A Frequency-Specific Factorization to Identify Commonalities with an Application to the European Bond Markets*

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We propose a frequency-specific framework to link the common features in the multivariate high-frequency price jumps with the low-frequency exogenous factors. We introduce the measure of commonality and the measure of multiplicity based on high-frequency data and define the notions of co-arrivals and co-jumps to explore the contribution of individual assets. We employ the framework to study the 10-year high-frequency European government bond yields over June 2009-April 2019 as a function of macro-factors, macro-announcements, bond auctions and unconventional monetary policy announcements. Both idiosyncratic and common jump arrivals are significant, with the idiosyncratic arrivals being more sensitive to financial distress as characterised by a low level of commonality in jump arrivals.

Keywords: Co-arrivals, Co-jumps, European Government Yields, Macro-factors, Macro-announcements, Auctions, Unconventional Monetary Policy Announcements.

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1. Introduction

The European sovereign debt crisis highlights the fact that bond markets can be as volatile as equity markets, thus diminishing the sense of safety—risk-free asset status—in particular when yields diverge across countries. Bond markets determine the cost of long-term borrowing for governments and the overall perception of countries' fiscal stability. Moreover, government bonds are assets widely used by financial investors. The financial and econometric literature suggests that price jumps embody specific risks (see, e.g., Jarrow and Rosenfeld, 1984, and Pan, 2002), affect the pricing mechanisms of various financial instruments (see, e.g., Duffie et al., 2000, and Johannes, 2004) and provide a better explanation of credit and market risks (see, e.g., Carr and Wu, 2010).

The existing literature reports significant links between high-frequency government bond returns and news announcements: for instance, Andersen et al. (2007), de Goeij and Marquering (2006), and Beechey and Wright (2009) find a strong impact of the US-related news, especially that related to the real economy such as non-farm payroll news. There is also evidence of statistically significant links between bond markets and macroeconomic factors: Ludvigson and Ng (2009) and Lustig et al. (2014) show the importance of industrial production in explaining bond returns; Chatrath et al. (2014) study the link between currency jumps and news announcements, while Aizenman et al. (2013) examine the role of forward looking indicators given that bonds are inherently related to a country's future performance; Law et al. (2018) analyse the intraday future prices around the news announcements taking into account business cycle phases, showing the presence of jumps when significant announcements occur. The evaluation of the relationship between price jumps and macro-announcements has appeared rather recently in the literature: Lee (2012) and Boudt and Petitjean (2014) focus on equities; Dungey et al. (2009), Dungey and Hvozdyk (2012), and Jiang et al. (2011) consider bond markets; Bibinger and Winkelmann (2015) introduce a new method allowing to disentangle co-jumps from the continuous part of the dynamics of the price process, and the method is used by Winkelmann et al. (2016) to identify co-jumps associated to ECB monetary policy news on short and long-term interest rate futures; Lahaye et al. (2011) cover different asset classes; Patton and Verardo (2012) evaluate jumps in beta stocks following quarterly earnings announcements. Dewachter et al. (2014) reconcile the evidence on testing for the effects of news on jumps by either conditioning on the presence of jumps or conditioning on the timing of news arrivals. Finally, Pelger (2019a) proposes limiting theory to identify and estimate the number of continuous jump factors, and for high-frequency S&P 500 prices reports that systemic jump risk differs from systematic continuous risk (see also Pelger, 2019b).

The contribution of this paper is threefold. First, we propose the *measures of commonality* and *multiplicity* to capture the degree of association between price jump arrivals in the portfolio. We use these measures to test for price jumps that arrive randomly across the portfolio. Further, using frequency-specific factorization to treat idiosyncratic and common price jumps separately, we explicitly link the underlying high-frequency instantaneous intensities of the arrival processes to the low-frequency exogenous (macro-) factors.

Second, based on the co-feature framework introduced by Engle and Kozicki (1993), we propose the notion of *co-arrivals* defined as a linear combination of the arrival processes such that the aggregate number of arrivals is minimized. This notion is then used to define two additional co-arrival measures, the *index* and the *grade*, which assess the relative number of the eliminated total price jump arrivals and common price jump arrivals, respectively. The notion of co-arrivals is then extended to *co-jumps*, where the magnitude of the price jumps is taken into account as well. It relates to the portfolio optimization as it allows identifying the portfolio with a minimum contribution of price jumps such that it would not be exposed to shocks in the economy.

Third, we employ our proposed framework to the high-frequency time series of European sovereign debt markets using the 10-year benchmark bonds for Belgium, France, Germany, Italy, the Netherlands and Spain over the period June 2009 to April 2019 including the Great Recession, the European sovereign debt crisis, and subsequent period of Unconventional Monetary Policies. The link between the properties of price jumps and the state of the economy is estimated through the evaluation of the dependence of price jumps on the economic indicators such as unemployment, industrial production and economic sentiment, observed at a monthly frequency, and the aggregate monthly surprise carried by macro-announcements and government bond auctions.

This paper provides a novel framework to the common price jumps literature, complementing important contributions: Jacod and Todorov (2009) and Bollerslev et al. (2008) investigate co-jumps in high-frequency equities, Li et al. (2017) propose a piecewise linear regression framework able to model the market-wide price jumps as a function of shared factors, and Li et al. (2019) develop a rank test to study common price jump arrivals across assets. In addition, our theoretical framework is specifically built to deal with the commonality of price jump arrivals across a large portfolio of time series and links the high-frequency price jump arrivals to the real economy indicators measured at a lower frequency. Thus, our framework complements alternative approaches such both the MIxed DAta Sampling (MIDAS) literature, which links data at the daily frequency with data sampled at a lower frequency such as monthly or quarterly and the class of Spline GARCH models proposed by Engle and Rangel (2008) and Rangel and Engle (2012), which account for a slow-moving (low frequency) average level of volatility and for a high-frequency dynamics of the conditional distribution of returns.

The remainder of the paper is as follows. In Section 2, we introduce the frequency-specific framework, define the measures of commonality and multiplicity with their formal link to low-frequency exogenous factors and provide the foundations of co-arrivals and co-jumps. In Section 3, we describe the data used for the empirical application, summarize the testing procedures for price jump identification and we report the empirical results. Section 4 concludes.

2. Theoretical Framework

We model the vector of N log-prices as an N-dimensional vector $P = \left(P^{(1)}, \ldots, P^{(N)}\right)'$, where the vector $P = \{P_t\}_{0 \leq t \leq T}$ is defined on the N-dimensional probability space $\left(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t\geq 0}, \mathbb{P}\right)$ over the time interval $[0, T]$. The vector of log-prices is a semi-martingale, $\mathcal{F}_t$-adapted and its continuous-time dynamics can be specified by the following stochastic differential equation

$$dP_t = \mu_t dt + \sigma_t dB_t + d\mathcal{J}_t \,, \tag{1}$$

where μ_t, $\sigma_t^{(j,j')}$, dB_t and $d\mathcal{J}_t$ are well behaving objects. In particular, μ_t is $(N \times 1)$ vector of the drift processes with $\mu_t^{(j)}$, $j = 1, \ldots, N$, each $\mathcal{F}_t$-adapted, locally bounded and predictable processes. The matrix elements $\sigma_t^{(j,j')}$, with $j' = 1, \ldots, N$, are $\mathcal{F}_t$-adapted, càdlàg and almost surely bounded away from zero. The vector dB_t contains N independent $\mathcal{F}_t$-adapted standard Brownian motions $dB_t^{(j)}$. The term $d\mathcal{J}_t$ represents the $(N \times 1)$-dimensional vector of doubly stochastic Poisson processes composed of a stochastic, though linear, combination of the finite activity processes. Our specification is general enough that each asset can follow a specific Poisson process.

In what follows, we provide a frequency-specific factorization to link the high-frequency jump process of financial assets to the low frequency domain of the macroeconomic indicators.

2.1. Frequency-Specific Factorization

The jump term $d\mathcal{J}_t$ in (1), capturing the jump dynamics of n mutually correlated financial assets, can be factorized as follows

$$d\mathcal{J}_t : \underbrace{U_t dJ_t}_{(N\times 1)} = \underbrace{U_t}_{(N\times M)} \underbrace{dJ_t}_{(M\times 1)} , \tag{2}$$

where the matrix of jump magnitudes U_t contains $\mathcal{F}_t$-adapted random processes $U_t^{(i,m)}$ driven by an unspecified distribution $G_U^{(j,m)}$ with mean $\mu_U^{(j,m)}$ and standard deviation $\sigma_U^{(j,m)}$, with $m = 1, \ldots, M$, where M denotes the number of independent jump processes affecting the set of N assets. The M-dimensional vector dJ_t drives the arrivals of jumps, where every $dJ_t^{(m)}$ is either zero or one.

The distinction between idiosyncratic and common jumps is introduced by restricting the matrix U_t to be

$$U_t = \underbrace{\big(U_t^I}_{(N\times N)}, \underbrace{U_t^C\big)}_{(N\times(M-N))} , \tag{3}$$

where $U_t^I \equiv \text{diag}\left(U_t^{I(1)}, \ldots, U_t^{I(N)}\right)$ and the j-th diagonal term $U_t^{I(j)}$ is almost surely non-zero and finite if there are idiosyncratic arrivals for the j-th asset. On the other hand, the matrix process U_t^C has at least two almost surely non-zero elements in each column corresponding to common arrivals among assets. The separate treatment of the common and idiosyncratic jumps is confirmed by the empirical evidence presented in Bormetti et al. (2015), who conclude that even for the self-excited processes, the common price jumps found in the data cannot be triggered dynamically by mutual self-excitation and rather need a common driver.

The corresponding vector of arrivals is decomposed as

$$dJ_t' = \underbrace{\left(dJ_t^{(1)}, \ldots, dJ_t^{(N)}\right.}_{(1\times N)}, \underbrace{\left. dJ_t^{(N+1)}, \ldots, dJ_t^{(M)}\right)}_{(1\times(M-N))}, \tag{4}$$

assuming that $M > N$. $dJ_t^{(1)}, \ldots, dJ_t^{(n)}$, last part of the vector dJ_t, correspond to the idiosyncratic shocks, where the shocks remain almost surely idiosyncratic even if the underlying intensities are correlated. The remaining $dJ_t^{(N+1)}, \ldots, dJ_t^{(M)}$ components correspond to the common shocks as they are observed at an empirically relevant frequency.[4] Thus, we assume that the number of independent jump processes is greater than the number of assets. This apparent over-identification issue is caused by explicitly assuming two types of arrivals: idiosyncratic (arriving independently) and common (arriving from two or more assets at the same time).

