begin{aligned} & -2.81 \\ & (2.76) \end{aligned}$ | $\begin{array}{r} -5.25^{* * *} \\ (1.84) \end{array}$ | $\begin{array}{r} -2.94^{*} \\ (1.68) \end{array}$ | $\begin{array}{r} -3.65^{*} \\ (2.06) \end{array}$ | $\begin{array}{r} -4.69^{* * *} \\ (1.54) \end{array}$ | $\begin{array}{r} -3.48^{* * *} \\ (1.30) \end{array}$ |
| Term Spread | $\begin{array}{r} 1.82^{* * *} \\ (0.59) \end{array}$ | $\begin{array}{r} -1.49^{* *} \\ (0.58) \end{array}$ | $\begin{aligned} & -1.10 \\ & (0.67) \end{aligned}$ | $\begin{gathered} 0.75^{*} \\ (0.43) \end{gathered}$ | $\begin{array}{r} -1.18^{* * *} \\ (0.45) \end{array}$ | $\begin{array}{r} -0.77^{*} \\ (0.42) \end{array}$ | $\begin{array}{r} 0.67 \\ (0.42) \end{array}$ | $\begin{aligned} & -0.75 \\ & (0.50) \end{aligned}$ | $\begin{aligned} & -0.27 \\ & (0.53) \end{aligned}$ | $\begin{array}{r} 0.06 \\ (0.29) \end{array}$ | $\begin{array}{r} -0.99^{* * *} \\ (0.32) \end{array}$ | $\begin{gathered} -0.54^{*} \\ (0.32) \end{gathered}$ |
| TED Spread | $\begin{array}{r} 3.63^{* * *} \\ (1.04) \end{array}$ | $\begin{gathered} 1.29^{* *} \\ (0.57) \end{gathered}$ | $\begin{gathered} 1.15^{*} \\ (0.59) \end{gathered}$ | $\begin{array}{r} 2.35^{* * *} \\ (0.63) \end{array}$ | $\begin{gathered} 1.04^{* *} \\ (0.42) \end{gathered}$ | $\begin{aligned} & 0.68^{*} \\ & (0.38) \end{aligned}$ | $\begin{aligned} & -0.37 \\ & (0.86) \end{aligned}$ | $\begin{array}{r} 0.28 \\ (0.59) \end{array}$ | $\begin{aligned} & -0.14 \\ & (0.63) \end{aligned}$ | $\begin{gathered} 1.02^{*} \\ (0.59) \end{gathered}$ | $\begin{gathered} 0.84^{*} \\ (0.44) \end{gathered}$ | $\begin{array}{r} 0.44 \\ (0.40) \end{array}$ |
| Economic Uncertainty | $\begin{array}{r} 0.51 \\ (0.60) \end{array}$ | $\begin{array}{r} 0.46 \\ (0.32) \end{array}$ | $\begin{array}{r} 0.46 \\ (0.30) \end{array}$ | $\begin{array}{r} 0.27 \\ (0.37) \end{array}$ | $\begin{array}{r} 0.26 \\ (0.26) \end{array}$ | $\begin{array}{r} 0.22 \\ (0.23) \end{array}$ | $\begin{array}{r} 1.24^{* * *} \\ (0.42) \end{array}$ | $\begin{aligned} & -0.01 \\ & (0.31) \end{aligned}$ | $\begin{aligned} & -0.15 \\ & (0.29) \end{aligned}$ | $\begin{gathered} 0.62^{* *} \\ (0.29) \end{gathered}$ | $\begin{array}{r} 0.08 \\ (0.21) \end{array}$ | $\begin{gathered} -0.01 \\ (0.18) \end{gathered}$ |
| Financial Regulations |  |  |  |  |  |  |  |  |  |  |  |  |
| Dodd-Frank |  | $\begin{array}{r} -7.76^{* * *} \\ (1.21) \end{array}$ | $\begin{array}{r} -5.90^{* * *} \\ (1.23) \end{array}$ |  | $\begin{array}{r} -5.14^{* * *} \\ (0.84) \end{array}$ | $\begin{array}{r} -3.98^{* * *} \\ (0.80) \end{array}$ |  | $\begin{array}{r} -3.57^{* * *} \\ (0.64) \end{array}$ | $\begin{array}{r} -1.07^{* *} \\ (0.51) \end{array}$ |  | $\begin{array}{r} -2.75^{* * *} \\ (0.47) \end{array}$ | $\begin{array}{r} -0.78^{* *} \\ (0.37) \end{array}$ |
| Basel II. 5 |  | $\begin{array}{r} -9.18^{* * *} \\ (1.01) \end{array}$ | $\begin{array}{r} -6.45^{* * *} \\ (1.01) \end{array}$ |  | $\begin{array}{r} -5.55^{* * *} \\ (0.73) \end{array}$ | $\begin{array}{r} -3.77^{* * *} \\ (0.63) \end{array}$ |  | $\begin{array}{r} -5.23^{* * *} \\ (1.02) \end{array}$ | $\begin{array}{r} -2.27^{* *} \\ (1.05) \end{array}$ |  | $\begin{array}{r} -4.24^{* * *} \\ (0.66) \end{array}$ | $\begin{array}{r} -2.11^{* * *} \\ (0.66) \end{array}$ |