Every $J_t^{(m)}$, with $m = N+1, \ldots, M$, drives a particular common pattern among a sub-set of time series. Further, we assume that at every time t, each column of the matrix process U_t^C has at least two fixed components with almost surely non-zero value. This ensures that U_t^C corresponds to the common jumps and is not contributing to the idiosyncratic shocks. In our model, we explicitly assume that common jumps are caused by a different mechanism as opposed to the one causing idiosyncratic price jumps. For instance, common price jumps can be interpreted as a reaction to macroeconomic news and sectoral shocks across a subset of assets. It is worth stressing that our approach is frequency-specific in the sense that all events which take place in the same time interval, i.e. 5-minute interval, are considered having the same timestamp.

In the next section, we assume a specific form of the price jump arrival process, which allows us to link the number of price jump arrivals to the exogenous low-frequency factors and establish the mixed-frequency framework.

[4]Though we use a continuous time framework to describe stylized facts as they are observed at a high-frequency domain and we assume perfect synchronicity in the jump arrivals, as in Aït-Sahalia et al. (2009) and Bollerslev et al. (2013), the framework is broad enough to encompass alternative multidimensional jump specifications with finite activity, as suggested in Barndorff-Nielsen and Shephard (2004, 2006), Lee and Mykland (2008), Andersen et al. (2012). Moreover, our framework relates to the one of Todorov and Bollerslev (2010) and Bollerslev et al. (2013), who discuss the distinction between common and idiosyncratic jumps following the same line of arguments.

2.2. Linking the High-Frequency Price Jump Arrivals to Low-Frequency Factors

We explicitly link the high-frequency price jump arrival processes to the low-frequency domain of the economic activity indicators. We have chosen the approach for modelling overall price jump arrivals as a factor of the low-frequency economic situation as we are interested to observe macro-economic dynamics without need to account for micro-structure effects. It can be perceived as a choice of time scale on which we perform our analysis.

We consider the M-dimensional arrival vector J_t at time t from equation (4) to be composed of mutually independent, doubly stochastic Poisson processes given as $X_t^{(m)} = \int_0^t dX_\tau^{(m)}$, with $m = 1, \ldots, M$, each driven by the instantaneous stochastic intensity $d\Lambda_{t,\mathcal{I}}^{(m)} = E\left[dX_t^{(m)} | \mathcal{I}_{t-}\right]$, conditional on the information set $\mathcal{I}_{t-}$, which denotes the information available up to time t, exclusive. The integrated stochastic intensity is then given as $\Lambda_{t,\mathcal{I}}^{(m)} = \int_0^t d\Lambda_{t,\mathcal{I}}^{(m)}$. The M-dimensional intensity process $\Lambda_{t,\mathcal{I}}$ can in general be mutually correlated; however, the price jump arrivals are drawn independently. The choice of the doubly stochastic Poisson processes allows us to explicitly link the high-frequency process with the low-frequency process driving the information set $\mathcal{I}_t$.

To establish the formal mixed-frequency link between the intensity process and the underlying macro-factors, let us focus on $d\Lambda_{t,\mathcal{I}}^{(m)}$ corresponding to the arrival process $X_t^{(m)}$. We assume a specific functional form of the intensity process as suggested by Lee (2012). The continuous-time extension of such an instantaneous intensity process at time t conditional on the information set $\mathcal{I}_{t-}$ takes the form

$$d\Lambda_{t,\mathcal{I}}^{(m)} = \frac{1}{\alpha_0 + \alpha_1 Z_t} dt \,, \tag{5}$$

where Z_t indicates a predictor variable of the price jump arrivals at time t, which incorporates all the information available up to time t, i.e., based on the information set $\mathcal{I}_{t-}$. Further, we assume that the parameters α_0 and α_1 are chosen such that the denominator is always positive. We consider the predictor variable to be a binary variable capturing the information about the presence of shock, revealed to markets at time t. We denote the random times when the shocks arrive as $t_1, \dots, t_L \in [0, T]$, with N_T being the random integer.

In the low-frequency domain, we are interested in the aggregate effect of the instantaneous intensity (5) over a certain time domain. This can be achieved by considering integrals of the intensity, as was done for instance in Lee and Wang (2020). The integrated intensity thus represent the main building block in the low-frequency domain and its suitable parametrisation is provided below.

We assume the definition of the (integrated) intensity process over the time window $[0, T]$ be linked to the instantaneous intensity in the instantaneous interval dt as

$$\int_0^T d\Lambda_{t,\mathcal{I}}^{(m)} = \int_0^T \frac{1}{\alpha_0^{(m)}} dt + \int_0^T \sum_{l=1}^{N_T} \frac{1}{\alpha_0^{(m)} + \alpha_1^{(m)}} \delta\left(t - t_l\right) dt \,, \tag{6}$$

where δ stands for the delta-function. Thus, the expected number of price jump arrivals of the process $J_t^{(m)}$ in the time interval $[0, T]$ is

$$E_{[0,T]}\left[N^{(m)}\right] = \int_0^T \frac{1}{\alpha_0^{(m)}} dt + \sum_{l=1}^{N_T} \frac{1}{\alpha_0^{(m)} + \alpha_1^{(m)}} = c_0^{(m)} + c_1^{(m)} N_T \,, \tag{7}$$

where N_T is a random integer, $c_0^{(m)} = T/\alpha_0^{(m)}$ and $c_1^{(m)} = 1/\left(\alpha_0^{(m)} + \alpha_1^{(m)}\right)$, and the expectations are conditional given the information available up to and including time T. Such a set-up corresponds to the doubly stochastic Poisson process and is based on the stochastic intensity employed by Lee (2012), Lee and Wang (2020) to explain the drivers for the price jump arrivals in high-frequency DJIA equities. In addition, correlations between the components of $d\Lambda_{t,\mathcal{I}}^{(m)}$ come in a straightforward manner through the dependence on the set of shared predictors.

Equations (6) and (7) express the high-frequency price jump arrival process as a function of the predictor variables and of the low-frequency number of price jump arrivals for a given period. The number of price jump arrivals depends on the number of shocks arriving at the economy. Considering the huge amount of information arriving at the markets, it is impossible to control for all these shocks directly. Therefore we model the number of shocks for a given period as a function of the prevailing low-frequency exogenous factors.

We model the link between the realized number of high-frequency price jumps and the low-frequency exogenous factors as follows. We split the time interval $[0, T]$ into K equidistant sub-periods $[T_{k-1}, T_k]$, with $0 = T_0 < \cdots < T_K = T$. The total number of shocks of the jumps arrival process J during each sub-period, N_k, is then assumed to be a function of the low-frequency exogenous factors, $f\left(\Upsilon_k^{(1)}, \ldots, \Upsilon_k^{(S)}\right)$, where $\Upsilon_k^{(s)}$, with $s = 1, \ldots, S$, is the value of the s-th exogenous factor during the period $[T_{k-1}, T_k]$. Further, we consider each $[T_{k-1}, T_k]$ to correspond to a calendar month and $f\left(\Upsilon_k^{(1)}, \ldots, \Upsilon_k^{(S)}\right)$ to be a linear function. Under such a setting, equation (7) gives the following specification linking the two mixed-frequency domains

$$N_{[T_{k-1},T_k]}^{(m)} = \beta_0^{(m)} + \sum_{s=1}^{S} \beta_s^{(m)} \Upsilon_k^{(s)} + \varepsilon_k \,, \tag{8}$$

where $N_{[T_{k-1},T_k]}^{(m)}$ represents a total number of price jump arrivals from the process $P_t^{(m)}$.

In the next section, we define the measure of commonality and the measure of multiplicity, which allow us to assess the degree of association between high-frequency price jump arrivals for a set of n assets. We then use the mixed-frequency framework to link the two measures to low-frequency market factors.

2.3. Commonality and Multiplicity

Let us consider an N-dimensional vector of assets to describe the commonality in the price jump arrival processes for a sub-period $[T_{k-1}, T_k] \subset [0, T]$.

2.3.1. The Measure of Commonality

The *measure of commonality* is defined as the ratio of common price jump arrivals to all arrivals from the aggregate—or portfolio—perspective. It asserts the probability of a price jump arrival observed at any asset to be accompanied by a jump at other asset(s).

For an N-dimensional process P_t specified by (1) in the time interval $[T_{k-1}, T_k]$, the measure of commonality is defined as

$$Q_{[T_{k-1},T_k]} = \frac{N^{(2+)}_{[T_{k-1},T_k]}}{N_{[T_{k-1},T_k]}}\,, \tag{9}$$

where $N_{[T_{k-1},T_k]}$ corresponds to the number of distinct price jump arrival times, and $N^{(2+)}_{[T_{k-1},T_k]}$ is the number of all distinct common price jump arrival times. In particular, $Q_{[T_{k-1},T_k]}$ measures the ratio of the aggregate intensity of the common Poisson processes to the overall aggregate intensity of all Poisson processes in the n-dimensional process P_t. The measure of commonality takes values $Q_{[T_{k-1},T_k]} \in [0,1]$, where $Q_{[T_{k-1},T_k]} = 0$ denotes the case when all arrivals are idiosyncratic , while $Q_{[T_{k-1},T_k]} = 1$ corresponds to the case when idiosyncratic arrivals are completely absent. Note that the measure of commonality $Q_{[T_{k-1},T_k]}$ can be interestingly linked to the standard Pearson correlation coefficient for ϕ.

2.3.2. The Measure of Multiplicity

The *measure of multiplicity* estimates the average multiplicity of each arrival across the portfolio. It asserts how many assets jump on average, given that we observe a jump for any of the assets.

For an n-dimensional process P_t specified by (1) in the time interval $[T_{k-1}, T_k]$, the measure of multiplicity is defined as

$$Q^{\mu}_{[T_{k-1},T_k]} = \frac{\sum_{j=1}^{N} NJ^{(j)}_{[T_{k-1},T_k]}}{N_{[T_{k-1},T_k]}}\,, \tag{10}$$

where $NJ^{(j)}_{[T_{k-1},T_k]}$ corresponds to the number of all distinct price jump arrival times for the asset j. To have the measure of multiplicity independent of the number of assets, we standardize $Q^{\mu}_{[T_{k-1},T_k]}$ by the number of assets

$$\bar{Q}^{\mu}_{[T_{k-1},T_k]} = \frac{Q^{\mu}_{[T_{k-1},T_k]}}{N} \,. \tag{11}$$

The standardized measure of multiplicity takes values $\bar{Q}^{\mu}_{[T_{k-1},T_k]} \in [0,1]$, where $\bar{Q}^{\mu}_{[T_{k-1},T_k]} = 1/N$ occurs only in the case of idiosyncratic arrivals, while $Q^{\mu}_{[T_{k-1},T_k]} = 1$ for the portfolio wide arrivals.

To link the number of price jump arrivals and the low-frequency factors, we proceed as follows: we split the time interval $[0,T]$ into K sub-periods $[T_{k-1},T_k]$ and for each period we calculate $Q_{[T_{k-1},T_k]}$ and $\bar{Q}^{\mu}_{[T_{k-1},T_k]}$. Each of the two measures is based on the particular combinations of the number of price jump arrivals. Therefore, following specification (8), we link the measures, $Q_{[T_{k-1},T_k]}$ and $\bar{Q}^{\mu}_{[T_{k-1},T_k]}$, to the exogenous low-frequency factors, $\left(\Upsilon^{(1)}_k, \ldots, \Upsilon^{(S)}_k\right)$. In particular, we consider a linear approximation such as

$$\begin{aligned} Q_{[T_{k-1},T_k]} &= \beta^q_0 + \sum_{s=1}^{S} \beta^q_s \Upsilon^{(s)}_k + \varepsilon^q_k \,, & (12)\\ \bar{Q}^{\mu}_{[T_{k-1},T_k]} &= \beta^{q\mu}_0 + \sum_{s=1}^{S} \beta^{q\mu}_s \Upsilon^{(s)}_k + \varepsilon^{q\mu}_k \,. & (13) \end{aligned}$$

The measures of commonality and multiplicity capture the common properties of price jump arrivals; in a first step the high-frequency information extracted from the time series is aggregated at a monthly level; in a second step, this information is regressed on low-frequency factors. The two measures provide an overall picture of jumps commonality without identifying the contribution of each asset.

2.3.3. Critical values for commonality and multiplicity measures

To identify standardized statistics, i.e. critical values, for the commonality and multiplicity measures, we formulate a null hypothesis of no true common arrivals across the assets and construct the critical values.

In the simulation exercises, performed for three assets, the underlying data generating process is a stochastic volatility model with intraday volatility patterns as proposed in Andersen et al. (2012):

$$
\begin{aligned}
d\log P_t^{(i)} &= u_t \sigma_t^{(i)} dW_t^{(i)} + U_{P,t}^{(i)} dJ_{P,t}^{(i)}\,, && (14)\\
d\sigma_t^{(i)2} &= \kappa^{(i)}\left(\theta^{(i)} - \sigma_t^{(i)2}\right)dt + \omega^{(i)}\sigma_t^{(i)} dB_t^{(i)} + U_{\sigma,t}^{(i)} dJ_{\sigma,t}^{(i)}\,, && (15)\\
E\left[dW_t^{(i)} dB_t^{(i)}\right] &= \rho^{(i)} dt\,, && (16)\\
E\left[dW_t^{(i)} dB_t^{(j)}\right] &= 0\,,\ i \neq j\,, && (17)\\
E\left[dW_t^{(i)} dW_t^{(j)}\right] &= \rho_W^{(i,j)} dt\,, && (18)
\end{aligned}
$$

where $i = 1, \ldots, 3$, and

$$
u_t = c_1 + c_{open}\exp\left(-a_{open}\left(t - t_{open}\right)\right) + c_{close}\left(-a_{close}\left(t_{close} - t\right)\right)\,,
$$

where t denotes the time in the trading day, t_{open} is the opening time, t_{close} is the closing time and parameters are set as $c_1 = 0.8892$, $c_{open} = 0.75$, $c_{close} = 0.25$, $a_{open} = 10$, and $a_{close} = 10$. We consider the same volatility pattern for each asset. The parameters for each asset are the same: $\kappa^{(i)} = \kappa = 0.0162$, $\theta^{(i)} = \theta = 0.573$, $\omega^{(i)} = \omega = 0.58$, and $\rho^{(i)} = \rho_{vol} = -0.46$. This ensures that the portfolio has N assets of the same type. The correlation coefficients, $\rho_W^{(i,j)}$, are the same for all pairs with values $\rho_W^{(i,j)} = 0.2$. The magnitude $U_{P,t}^{(i)}$ is set relative to the prevailing level of stochastic volatility as $U_{P,t}^{(i)} = \nu\sigma_{t-}^{(i)}$, where $\sigma_{t-}^{(i)}$ is the prevailing volatility immediately before the jump occurs and ν is the parameter common to all assets, for which we consider $\nu_i = 4$, $\nu_i = 8$, and $\nu_i = 12$, respectively, for all i. The magnitude of the volatility jumps $U_{\sigma,t}^{(i)}$ follows for every i an exponential distribution with mean $\mu_\sigma = 1.25$. For every asset, we assume that $U_{\sigma,t}^{(i)}$ is drawn independently of each other. Further, for each asset i, the arrival process $dJ_{P,t}^{(i)}$ and $dJ_{\sigma,t}^{(i)}$ is assumed to be driven by the same stochastic intensity function $d\Lambda_t^{(i)}$. The realization of the price jump arrival is drawn independently. We thus use a stochastic volatility model calibrated by Eraker (2004) to equity markets, which is also used by Lee (2012).

We consider the null hypothesis to be one price jump arrival per asset per day, where the arrival times are strictly different from each other. We estimate the price jump arrivals using the Lee and Mykland (2008) procedure and evaluate the measure of commonality and multiplicity.

The simulation design is as follows: We set the number of days per month and simulate 1,100 months under the null hypothesis; The first 100 months are used to properly initialize the simulation and therefore are discarded. For each of the 1,000 months, we estimate the measure of commonality and multiplicity and record the 90-*th*, 95-*th*, 99-*th* and 99.9-*th* percentiles. We consider 5, 10, and 20 days per month, respectively.

[Table 1 should be inserted here]

Table 1 reports the results of the simulation exercise. The percentiles can be used as critical values in the empirical application to test the null hypothesis of independence for the arrival of price jumps across a portfolio[5].

[5]It is worth noticing that the measures of commonality and multiplicity introduced here are strongly related to the networks literature. Diebold and Yılmaz (2014) show how VAR literature maps into networks. It also offers some very strong linkages with our paper, i.e., commonality and multiplicity,

2.4. Co-arrivals

We now follow the co-feature framework introduced by Engle and Kozicki (1993) and define the notion of co-arrivals as a linear combination of price jump arrivals which eliminates them in the aggregate index.

Let us consider the following mapping

$$P_t^{(j)} \to j_t^{(j)} = \begin{cases} 1 & \text{if price jump is present} \\ 0 & \text{otherwise} \end{cases} \quad , \; j = 1, \ldots, N \tag{19}$$

where the N-dimensional log-price process P_t maps into an N-dimensional indicator process j_t.

For an N-dimensional log-price process P_t from (1) mapped into the vector j_t using (19) for the time interval $[T_{k-1}, T_k] \subset [0, T]$, *co-arrival* is defined as the non-zero vector $w = \left(w^{(1)}, \ldots, w^{(N)}\right)'$ such that $N_{[T_{k-1},T_k]}^{(w)}$ is minimized, where $N_{[T_{k-1},T_k]}^{(w)} = \sum_c \mathbf{1}\left(w' j_{t_c} \neq 0\right)$ and the sum runs over all non-zero elements of the indicator time series j_t. The vector of weights, w, is the *co-arrival vector*.

The notion of co-arrivals is thus defined as the solution to the minimization problem

$$w = \arg\min_{\tilde{w}} \sum_c \mathbf{1}\left(\sum_{m=1}^{M} \tilde{w}^{(m)} j_{t_c}^{(m)} \neq 0\right), \tag{20}$$

conditioned on w being non-zero.

The interesting case to explore occurs when all price jump arrivals are eliminated, i.e. $N_{[T_{k-1},T_k]}^{(w)} = 0$. Such a situation can be tested using the following rank test

allowing to establish some relationships between the two measures we introduced here and centrality measures proposed in network theory, i.e. measures of connection and paths. For instance, the measure of commonality is closely related to the measures of connectivity commonly used in the network literature, while the measure of multiplicity seems to be connected to a form of centrality.

$$H_0 : \text{rank}\,(\mathbf{J}) = N\,,\; H_A : \text{rank}\,(\mathbf{J}) < M\,, \tag{21}$$

where the matrix $\mathbf{J}$ contains the realization of the indicator process j_t over the time interval $[T_{k-1}, T_k]$, keeping only the non-zero elements. Due to the finite activity of the arrival processes, there is almost surely a finite number of non-zero columns in the matrix $\mathbf{J}$.

Based on the notion of co-arrivals, we define two additional measures for every co-arrival vector: the *index* and the *grade.* In the same way as in (9) and (11), we split the time interval $[0, T]$ into K sub-periods $[T_{k-1}, T_k]$ and calculate the two measures.

The Index. The *index* evaluates how successful the co-arrival vector is in eliminating the jump arrivals from the composite index. For an M-dimensional process P_t specified by (1) in the time interval $[T_{k-1}, T_k]$ and the co-arrival vector w, the index is given by

$$i_{w,[T_{k-1},T_k]} = \frac{N_{[T_{k-1},T_k]} - N^{(w)}_{[T_{k-1},T_k]}}{N_{[T_{k-1},T_k]}}\,, \tag{22}$$

where $N^{(w)}_{[T_{k-1},T_k]}$ corresponds to the number of all distinct price jump arrivals where w is a solution to problem (20).

The *index* can be interpreted as a measure of the ratio of the aggregate intensities of the stochastic Poisson processes, which are removed from the composite index, to the overall aggregate intensities of all Poisson processes involved. The index takes values $i_{w,[T_{k-1},T_k]} \in [0, 1]$, with $i_{w,[T_{k-1},T_k]} = 0$ corresponding to the case of no elimination of arrivals captured by the co-arrival vector, while the case of $i_{w,[T_{k-1},T_k]} = 1$ specifies the full elimination of arrivals by the co-arrival vector w. If the null of (21) is rejected, then $i_{w,[T_{k-1},T_k]} < 1$. This measure considers both idiosyncratic and common arrivals, as defined in (2).

The Grade. The *grade* quantifies the elimination of the common jump arrivals from the composite index. For an M-dimensional process P_t specified by (1) in the time interval $[T_{k-1}, T_k]$ and the co-arrival vector w, the *grade* is given by

$$g_{w,[T_{k-1},T_k]} = \frac{N^{(2+)}_{[T_{k-1},T_k]} - N^{(w;2+)}_{[T_{k-1},T_k]}}{N^{(2+)}_{[T_{k-1},T_k]}}, \tag{23}$$

where $N^{(w;2+)}_{[T_{k-1},T_k]}$ corresponds to the number of all distinct common price jump arrivals where w is a solution to (20).

The *grade* can be interpreted as a ratio of the aggregate intensity of the common Poisson processes, which are not present in the composite index, to the overall aggregate intensity of all common Poisson processes in the N-dimensional process Y_t. The *grade* focuses solely on the common arrivals in (2) and ignores the idiosyncratic arrivals. The *grade* takes values $g_{w,[T_{k-1},T_k]} \in [0,1]$, with $g_{w,[T_{k-1},T_k]} = 0$ corresponding to the case where none of the co-arrivals was eliminated by the vector w, while $g_{w,[T_{k-1},T_k]} = 1$ indicates that all co-arrivals were eliminated in the composite index. Both measures therefore provide additional information on how many (co-)arrivals were eliminated due to the co-arrival vector w.