| Basel III |  | $\begin{array}{r} 6.71^{* * *} \\ (2.22) \end{array}$ | $\begin{gathered} 4.78^{* *} \\ (2.22) \end{gathered}$ |  | $\begin{array}{r} 2.53 \\ (1.70) \end{array}$ | $\begin{array}{r} 1.41 \\ (1.72) \end{array}$ |  | $\begin{array}{r} 3.70^{* * *} \\ (0.69) \end{array}$ | $\begin{array}{r} 1.54 \\ (0.94) \end{array}$ |  | $\begin{array}{r} 2.66^{* * *} \\ (0.53) \end{array}$ | $\begin{gathered} 1.69^{* *} \\ (0.84) \end{gathered}$ |
| Volcker Rule |  | $\begin{array}{r} -6.35^{* * *} \\ (1.22) \end{array}$ | $\begin{array}{r} -7.09^{* * *} \\ (1.28) \end{array}$ |  | $\begin{array}{r} -3.03^{* * *} \\ (0.57) \end{array}$ | $\begin{array}{r} -3.40^{* * *} \\ (0.72) \end{array}$ |  | $\begin{array}{r} 1.40^{* * *} \\ (0.51) \end{array}$ | $\begin{array}{r} 3.44^{* * *} \\ (0.78) \end{array}$ |  | $\begin{array}{r} 0.88 \\ (0.76) \end{array}$ | $\begin{gathered} 2.04^{* *} \\ (0.85) \end{gathered}$ |
| Economic Events |  |  |  |  |  |  |  |  |  |  |  |  |
| Lehman Brothers |  | $\begin{array}{r} 9.43^{* * *} \\ (1.49) \end{array}$ | $\begin{array}{r} 6.97^{* * *} \\ (1.41) \end{array}$ |  | $\begin{array}{r} 5.12^{* * *} \\ (1.00) \end{array}$ | $\begin{array}{r} 3.94^{* * *} \\ (0.90) \end{array}$ |  | $\begin{array}{r} 4.70^{* * *} \\ (1.25) \end{array}$ | $\begin{array}{r} 1.67 \\ (1.09) \end{array}$ |  | $\begin{array}{r} 2.81^{* * *} \\ (0.93) \end{array}$ | $\begin{array}{r} 0.84 \\ (0.80) \end{array}$ |
| U.S. Downgrade |  | $\begin{array}{r} 6.46^{* * *} \\ (0.94) \end{array}$ | $\begin{array}{r} 5.63^{* * *} \\ (1.00) \end{array}$ |  | $\begin{array}{r} 3.41^{* * *} \\ (0.78) \end{array}$ | $\begin{array}{r} 2.84^{* * *} \\ (0.72) \end{array}$ |  | $\begin{gathered} 1.60^{* *} \\ (0.69) \end{gathered}$ | $\begin{aligned} & -0.48 \\ & (0.81) \end{aligned}$ |  | $\begin{array}{r} 1.34^{* * *} \\ (0.47) \end{array}$ | $\begin{array}{r} 0.03 \\ (0.43) \end{array}$ |
| Fed Tapering Announcement |  | $\begin{aligned} & 3.61^{*} \\ & (2.03) \end{aligned}$ | $\begin{array}{r} 6.95^{* * *} \\ (2.31) \end{array}$ |  | $\begin{gathered} 3.78^{* *} \\ (1.68) \end{gathered}$ | $\begin{array}{r} 5.18^{* * *} \\ (1.81) \end{array}$ |  | $\begin{array}{r} -6.38^{* * *} \\ (1.05) \end{array}$ | $\begin{array}{r} -7.54^{* * *} \\ (1.32) \end{array}$ |  | $\begin{array}{r} -3.23^{* * *} \\ (0.65) \end{array}$ | $\begin{array}{r} -4.78^{* * *} \\ (1.07) \end{array}$ |
| Start of Fed Tapering |  | $\begin{array}{r} 3.36^{* * *} \\ (0.76) \end{array}$ | $\begin{array}{r} 2.37^{* * *} \\ (0.63) \end{array}$ |  | $\begin{gathered} 0.99^{* *} \\ (0.41) \end{gathered}$ | $\begin{array}{r} 0.07 \\ (0.55) \end{array}$ |  | $\begin{array}{r} 1.88^{* * *} \\ (0.71) \end{array}$ | $\begin{array}{r} 0.80 \\ (0.64) \end{array}$ |  | $\begin{array}{r} 2.18^{* * *} \\ (0.72) \end{array}$ | $\begin{gathered} 1.80^{* *} \\ (0.77) \end{gathered}$ |
| Stock Spillovers |  |  | $\begin{array}{r} 0.52^{* * *} \\ (0.11) \end{array}$ |  |  | $\begin{array}{r} 0.42^{* * *} \\ (0.08) \end{array}$ |  |  |  |  |  |  |
| Corporate Bond Spillovers |  |  |  |  |  |  |  |  | $\begin{array}{r} 0.32^{* * *} \\ (0.06) \\ \hline \end{array}$ |  |  | $\begin{array}{r} 0.38^{* * *} \\ (0.05) \\ \hline \end{array}$ |
| Adjusted R-Squared | 0.20 | 0.68 | 0.74 | 0.14 | 0.55 | 0.62 | 0.18 | 0.69 | 0.74 | 0.11 | 0.53 | 0.60 |
| Observations | 393 | 393 | 393 | 393 | 393 | 393 | 393 | 393 | 393 | 393 | 393 | 393 |