Once again, the introduction of the *grade* measure allows to establish a relationship between our framework and the network literature, in particular with delta-networks discussed in Acemoglu et al. (2015) and considering the key linkages between networks within a larger network. We will be more specific on this point in the empirical section of the paper.

The test for co-arrivals can be thought as an extension of the univariate testing methodology proposed by Dumitru and Urga (2012) adopting the testing framework proposed in Neuhäuser (2003) and Harvey et al. (2009, 2012), who combine independent p-values using the union of rejections decision rule, and the combination of independent p-value combinations as discussed in Loughin (2004) and Sheng and Cheng (2017).

2.5. Co-Jumps

So far, we have exploited the commonality in the price jump arrivals. We now consider the magnitude of price jumps and introduce the notion of co-jumps.

Let us now consider the $\hat{G}$-statistic as introduced by Barndorff-Nielsen and Shephard (2006):

$$\hat{G} = M^{1/2} \frac{\widehat{IV}_M - \widehat{QV}_M}{\widehat{IQ}_M}, \tag{24}$$

where $\widehat{IV}_M$ is the estimator of the Integrated Variance $\left(\widehat{IV}_M \xrightarrow{p} \int_0^t \sigma_s^2 ds\right)$, $\widehat{QV}_M$ is the estimator of the Quadratic Variance $\left(\widehat{QV}_M \xrightarrow{p} \int_0^t \sigma_s^2 ds + \sum_{j=1}^{N_t} c_j^2\right)$, $\widehat{IQ}_M$ is the estimator of the Integrated Quarticity $\left(\widehat{IQ}_M \xrightarrow{p} \int_0^t \sigma_s^4 ds\right)$. For a univariate log-price process P_t generated by (1), under the null hypothesis of no price jumps, $\hat{G} \xrightarrow{\mathcal{D}} N(0, \vartheta)$ with $\xrightarrow{\mathcal{D}}$ denoting a stable convergence in law and ϑ being some known constant depending on the particular choice of the estimator used.

Thus, for the N-dimensional process P_t in the interval $[0, T]$ there is a co-jump if a vector w exists such that the $\hat{G}$-statistic for the univariate process wP_t does not reject the null hypothesis. The asymptotic properties of the $\hat{G}$-statistic under the null hypothesis hold true when there is no discontinuous part of the price process wP_t. This follows from the M-dimensional process P_t being closed under the linear combination in terms of its properties and therefore the $\hat{G}$-statistic can be applied for any linear combination of P_t as well.

Given the properties of the $\hat{G}$-statistic, we define co-jumps as follows.

Co-jumps. For an M-dimensional log-price process P_t from (1) in the time interval $[T_{k-1}, T_k] \subset [0, T]$, the *co-jump* is defined as the non-zero linear combination $w = \left(w^{(1)}, \ldots, w^{(N)}\right)'$, such that the null hypothesis of the $\hat{G}$-statistic for $w'P_t$, denoted as the $\hat{G}^{(w)}$-statistic, cannot be rejected. The vector w is called the *co-jump vector*.

In the case of complex common price jump patterns or the presence of idiosyncratic price jumps for each component of P_t, the null may be rejected for every w. In such a case, we proceed to identify co-jumps as a solution to an optimization problem analogous to (20), where the objective function is the p-value of the $\hat{G}^{(w)}$-statistic to be minimized as the null hypothesis of the test is no price jumps.

2.5.1. Monte Carlo Exercise

For each scenario, we simulate 1,100 trading days and consider 5 alternative scenarios of price jumps occurring across three times series:

Scenario 1 (Co-jumps) Price jumps are perfectly aligned, arriving at random.

Scenario 2 (No co-jumps) Price jumps occur at random but at distinct times.

Scenario 3 (Sequence of jumps) Price jump of the first time series occurs in the first 5-minute interval of the trading day, the price jump of the second time series occurs in the second 5-minute interval of the trading day, and the price jump of the third time series occurs in the third 5-minute interval of the trading day.

Scenario 4 (Distant jumps) Price jumps arrive far from each other. Specifically, the price jump of the first time series occurs in the first 5-minute interval of the trading day, the price jump of the second time series occurs in the 39-th 5-minute interval of the trading day, and the price jump of the third time series occurs in the last 5-minute interval of the trading day.

Scenario 5 (No jumps) This is the baseline case with no price jumps.

Table 2 reports the size and the power of the co-jumps $\hat{G}^{(w)}$-statistic for Scenarios 1-5 using two significance levels of the test. First, we set $\alpha = 0.05$; Second, we employ the correction proposed by Bajgrowicz et al. (2016) for the multiple testing bias consisting of $\alpha = \left(1 - \Phi\left(\sqrt{2 \cdot \log \tilde{N}}\right)\right) = 1.008 \cdot 10^{-4}$, where $\tilde{N}$ denotes the number of trading days in the simulated sample. This should correct for any false price jump detection.

The results for Scenario 1 show that the power of the test is slightly higher compared to the univariate test. Thus, testing for the co-jumps in the case of true co-jumps is more efficient than if we were testing for jumps in the single time series. The size of the co-jump test is further evaluated under Scenarios 2-5. In the benchmark case of no price jumps (Scenario 5), the size improves as compared to the univariate test and it is well below α. When there are some price jumps, but no true co-jumps (Scenarios 2-4), the test is oversized as compared to the univariate test (see in particular the results of Scenario 2). This can be explained by the nature of the Bipower test. If two price jumps arrive in sequence, the Bipower Variation is biased upwards and thus does not consider them as two price jumps, but rather as a regime with increased volatility. From the empirical perspective, however, such an error is not as severe as false detection of co-jumps with distant price jumps (Scenario 4). The sequence of price jumps resembles the delayed co-jumps and tends to be caused by a single source, thus representing a systemic response rather than a set of independent idiosyncratic shocks. Let us also point out that the multiple testing bias correction has a significant effect on the power of the test with smaller price jumps. As the magnitude of price jumps increases, the power converges towards the uncorrected test.

[Table 2 should be inserted here]

3. Empirical Results

3.1. Data

In this section, we describe the main characteristics of government bond yields used in this study. We then review the macro-factors, news announcements and bond auctions employed as the explanatory variables. The details of the data selection and the overview statistics for each set of variables can be found in the Internet Appendix. The choice to focus our attention on European government bond yields following the evolution after the sovereign crisis and in particular the era of the unconventional monetary policies, which shaped the European fixed income market for a number of years. Our data set thus spans from June 2009 until April 2019 and covers the whole period of European sovereign debt crisis, which started just after the end of the financial crisis and lasts at a certain level until now (end of 2019).

The creation of the common monetary union, spreads between European countries converged to close levels. However, the subprime crisis in 2007 set a turning point and government yields spiralled in parallel with the rise in global financial instability. In 2008 and 2009, interest rate differentials became sizeable but it was in 2010 and 2011 that they went back to the levels (or even higher) than those of the pre-Euro era: in only four years the EMU bond markets moved from a situation of stability and tranquillity to a very worrying turmoil phase. The resulting remarkable compression of sovereign risk premium differentials, experienced in the first years of the Euro era, raised doubts about financial markets ability to provide fiscal discipline across Euro area members, to discriminate between the qualities of fiscal policies and to be coherent with economic rationality. Starting from the sovereign debt crisis, this ability was by far regained by markets which became more careful in monitoring the fiscal performance of member states and restarted to exert disciplinary pressure on their governments. While in the previous period the main concern was that government spreads were too low and too close, the question during the sovereign crisis was whether the high spreads reflected the fundamentals of a country or whether they also responded to a regime shift in the market pricing of government credit risk. Understanding what has prompted recent developments in sovereign risk is particularly relevant for policymaking in particular for the macroeconomic consequences that their movements can have. Persistently higher spreads could, in fact, have a major impact on many Euro area governments marginal funding costs, possibly undoing the benefits.

3.1.1. Yields

We consider bid data for the 10-year government bonds of Belgium, France, Germany, Italy, the Netherlands and Spain over the period from June 2009 to April 2019. We choose 10-year maturities as Attinasi et al. (2011) and Bikbov and Chernov (2010) provide evidence that long-term maturities are more sensitive to macro-factors relative to short term maturities. The set of countries is determined by consideration of market depth. We study quotes bid prices, rather than mid quotes, data as more representative of the spreads during crisis periods because it better reflects the market value of bonds. During crisis periods, the flow is one side where investors tend to liquidate their bonds exposure. The 10-year bonds are market benchmarks defined as the most active at that maturity. Data were provided by Morningstar and come at a tick-by-tick frequency which we re-sampled at 5-minute frequency using calendar time and excluding time intervals with values missing for at least one country. The 5-minute frequency is robust to micro-structure noise while offering sufficiently high frequency to properly evaluate the impact of specific events. The trading period considered in this paper is from 8:00 a.m. to 3:30 p.m. (UTC). We remove outliers by applying a filter which is very close to the one proposed in Brownlees and Gallo (2006) and further elaborated by Barndorff-Nielsen et al. (2011, p. 156).

Note that although some literature since the 2008 crisis has moved to analyse Credit Default Swaps (CDS) data in preference to bonds due to the problems of very low interest rates, CDS markets are thinner than conventional government bonds markets. CDS reflects an insurance premium on a notional outstanding amount, thus offers an alternative view of the market's perception of default risk.

3.1.2. *Macro-factors*

We employ two real economy indicators, unemployment and industrial production, and a forward-looking indicator, the economic sentiment (ES).[6] We use vintage data as available on the date of release. Our choice is motivated by the existing literature, for example Mody (2009) and Aizenman et al. (2013); industrial production is often found to be particularly relevant to describe asset behaviour in a number of studies, for example Schwert (1989), Ludvigson and Ng (2009) and Lustig et al. (2014). Data are obtained from Eurostat. Time series of unemployment and industrial production are non-stationary and thus they are used as a rate of change.

3.1.3. *Macro-announcements*

We consider macro-announcements related to the US, the Euro area, Belgium, France, Germany, Greece, Italy, the Netherlands, Portugal and Spain. In some cases, we are unable to use all available macro-announcements as they are released when markets are still closed. For instance, this is the case of France with releases occurring between 6:30 and 7:45 a.m. UTC. Data related to macro-announcements are median expected value by survey of panellists E, forecasts standard deviation σ and actual value of the release denoted as A. Data are collected from Bloomberg. In our application, we adopt the standard surprise measure ζ defined as

$$\zeta = \frac{(A - E)}{\sigma} \, . \tag{25}$$

3.1.4. *Auctions*

We consider auctions of European countries issuing Euro-denominated bonds: Austria, Belgium, France, Germany, Italy, the Netherlands, Portugal and Spain. Most

[6] Economic sentiment is provided by Eurostat and is a weighted index comprising five sectoral confidence indicators: industrial confidence, services confidence, consumer confidence, construction confidence, and retail trade confidence indicators.

auctions take place between 8 and 10 a.m. UTC. To capture the performance of an auction, we consider the average yield at which the government sells the bonds. Average yields were collected just for auctions relative to 10-year bonds as they not only correspond to the maturity of the bonds analysed but they even account for the most part of issues and they are considered a standard indicator of long-term interest rates.

3.1.5. Unconventional Monetary Policy Announcements

We consider the unconventional monetary policies (UMP) as another set of events which have been shaping the European government bond space following the sovereign debt crisis. The UMP is in general understood to be any policy which affects the cost of finance for market participants, see Bubeck et al. (2018), Falagiarda and Reitz (2013) and Falagiarda and Reitz (2015). UMPs have been usually announced during the dedicated announcement events or public speeches. We consider the moment of its announcement as the defining event for a policy. During its announcement, markets adjust to the new reality and price in the anticipated effects. In the Internet Appendix, we provide more details about the selected UMPs.

In order to illustrate the empirical validity of our methodology introduced in Section 2, first, we identify price jump arrivals using the Lee and Mykland (2008) test (LM henceforth), where the volatility is adjusted by its intraday pattern as suggested by Andersen and Bollerslev (1998). In addition to the dating of the jump arrivals, we also need a test statistic which allows us to decide on the significance of jump(s) over a certain time interval $[T_{k-1}, T_k]$. To this purpose, we employ the $\hat{G}^{(w)}$-statistic.

3.2. Frequency-specific Factorization

We empirically validate the frequency-specific framework (3) and (4) and show that idiosyncratic and common price jump arrivals have different drivers. Figure 1 reports the cross-sectional average of the arrivals per month. It shows that in the aftermath of the Lehman Brothers collapse, the number of jump arrivals significantly increases. Then, following the tranquil period from June 2009 to April 2010, the overall number of arrivals increases again as the European debt crisis emerged with the Greek bailout in May 2010. The number of jump arrivals spiked in mid-2012 and then reverted back and stayed stable for the remainder of the period considered in this study.

[Figure 1 should be inserted here]

In order to find a link between the price jump arrivals and macro-economy, we test specification (8), where we focus on the difference between the idiosyncratic and common arrivals. For every asset j, the common arrivals are defined in this case as all price jump arrivals from $dP_t^{(N+1)}, \ldots, dP_t^{(M)}$ present at asset j.

We estimate the following specification

$$N_k^{(j;\omega)} = \alpha_0^{(j;\omega)} + \sum_{s=1}^{S} \alpha_s^{(j;\omega)} \Upsilon_k^{(j;s)} + \varepsilon_k^{(j;\omega)}\,, \qquad j = 1, \ldots, 6\,,\ \omega = \{\Sigma, I, C\}\ , \tag{26}$$

where j indexes the countries and $\omega = \{\Sigma, I, C\}$, where Σ refers to the total number of arrivals for country j, I is the number of idiosyncratic arrivals for country j, and C the number of common arrivals for country j with any other country, respectively; $N_k^{(j;\omega)}$ is the number of ω price jump arrivals for month k for country j, and $\Upsilon_k^{(j,s)}$ is the set of S country-specific covariates for every month k. Let us stress that k is the month index, while t is general time, $t \in k$ is all time observations in month k. We estimate the system (26) using the SURE estimation method to take into account the contemporaneous correlation across countries.

In particular, we consider two possible sources of price jump arrivals: the overall macroeconomic factors and the amount of surprising information which the economy absorbs during the particular time window. We use three different specifications:

$$
\begin{aligned}
N_k^{(j;\omega)} &= \alpha_0^{(j;\omega)} + \alpha_1^{(j;\omega)} dE_k^{(j)} + \alpha_2^{(j;\omega)} dIP_k^{(i)} + \alpha_3^{(j;\omega)} dES_k^{(j)} + \varepsilon_k^{(j;\omega)}\,, && (27)\\
N_k^{(j;\omega)} &= \beta_0^{(j;\omega)} + \beta_1^{(j;\omega)} L_k^{(US)} + \beta_2^{(j;\omega)} L_k^{(EA)} \\
&\quad + \beta_3^{(j;\omega)} L_k^{(j)} + \beta_4^{(j;\omega)} L_{\bar{y},k}^{(j)} + \beta_5^{(j;\omega)} UMP_k + \varepsilon_k^{(j;\omega)}\,, && (28)\\
N_k^{(j;\omega)} &= \gamma_0^{(j;\omega)} + \gamma_1^{(j;\omega)} Z_k^{(US)} + \gamma_2^{(j;\omega)} Z_k^{(EA)} \\
&\quad + \gamma_3^{(j;\omega)} Z_k^{(j)} + \gamma_4^{(j;\omega)} Z_{\bar{y},k}^{(j)} + \gamma_5^{(j;\omega)} UMP_k + \varepsilon_k^{(j;\omega)}\,. && (29)
\end{aligned}
$$

Specification (27) contains three country-specific covariates: the employment (E), industrial production (IP) and economic sentiment (ES), all of them expressed as a monthly percentage change. This specification captures the effect of the prevailing macro-economic environment on the intensity of jump arrivals. Specification (28) contains four covariates: $L^{(US)}$, $L^{(EA)}$and $L^{(j)}$ being the number of macro-announcements with large surprise originating from the US, the Euro area and the j-th country, respectively; $L_{\bar{y}}^{(j)}$ represents the number of government bond auctions held in the j-th country with large surprise. An announcement is considered to carry a large surprise to the market if $|\zeta| > \sigma(\zeta)$, where ζ is specified in (25), while in the case of auctions, ζ is defined as the difference in the average yield between current and previous 10-year auctions. This specification captures the effects of large surprises on the integrated jump arrival intensity. Further, we include the unconventional monetary policies, UMP_k, released during the given month. The UMPs take a form of dummy variables with no assessment of the magnitude of the surprise carried by each single release. Specification (29) contains four covariates: $Z^{(US)}$, $Z^{(EA)}$ and $Z^{(j)}$ accounting for the overall amount of absolute surprises delivered by macro-announcements originating from the US, the Euro area, respectively, and the j-th country; $Z_{\bar{y}}^{(j)}$ represents the sum of absolute surprises from auctions held in the j-th country, measured as the difference in the yield associated to the latest auction with respect to previous one. We define the cumulative absolute surprise effect for each country j as

$$Z_k^{(j)} = \sum_{t \in k} \left| \zeta_t^{(j)} \right| , \tag{30}$$

where the sum covers all individual surprises $S^{(x)}$ for all macro-announcements or auctions originating from the country j in a given month k. This specification captures the effects of all surprising announcements on the integrated intensity of jump arrivals.

3.2.1. Results for monthly arrivals

Table 3 reports the estimated specifications (27)-(29). The contribution of the three groups of covariates varies for idiosyncratic and common arrivals, indicating the presence of different mechanisms underlying the drivers of arrival processes. This represents further evidence of the need to distinguish the two arrival processes, as our proposed frequency-specific factorization approach allows. For instance, results in Table 3 show that macroeconomic announcements from US are more related to common arrivals than idiosyncratic ones. This result is in line with Ehrmann et al. (2011), where it is highlighted that European markets react to US announcements more than to European ones. In addition, the higher statistical significance of the loading coefficients associated to large surprises, L_{US}, L_{EU}, and $L^{(j)}$ relative to those associated to all the releases, Z_{US}, Z_{EU} and $Z^{(j)}$, suggests that the larger the surprises, the higher is the probability of observing jumps and co-jumps. This result is consistent with the existing literature as reported for instance in Dewachter et al. (2014) and Dungey et al. (2009), where the authors show that although large surprises are associated with the occurrence of jumps, the same conclusion cannot be drawn for the size of the surprise in general. As far as government bond auctions are concerned, the results in Table 3 indicate that although auctions held in distressed countries, such as Italy and Spain, determine idiosyncratic jumps; they do no impact on the other countries. Finally, we see that improved macroeconomic conditions, in terms of employment and industrial production, determine a lower number of jumps as witnessed by the negative coefficients associated with these two macroeconomic factors.

[Table 3 should be inserted here]

Thus far, we have provided empirical evidence that frequency-specific factorization (2) is a useful approach to mimic the arrival processes. In particular, the empirical evidence suggests that the idiosyncratic and common price jump arrivals tend to have different dynamics and are caused by different factors. The idiosyncratic jumps can be related to country-specific dynamics not captured by macroeconomic conditions. Frequently, the important factors causing the idiosyncratic jumps are related to specific news linked to national politics.

3.2.2. Results for core and periphery-specific components

The empirical results reported above suggest that core (Germany, Belgium, Netherlands, and France) and periphery countries (Italy and Spain) show different price jump dynamics, in line with the intuition that periphery countries show higher variability and a large number of jumps than core economies. We observe that volatility of the average number of jumps per month is 14.5 for periphery countries with respect to 9.6 for core economies, while the average number of jumps per month is 35 for periphery countries with respect to 23 for core ones. We investigate further this point by estimating (27)-(29) for the two groups of countries. We define a common core price jump as a price jump occurring at the same time in at least two of the four core countries, irrespective of price jump being observed at periphery countries. In the same way, we define a common periphery price jump as a price jump occurring at the same time for Italy and Spain, irrespective of price jumps at core countries.

[Table 4 should be inserted here]

Table 4 reports the results of the estimation. First, the common price jumps for core countries show higher R^2, with values exceeding the one observed for the individual countries. Second, the parameters are structurally the same, suggesting that there is no significant difference in terms of macro-economic factors driving the behaviour of the two groups of countries. The lower R^2 for periphery countries confirms the presence of a noisier distribution of monthly jumps which respect to the core countries.

In the next section, we calculate the measure of commonality and the measure of multiplicity and link them to the exogenous macro-factors and surprises.

3.3. Commonality and Multiplicity

In Figure 2, we report the measure of commonality on $[T_{k-1}, T_k]$ and the measure of multiplicity as defined in (9) and (11), respectively. Panel a of Figure 2 plots the measure of Q on a monthly basis. Q takes values between 0.1 and 0.8. The commonality reached the lowest level during 2012 when the decreasing trend in the commonality stopped. Since that period, it increased and stabilised around 0.4-ish levels. From there, the level of commonality is stable with large levels of variance. The culmination of commonality in the second half of 2015 when it reached values 0.8, or 80% of price jump arrivals being common, can be assigned to increased variance without an obvious tipping point. This period corresponds to the post-QE which suggests a link to the purchase programme which was able to remove idiosyncratic effects. The lowest values (December 2010 up to mid 2012) are observed in correspondence to the most severe phase of the crisis and ending end of 2012 (after "whatever it takes" announcement in July 2012).