## References

Acharya, V. V., Cooley, T., Richardson, M., Sylla, R., and Walter, I. (2011). The DoddFrank Wall Street Reform and Consumer Protection Act: Accomplishments and limitations. Journal of Applied Corporate Finance, 23(1):43-56.

Allen, F. and Gale, D. (2000). Financial contagion. Journal of Political Economy, 108(1):1-33.
Bai, J. (1997). Estimating multiple breaks one at a time. Economic Theory, 13(3):315-352.
Bai, J. and Perron, P. (1998). Estimating and testing linear models with multiple structural changes. Econometrica, 66(1):47-78.

Bai, J. and Perron, P. (2003). Computation and analysis of multiple structural changes models. Journal of Applied Econometrics, 18(1):1-22.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. Quarterly Journal of Economics, 131(4):1593-1636.

Bao, J., O'Hara, M., and Zhou, X. (2018). The Volcker Rule and market-making in times of stress. Journal of Financial Economics, 130(1):95-113.

Bayoumi, T. and Bui, T. (2012). Global bonding: Do U.S. bond and equity spillovers dominate global financial markets? IMF Working Paper No. 12/298. International Monetary Fund, Washington/DC.

Beaupain, R. and Heck, S. (2016). A repeat-sales index for pricing US corporate bonds. Finance, 37(2):75-117.

Belke, A. and Dubova, I. (2018). International spillovers in global asset markets. Economic Systems, 42(1):3-17.

BenSaida, A. (2019). Good and bad volatility spillovers: An asymmetric connectedness. Journal of Financial Markets, 43:78-95.