In addition, the figure depicts the region in between two dashed lines which corresponds to $[\text{1-st}, \text{99-th}]$ centiles of the empirical distribution of Q based on the 10,000 realizations of a Monte Carlo simulation, where the same number of price jump arrivals arrive independently. For each month, the observed Q is out of the region and therefore we may assess that Q is taking a value significantly different from the Monte Carlo simulation based on the randomly arriving price jumps. In particular, Q is significantly higher and thus the bonds tend to have significantly common price jump arrival processes.

Panel b of Figure 2 captures the measure of multiplicity $\bar{Q}^{\mu}_{[T_{k-1},T_k]}$ on a monthly basis, taking values between 1.2 and 3.4, respectively. First, the measure of multiplicity is highly correlated to the measure of commonality, with a correlation coefficient equal to 0.95. The high correlation between the two measures suggests the presence of two significant clusters, the first is formed by Germany and the second by all remaining countries, a result very close to Caporin et al. (2018), Broto and Perez-Quiros (2015) and Dungey and Renault (2018). Second, the difference between the measure of multiplicity and the measure of commonality is higher in the beginning of the sample, namely, in October 2009, when the measure of multiplicity reached all-time maxima, while the measure of commonality stayed far from its global maximum seen in 2015. This suggests that in the aftermath of the financial crisis, there have been a large proportion of common price jumps occurring across multiple assets.

This result seems in contrast to the seminal contributions in the literature, such as Forbes and Rigobon (2002), and Bekaert et al. (2005, 2009, 2014), who found that, during financial distress, the correlation among financial time series increases. This is not our case, as we define "correlation" between jumps as the proportion of common jumps to the totality of jumps. Thus, if during the distress the proportion of idiosyncratic jumps increases—as it may happen due to contagion effects in presence of a large number of idiosyncratic jumps occurring across assets—more than the number of common jumps, it may appear that the correlation between jumps decreases, though the presence of more common jumps. The figure also contains the shaded region corresponding to [1-st, 99-th] centiles of the empirical distribution of $\bar{Q}^{\mu}_{[T_{k-1},T_k]}$ using the same Monte Carlo simulation set-up as for $Q_{[T_{k-1},T_k]}$. The results also suggest that for each month, $\bar{Q}^{\mu}_{[T_{k-1},T_k]}$ is taking values significantly higher than the value based on the randomly arriving price jumps, and thus the price jump arrivals tend to overlap significantly.

[Figure 2 should be inserted here]

To further understand the link between the macro-economic conditions and the measure of commonality and the measure of multiplicity, we estimate (12) and (13), respectively. Given the high correlation between the measure of commonality and the measure of multiplicity, we only report results for the measure of commonality, while the results for multiplicity are available from authors upon request. In particular, we are interested in explaining the role of the macro-announcements carrying a large surprise, as defined in (29), and therefore we employ the following linear specification

$$Q_k = \alpha_0 + \sum_{q=1}^{G} \alpha_q Z_t^{(q)} + \varepsilon_t \, , \tag{31}$$

where the set of covariates $Z_k^{(q)}$ represents the sum of all surprises, which hit the economy for a particular type of news announcement and from a particular country or group of countries q with G being total number of different types evaluated. We group the available macro-announcements according to the nature of the economic variable they refer to: real economy, forward-looking and price while distinguishing whether they were issued by the United States (US), the Euro Area (EA), by one of the Individual Country (IC), or aggregated across all the countries (ALL) listed in the Internet Appendix. We standardized the sum of large releases per month by the number of news belonging to each category.

We use OLS with the Huber-White sandwich estimator to control for heteroskedastic errors to estimate equation (31), selecting the explanatory variables adopting a two-stage forward stepwise procedure. In the first stage, we preselect variables by running a univariate regression for each of the covariates. Variables which are significant at the 0.30 level are kept. Then, in the second stage, we start with the constant term and add one-by-one the preselect variables. The algorithm stopping rule is at p-value of 0.1, i.e., no new variable added to the model has p-value below. Any added variable whose significance dropped in the second stage below 0.1 has been removed as well. The estimated specification (31)

$$\begin{aligned} Q_k &= \underset{[0.1382]}{-0.0455} - \underset{[0.0451]}{0.0719}\, Z_k^{US} + \underset{[0.0700]}{0.0235}\, Z_k^{EA} \\ &\quad + \underset{[0.0610]}{0.0863}\, Z_k^{IC} - \underset{[0.005]}{0.0151}\, Auctions_k + \underset{[0.0238]}{0.0120}\, UMP_k + \hat{\epsilon}_k \,. \end{aligned} \tag{32}$$

with $R^2 = 0.101$ and F-statistics being 2.52106 with p-value of 0.033. The overall explanatory power is rather low, we are able to explain 10% of the variance. This does not necessarily mean that markets do not respond to surprises in a synchronised manner. Rather, aggregating all the news into one variable decreases signal to noise ratio in such aggregated measures and thus we are not able to explain much of the variance.

Further, we extend the previous model by considering the individual macro-economic news announcements, bond auctions and UMPs. Altogether, we start with 48 different types of news at the begging. We employ the two-stage forward stepwise procedure:

$$
\begin{aligned}
Q_k \;=\;& +\underset{[0.000]}{0.000} - \underset{[0.0326]}{0.01790}\, HICP_k^{EA} \\
& +\underset{[0.0144]}{0.0238}\, BusinessConfidence_k^{EA} + \underset{[0.0365]}{0.0533}\, UnemploymentRate_k^{Spain} \\
& -\underset{[0.0113]}{0.0176}\, InitialJoblessClaims_k^{US} - \underset{[0.0123]}{0.0198}\, PhiladelphiaFEDOutlook_k^{US} \\
& -\underset{[0.0139]}{0.0326}\, AvgYield_k^{Spain} - \underset{[0.0318]}{0.0775}\, AvgYield_k^{France} \\
& -\underset{[0.0124]}{0.0280}\, AvgYield_k^{Italy} + \underset{[0.0137]}{0.0135}\, AvgYield_k^{Portugal} \\
& -\underset{[0.1132]}{0.0563}\, COLL_k + \underset{[0.0861]}{0.0266}\, FRTFA_k \\
& -\underset{[0.1472]}{0.1784}\, OMT_k + \underset{[0.0789]}{0.1936}\, APP_k + \hat{\epsilon}_k\,, \qquad (33)
\end{aligned}
$$

with $R^2 = 0.241$ and F-statistics 8.9459 with p-value of 0.000; the variables are defined as a sum of absolute surprise for given month k, see Z in model (29). The unconventional monetary policies are: $FRTFA$ – the unlimited provisions of liquidity through fixed rate tenders with full allotment for the main refinancing operations; $COLL$ – the extensions of the list of collateral assets; OMT – the outright monetary transactions; and APP – the asset purchase programme. The events classified as APP include the launch of the Quantitative Easing (QE) on the 22th January 2015 as well as further decisions in support of this new regime of expansive monetary policy including the increase of the monthly purchases (on the 10th March 2016, from €60bn to €80bn per month, for instance); the rules to carry out country purchases (on the 3rd September 2015, the maximum limit per issuer was increased from 25% to 33%); the decision on the 8th December 2016 to extend QE from March 2017 to December 2017. The variable is highly statistically significant which shows that the news classified as APP played a paramount role in the dynamics of the European government bond market for both groups of countries.

In order to strengthen our findings, we further extend the simulation set-up presented in Table 1 based on eqs. (14) - (18) for 5 assets. Under the null hypothesis of idiosyncratic price jump arrivals based on 1,000 simulations, the 90-th and 99.9-th percentile of the distribution of the measure of commonality is 0.11 and 0.29, respectively, while for the measure of commonality, it is 1.11 and 1.30, respectively.

It is worth noticing that our framework allows us to model the link between the exogenous factors and the common price jumps, which are instantaneous within the sampling frequency. Of course, the impact of the released news can spread across the markets over a longer period. Our co-feature based framework is unable to measure the economic impact of the events which spillover across markets over time. The evaluation of the spillover dynamics is beyond the scope of this paper and we leave it for further research which will target the dynamic structure of jump spillovers.

In the next section, we analyse the commonality in jumps using the notion of co-arrivals.

3.4. Co-arrivals

We test for the presence of co-arrivals by evaluating the null hypothesis in (21). In economic terms, co-arrivals serve as a proxy to measure the degree of market integration. Fully integrated markets tend to show synchronized reactions to shocks and thus higher presence of common price jump arrivals. For every month, the **J** matrix is of full rank and therefore co-arrivals, corresponding to $N_k^{(w)} = 0$, do not exist. We therefore proceed to search for the co-arrival vectors w, which minimizes the objective function (20). In particular, we focus on the adjoint measures to co-arrival vectors: the grade and the index. Let us stress out that for some months there have been more than one co-arrival vector.

For every identified co-arrival vector, we calculate the index and the grade as defined in (22) and (23), respectively. Panel a of Figure 3 depicts the index for every estimated co-arrival vector, where each point denotes the proportion of the overall amount of Poisson processes, which were removed from the portfolio built using the weights corresponding to a given co-arrival vector. Overall, we see that co-arrival vectors remove a large proportion of Poisson process. In January 2011, the 98.48% of the Poisson processes have been removed, which is global maximum the index reaches. This month splits the sample into two parts: Prior to this month, the index was steadily increasing with the global minimum being reached in September 2009 at value 73.91%, close to the beginning of our sample; and after January 2011, where the index is more stable.

Panel b of Figure 3 depicts the grade for every identified co-arrival vector, where each point denotes the proportion of the overall number of common Poisson processes removed from the portfolio with weights corresponding to a given co-arrival vector. The grade resembles the shape of the index. This suggests that the majority of the price jump arrivals are in fact co-arrivals. The similarity is in particular close since 2015, where the grade is less disperse and reaching higher values—in the number of cases reaching a value of 1.0, i.e.,100% of all co-arrival vectors being removed. Prior to 2015, the grade is more disperse with a mean around 0.8. Both the index and the grade suggests that immediately following the financial crisis, the assets studied in this paper have been undergoing various co-arrivals with rather irregular patterns. On the other hand, since 2015, the markets have been more regular and operating in a more normalised way.

[Figure 3 should be inserted here]

In the next section, we analyse commonality in price jumps using both their price jump arrival times and magnitudes.

3.5. Co-jumps

First, we test for the presence of co-jumps as the existence of a linear combination $w'P_t$ such that the G_n-statistic cannot reject the null hypothesis for each month k, where each month was sampled into 5-minute steps. In particular, we search for w such that the p-value is maximized.

Figure 4 depicts the $\hat{G}^{(w)}$-statistic for the identified co-jump vector implied by the p-value minimization. For example, in October 2011, the $\hat{G}^{(w)}$-statistic takes value $-0.29 \cdot 10^{-3}$, the global minimum the $\hat{G}^{(w)}$-statistic reaches in our data set. On the other hand, in May 2011, the $\hat{G}^{(w)}$-statistic reaches $-2.20 \cdot 10^{-6}$, the highest value observed. Thus, we can conclude that for every identified co-jump vector at each month k, we cannot reject the null of no co-jumps, given that the $\hat{G}^{(w)}$-statistic in all instances is well below the critical value of -2.11, for the 5% confidence level.

[Figure 4 should be inserted here]

Figures 5 and 6 report the individual components of the (weak) global co-jump vectors, which were used to depict the $\hat{G}^{(w)}$-statistic in Figure 4. In all the cases, every country contributes to the co-jump vectors, as the values of the individual components are different from zero. Let us note that the co-jump optimal portfolio is estimated ex-post given the knowledge of realization of the price process. We estimate price jumps for each month and each country independently and that we reject the null of no price jumps for every case.

First, let us focus on German yields. There are apparently two regimes: The first regime up to and including the year 2012, where the weights have been very volatile. And after 2012, where the weights have been more homogeneous with much less variance and surprises. This is also in line with previous insight learnt from the two co-arrival measures and behaviour of the index and grade of the co-arrival vector. The components for German yields even change the sign between December 2010 and May 2011. This implies that either a change in the structure of the jump process, and/or a change in the covariance structure of Germany with respect to all other countries. As suggested in Caporin et al. (2018), we like to interpret this result as evidence of increasing disconnection rather than connection among European countries during the sovereign crisis, with Germany acquiring the role of safe haven with respect to peripheral countries. In addition, the worsening of the European debt crisis explains the higher variance in the absolute values of the global co-jump components.10-year high-frequency European government bond yields

Second, for other countries, we see a variance throughout the date range but anything comparable to the German bonds is found. Further, individual countries are always contributing to the co-jump vector with non-zero co-jump vector in every month. The minimum magnitude of the co-jump vector is reached in January 2014 for France, with a magnitude of 0.0005, suggesting that during this month, French yields have not been contributing to the optimal portfolio. On the other hand, the maximum contribution to the co-jump vector has been reached in December 2011 with 0.4981 for Spanish yields.

[Figure 5 should be inserted here]

4. Conclusions

In this paper, we proposed a novel frequency-specific framework to link common features in high-frequency price jumps with low-frequency exogenous factors. We introduced the measure of commonality and the measure of multiplicity based on high-frequency data and defined the notions of co-arrivals and co-jumps. We employed the framework to study the 10-year high-frequency European government bond yields for Belgium, France, Germany, Italy, the Netherlands and Spain from June 2009 to April 2019, sampled at a 5-minute frequency, as a function of monthly real economy indicators. To identify the main drivers of commonality and multiplicity, we linked the two measures to relevant macro-factors (unemployment, industrial production and economic sentiment) observed at a monthly frequency, to the aggregate monthly surprise carried by macro-announcements, to government bond auctions, and to the unconventional monetary policy announcements. We further explored the bond characteristics via the notion of co-arrivals, which measures the degree of market integration, and co-jumps, which captures the presence of common jumps.

We run a series of alternative models where the number of price jump arrivals, idiosyncratic price jump arrivals and common price jump arrivals were function of surprises and found that the strongest drivers were factors defined as a sum of surprises from combinations of news. We also performed a sensitivity analysis by defining two clusters, the core countries and the peripheral countries, with the model for core countries showing the best performance. Further, we found that the commonalities of the jump arrivals are mainly explained by news announcements from the US and the EA, bond auctions, and the UMPs. The commonality reached the lowest level in 2012, while in the following years the commonality increased and approximately 40% of price jumps were common. For the European debt crisis, we observed a significant change in the structure of common jumps in yields, providing clear evidence that the Euro area was hit by country-specific risks. Finally, from December 2010 to May 2011, the behaviour of German yields showed very specific features. Significant changes in correlation between German yields and yields from any other country in the sample are found. As the German bonds witnessed a sharp increase in bid-ask spread, our findings offer supportive evidence of the risk-awareness of investors.

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Table 1: Measure of commonality and multiplicity: Numerical simulation

	Commonality				Multiplicity			
3 assets	90-th	95-th	99-th	99.9-th	90-th	95-th	99-th	99.9-th
week	0.00	0.00	0.50	1.00	1.00	1.00	1.50	2.00
fortnight	0.00	0.14	0.33	1.00	1.00	1.14	1.33	2.00
month	0.00	0.14	0.25	1.00	1.00	1.14	1.25	2.00

Note: The table reports the 90-th, 95-th, 99-th, and 99.9-th percentiles of the distribution of the measure of commonality and multiplicity under the null hypothesis of idiosyncratic price jump arrivals based on 1,000 simulations. Each simulation is composed of 5 days (week), 10 days (fortnight), and 20 days (month), respectively.

Table 2: Size and power of the co-jumps test

	Scenario 1: True co-jumps (Power)						Scenario 3: Sequence of jumps (Size)						Scenario 5: No jumps (Size)	
	$\nu = 4$		$\nu = 8$		$\nu = 12$		$\nu = 4$		$\nu = 8$		$\nu = 12$		$\nu = 0$	
$\rho_W^{(i,j)}$	*(i)*	*(ii)*	*(i)*	*(ii)*	*(i)*	*(ii)*	*(i)*	*(ii)*	*(i)*	*(ii)*	*(i)*	*(ii)*	*(i)*	*(ii)*
-0.30	22.3	7.2	48.5	30.7	64.1	49.0	17.5	4.4	36.7	21.7	49.0	41.3	4.0	0.3
-0.20	18.5	6.0	48.9	29.9	67.6	52.0	19.3	5.1	35.4	21.8	50.0	35.8	3.7	0.0
0.00	18.9	7.0	45.8	29.8	68.4	54.3	18.4	5.5	37.3	20.6	51.8	37.4	3.5	0.0
0.20	20.4	7.8	45.7	28.9	64.9	51.9	18.8	4.6	41.0	26.0	46.8	36.6	3.6	0.1
0.30	18.9	6.7	51.6	32.1	61.7	51.0	15.7	5.4	36.7	22.5	48.7	38.8	3.7	0.0

	Scenario 2: No true co-jumps (Size)						Scenario 4: Distant jumps (Size)					
	$\nu = 4$		$\nu = 8$		$\nu = 12$		$\nu = 4$		$\nu = 8$		$\nu = 12$	
$\rho_W^{(i,j)}$	*(i)*	*(ii)*	*(i)*	*(ii)*	*(i)*	*(ii)*	*(i)*	*(ii)*	*(i)*	*(ii)*	*(i)*	*(ii)*
-0.30	16.8	3.6	19.9	10.8	23.2	16.4	14.5	4.8	17.1	9.3	17.3	10.1
-0.20	15.2	2.3	21.6	8.8	19.7	12.8	15.8	2.7	20.7	8.8	17.4	11.0
0.00	13.4	3.3	20.5	9.6	19.7	12.2	15.9	4.7	16.3	8.1	19.4	12.4
0.20	15.1	3.5	22.4	10.1	19.0	14.7	13.9	4.0	18.0	9.0	18.0	10.6
0.30	15.4	3.7	21.6	10.6	20.8	12.5	15.7	5.5	20.2	12.9	15.6	10.2

Note: The table reports the sample properties, power and size in %, for the co-jumps test using the Bipower variation. We use five scenarios and critical values: (i) $\alpha = 0.05$ representing a standard significance level, and (ii) $\alpha = \left(1 - \Phi\left(\sqrt{2 \cdot \log 1000}\right)\right) = 1.008 \cdot 10^{-4}$ corresponding to the multiple testing bias correction. ν denotes the size of the price jumps and $\rho_W^{(i,j)}$ is the correlation between assets.

Table 3: Modelling monthly arrivals.

	Italy			France			Spain			Belgium			Netherlands			Germany		
	$N_k^{(j;\Sigma)}$	$N_k^{(j;I)}$	$N_k^{(j;C)}$	$N_k^{(j;\Sigma)}$	$N_k^{(j;I)}$	$N_k^{(j;C)}$	$N_k^{(j;\Sigma)}$	$N_k^{(j;I)}$	$N_k^{(j;C)}$	$N_k^{(j;\Sigma)}$	$N_k^{(j;I)}$	$N_k^{(j;C)}$	$N_k^{(j;\Sigma)}$	$N_k^{(j;I)}$	$N_k^{(j;C)}$	$N_k^{(j;\Sigma)}$	$N_k^{(j;I)}$	$N_k^{(j;C)}$
Panel A																		
α_0	2.91^a	2.2^a	2.36^a	2.48^a	0.85^a	2.39^a	3.02^a	2.43^a	2.31^a	2.58^a	1.11^a	2.4^a	2.45^a	0.59^a	2.44^a	2.57^a	0.75^a	2.5^a
E	0.00	0.1	0.02	0.01	0.16	0.11	-0.01	0.03	0.17^b	0.05	-0.12	0.21^c	0.08	-0.14	0.16^c	0.02	0.13	-0.01
IP	0.01	0.03	0	-0.03	0.03	0	0.00	-0.03	0.03	0.02	-0.03	0.01	0.00	-0.02	-0.01	-0.02	0.01	-0.01
ES	-0.04^b	-0.07^a	-0.01	0.00	-0.02	0	-0.02	-0.03	0.02	-0.03^b	-0.04	-0.01	-0.01	0.01	-0.01	-0.05^a	-0.05	-0.04^b
R^2	0.03	0.08	0.32	0.01	0.02	0.15	0.01	0.01	0.27	0.07	0.02	0.15	0.01	0.01	0.04	0.07	0.01	0.01
Panel B																		
α_0	2.47^a	1.87^a	2.23^a	2.19^a	0.89^a	2.37^a	2.62^a	1.99^a	2.14^a	2.16^a	0.59 **	2.3^a	2.3^a	0.44^b	2.43^a	2.35^a	0.5^b	2.48^a
L_{US}	0.04^c	0.05^c	0.02	0.04^b	0.02	0.02	0.07^b	0.06	0.03	0.05^b	0.05	0.02	0.03^c	0.04	0.01	0.02	-0.01	0.01
L_{EA}	-0.02	-0.13^b	-0.02	0	-0.11^b	-0.02	0.02	0.04	0.02	0.07^c	0.08	0	-0.01	-0.04	-0.01	0.05^c	0.05	-0.02
$L^{(j)}$	0.04	0.03	0.04	-	-	-	0.14	0.25	0.22^c	-0.08	-0.09	0.12^c	-	-	-	-0.04	0.01	0.02
$L_{\bar{y}}^{(j)}$	0.15^c	0.36^a	0.05	0.03	0.73^a	-0.37^a	0.02	0.11	-0.05	0.06	0.03	-0.07	0.03	0.29^a	-0.05	0.12^b	0.47^a	-0.01
UMP	0.04	-0.06	0.01	0.09^b	-0.03	-0.01	0.09	0.03	0.03	0.09^c	0.1^c	-0.02	-0.01	-0.03	-0.02	-0.02	-0.02	-0.02
R^2	9.03%	14.64%	2.14%	9.88%	14.13%	3.89%	11.71%	5.59%	5.81%	13.71%	5.11%	6.52%	3.73%	8.30%	0.00%	14.14%	14.70%	2.07%
Panel C																		
α_0	2.35^a	1.84^a	2.31^a	1.97^a	0.39	2.32^a	2.59^a	1.76^a	2.37^a	1.97^a	0.05	2.19^a	2.09^a	0.23	2.35^a	2.14^a	0.13	2.43^a
Z_{US}	0.01^b	0.02^b	0	0.02^a	0.01^c	0.01^c	0.01	0.01	-0.01	0.01^b	0.01	0.01	0.01^b	0.01	0^c	0.01^b	0	0
Z_{EA}	-0.02	-0.03^c	-0.01	0	0	-0.01	0	0.01	0	0.02^b	0.04^b	0	0	0.01	0	0.01	0.03	0
$Z^{(j)}$	0	-0.02	0.02	-	-	-	0.04	0.04	0.08^c	0	-0.02	0.03^c	-	-	-	-0.01	0.01	0
$Z_{\bar{y}}^{(j)}$	0.06^a	0.08^a	0.01	0.02	0.23^a	-0.08^b	0.05^b	0.12^a	0.01	0.04^c	0.16^a	-0.01	0.01	0.09^b	-0.01	0.08^a	0.21^a	0
UMP	0.02	-0.07	0.01	0.07^c	-0.01	-0.02	0.06	-0.01	0.02	0.07	0.07	-0.02	-0.02	-0.02	-0.02	-0.03	-0.01	-0.01
R^2	15.89%	15.00%	2.58%	13.47%	12.45%	10.97%	12.07%	13.76%	6.38%	14.95%	19.44%	6.11%	7.06%	6.80%	5.23%	20.23%	16.18%	2.86%