Bessembinder, H., Jacobsen, S., Maxwell, W., and Venkataram, K. (2018). Capital commitment and illiquidity in corporate bonds. Journal of Finance, 73(4):1615-1661.

Bongaerts, D., De Jong, F., and Driessen, J. (2011). Derivative pricing with liquidity risk: Theory and evidence from the credit default swap market. Journal of Finance, 66(1):203240.

Brennan, M. J., Chordia, T., Subrahmanyam, A., and Tong, Q. (2012). Sell-order liquidity and the cross-section of expected stock returns. Journal of Financial Economics, 105:523514.

Case, K. E. and Shiller, R. J. (1987). Prices of single family homes since 1970: New indexes for four cities. Working Paper, NBER.

Collet, J. and Ielpo, F. (2018). Sector spillovers in credit markets. Journal of Banking and Finance, 94:267-278.

Dastarac, H. (2020). Market making and proprietary trading in the U.S. corporate bond market. Working Paper, Banque de France.

Davidson, S. N. (2020). Interdependence or contagion: A model switching approach with a focus on latin america. Economic Modelling, 85:166-197.

De Santis, R. A. and Zimic, S. (2018). Spillovers among sovereign debt markets: Identification through absolute magnitude restrictions. Journal of Applied Econometrics, 33(5):727-747.

Dick-Nielsen, J. (2014). How to clean enhanced TRACE data. Technical report.
Dick-Nielsen, J. and Rossi, M. (2018). The cost of immediacy for corporate bonds. Review of Financial Studies, 32(1):1-41.

Diebold, F. X. and Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. International Journal of Forecasting, 28(1):57-66.

Diebold, F. X. and Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. Journal of Econometrics, 182(1):119-134.

Diebold, F. X. and Yilmaz, K. (2015). Financial and macroeconomic connectedness: A network approach to measurement and monitoring. .

Edwards, A. K., Harris, L. E., and Piwowar, M. S. (2007). Corporate bond market transaction costs and transparency. Journal of Finance, 62(3):1421-1451.

Ehrmann, M., Fratzscher, M., and Rigobon, R. (2011). Stocks, bonds, money markets and exchange rates: Measuring international financial transmission. Journal of Applied Econometrics, 26(6):948-974.

Fama, E. F. and French, K. R. (1989). Business conditions and expected returns on stocks and bonds. Journal of Financial Economics, 25(1):23-49.

Finta, M. A., Frijns, B., and Tourani-Rad, A. (2017). Contemporaneous spillover effects between the U.S. and the U.K. equity markets. Financial Review, 52(1):145-166.

Finta, M. A., Frijns, B., and Tourani-Rad, A. (2019). Volatility spillovers among oil and stock markets in the US and Saudi Arabia. Applied Economics, 51(4):329-345.

Forbes, K. (2012). The big C: Identifying contagion. Working Paper, NBER.
Forbes, K. J. and Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market comovements. Journal of Finance, 57(5):2223-2261.

Getter, D. (2014). The U.S. implementation of the Basel capital regulatory framework.

Gilchrist, S., Yankov, V., and Zakrajsek, E. (2009). Credit market shocks and economic fluctuations: Evidence from corporate bond and stock markets. Journal of Monetary Economics, 56(4):471-493.

Harris, L. E. and Piwowar, M. S. (2006). Secondary trading costs in the municipal bond market. Journal of Finance, 61(3):1361-1397.

Kiyotaki, N. and Moore, J. (1997). Credit cycles. Journal of Political Economy, 105(2):211248.

Koop, G., Pesaran, M., and Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. Journal of Econometrics, 74(1):119-147.

Newey, W. K. and West, K. (1987). A simple, positive semi-definite, heteroskedacity and autocorrelation consistent covariance matrix. Econometrica, 55(3):703-708.

Pesaran, H. and Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. Economics Letters, 58(1):17-29.

Rigobon, R. (2003). Identification through heteroskedasticity. The Review of Economics and Statistics, 85(4):777-792.

Thakor, A. (2012). The economic consequences of the Volcker Rule.
Trebbi, F. and Xiao, K. (2019). Regulation and market liquidity. Management Science, 65(5):1949-1968.

Wiesen, T. F. P., Beaumont, P. M., Norrbin, S. C., and Srivastava, A. (2018). Are generalized spillover indices overstating connectedness? Economics Letters, 173:131-134.

Yang, Z. and Zhou, Y. (2017). Quantitative easing and volatility spillovers across countries and asset classes. Management Science, 63(2):333-354.

## A Repeat sales methodology

Repeat-sales indices have at first been developed in the real estate market to account for the low trading frequency of houses and their large heterogeneity. The use of those indices has however extended to some securities' markets as well. In particular, it has been applied by Harris and Piwowar (2006) to municipal bond market transactions and by Edwards et al. (2007) to corporate bond market transactions. Both model individual returns as a function of an aggregate index return and several sub-indices returns, where indices are constructed with a repeat-sales technique. Beaupain and Heck (2016) use a repeat-sales methodology to construct U.S. corporate bond price indices. Using several performance tests, they show that this methodology provides superior index estimates. In particular when assets trade at infrequent and irregular intervals the repeat-sales index is superior to taking an arithmetic price average. Bongaerts et al. (2011) use the repeat-sales method to construct portfolio returns of CDS contracts.

Several repeat-sales methodologies exist. In this paper, we rely on the arithmetic price index which is built from price level data, as opposed to the geometric index, which uses logarithms of prices to obtain geometric averages. The arithmetic repeat-sales index is based on a simple regression of previous prices on current prices. In practice, all transactions of the dataset are considered as trade pairs (or repeat sales), where each pair has an opening and a closing date. The opening date is the date of the previous transaction on the bond and the closing date is the date of the current transaction. Similarly, each pair is considered along with its opening and closing prices. Only adjacent pairs are considered. If a bond trades four times for instance, one does not consider the trading pair between the first and third trade. The pairs are used to construct the vector of dependent variables $Y$ and the matrix of independent variables $X$. The $Y$ vector contains the opening price of the pair if the latter was opened in the base period and zero otherwise. The base period is the first period (in our case, the first week) of the sample. Each column of the $X$ matrix refers to one period of the sample, and the elements of $X$ are either prices or zeros. The arithmetic index is then defined as the reciprocal of the coefficient in the simple regression model, of $Y$ on $X$. The regression coefficient can be seen as a discounting factor and its inverse provides the index value. More details on the methodology as well as practical examples are provided in Beaupain and Heck (2016).


[^0]:    ${ }^{1}$ We also use the terms connectedness between firms or time series of connectedness.

[^1]:    ${ }^{2}$ Introduced in July 2002, TRACE consolidates transaction data for all eligible public and private corporate bonds (investment grade, high yield and convertible debt), agency debt, and securitized products. We use the academic corporate bond TRACE data containing historic transaction-level data on all transactions of corporate bonds reported to TRACE and disseminated with some lag.
    ${ }^{3}$ When more than one trade a week is available on a single issue, we retain the last trade of the week.

[^2]:    ${ }^{4} \mathrm{~A}$ brief outline of the history and methodology of repeat-sales price indexes is provided in Appendix A .

[^3]:    ${ }^{5}$ We outline the main steps and refer to the paper by Diebold and Yilmaz (2014) for further technical illustrations.

[^4]:    ${ }^{6}$ We show detailed results of the analysis of 2 -week and 10 -week forecast horizons. The results on the 26 -week forecast horizon are not shown to save space but are available upon request.

[^5]:    ${ }^{7}$ Unreported results of the forecast error variance decomposition at a 26 -week horizon further confirm that the 'own' transmission is even lower at the 26 -week forecast horizon than at the 10 -week forecast horizon.

[^6]:    

[^7]:    

[^8]:    ${ }^{8}$ The period from 23 June 2006 to 22 June 2007 is used to compute the first index value and there are therefore no weekly index observations over this starting period.

[^9]:    ${ }^{9}$ Our results are nevertheless unchanged under the assumption of homogeneous error distributions.

[^10]:    ${ }^{10}$ We report the contemporaneous relation between the two markets. However, the results are robust to including the lagged intensity of the other market as an explanatory variable.