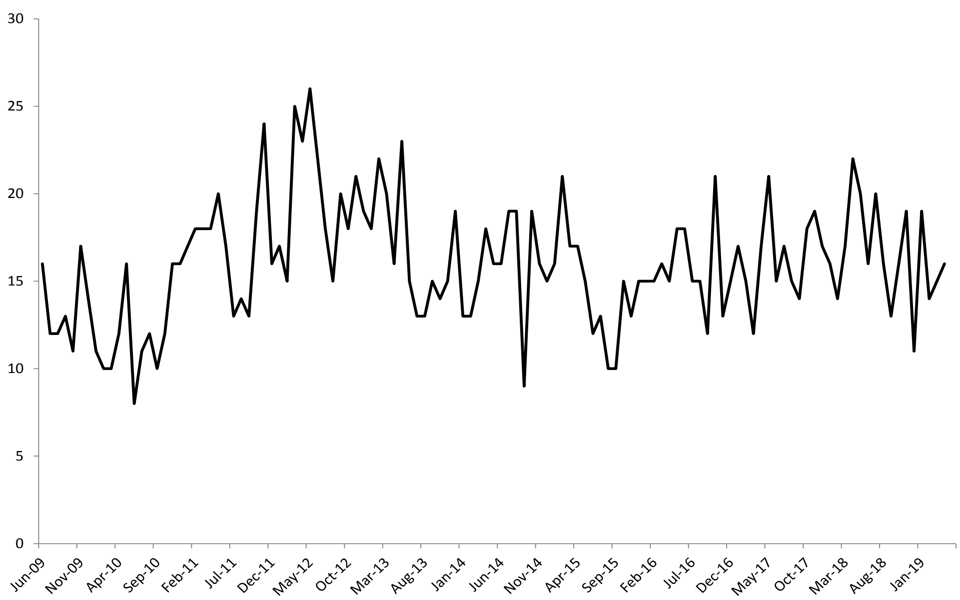
Note: $N_k^{(j;\Sigma)}$ refers to the dependent variable denoting the total number of arrivals for a given country j and month k; $N_k^{(j;I)}$ is the dependent variable denoting the total number of idiosyncratic arrivals for a given country j and month k; and $N_k^{(j;C)}$ is the dependent variable denoting the total number of common arrivals for a given country j and month k. All the variables are introduced in (26). In Panel A, we report specification in (27), which employs the rate of change for Employment (E), Industrial Production (IP), and Economic Sentiment (ES) for the j-th country, respectively. In Panel B, we report specification in (28), which employs the number of macro-announcements per month which brought to the market a large surprise, defined as $|\zeta| > SD(\zeta)$, where ζ is specified in (25): L_{US}, $L^{(US)}$, $L^{(EA)}$ and $L^{(j)}$denoting the number of macro-announcements with large surprise originating from the US, the Euro area, and the country j. $L_{\bar{y}}^{(j)}$ denotes the number of surprising auctions held in the corresponding j-th country. The UMP stands for the unconventional monetary policy. In Panel C, we report specification in (29), which employs the total amount of surprise from macro-economic announcements per month, defined as $Z_k^{(j)} = \sum_{t \in k} \left|\zeta_t^{(j)}\right|$ with the sum running over all individual surprises $\zeta^{(j)}$ for all macro-announcements originating from the country/region j. The significance levels are defined as follows: a for 1%, b for 5%, and c for 10%.

Table 4: Modelling common monthly arrivals for core and periphery.

	Panel A			Panel B			Panel C	
	$N_k^{(j;C)}$	$N_k^{(j;P)}$		$N_k^{(j;C)}$	$N_k^{(j;P)}$		$N_k^{(j;C)}$	$N_k^{(j;P)}$
α_0	3.16^a	3.51^a	α_0	2.9^a	3.25^a	α_0	2.61^a	3.08^a
E	-0.16	-0.04	L_{US}	0.03^a	0.04^a	Z_{US}	0.01^b	0.01^b
IP	0	0	L_{EA}	-0.02	-0.04	Z_{EA}	0.01	-0.01
ES	-0.07^a	-0.06^b	$L^{(j)}$	0.01	0.05	$Z^{(j)}$	0	0
			$L_{\bar{y}}^{(j)}$	0.11^a	0.06	$Z_{\bar{y}}^{(j)}$	0.04^a	0.05^a
			UMP	0	-0.01	UMP	0.01	-0.03
R^2	0.10	0.05	R^2	0.23	0.08	R^2	0.26	0.16

Note: $N_k^{(j;C)}$ is the dependent variable denoting the total number of common arrivals for core countries—Germany, Belgium, Netherlands, and France—and month k, $N_k^{(j;P)}$ is the dependent variable denoting the total number of common arrivals for periphery countries—Italy and Spain—and month k. All the variables are introduced in (26). In Panel A, we report specification in (27), which employs the rate of change for Employment (E), Industrial Production (IP), and Economic Sentiment (ES) for the core/periphery, respectively. In Panel B, we report specification in (28), which employs the number of macro-announcements per month which brought to the market a large surprise, defined as $|\zeta| > SD(\zeta)$, where ζ is specified in (25): L_{US}, $L^{(US)}$, $L^{(EA)}$ and $L^{(j)}$denoting the number of macro-announcements with large surprise originating from the US, the Euro area, and the core/periphery. $L_{\bar{y}}^{(j)}$ denotes the number of surprising auctions held in the corresponding set of core/periphery countries. The UMP stands for the unconventional monetary policy. In Panel C, we report specification in (29), which employs the total amount of surprise from macro-economic announcements per month, defined as $Z_k^{(j)} = \sum_{t \in k} \left| \zeta_t^{(j)} \right|$ with the sum running over all individual surprises $\zeta^{(j)}$ for all macro-announcements originating from the region j. The significance levels are defined as follows: a for 1%, b for 5%, and c for 10%.

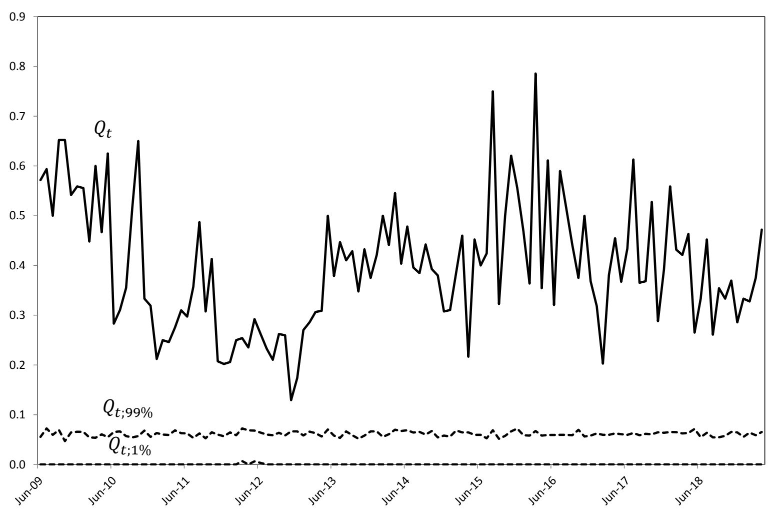
Figure 1: Cross-sectional averages of monthly arrivals.



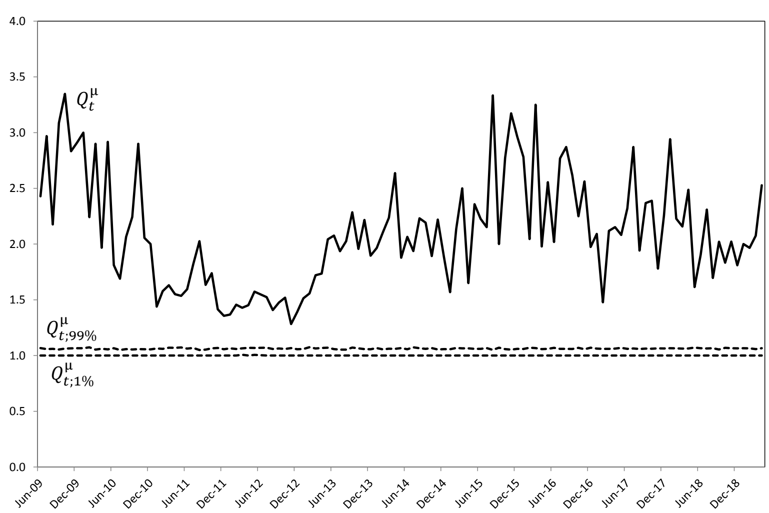
Note: The figure reports the cross-sectional average of the arrivals per month.

Figure 2: The measures of commonality, Q_t, and multiplicity, Q_t^{μ}, on monthly basis.

(a) The measure of commonality.



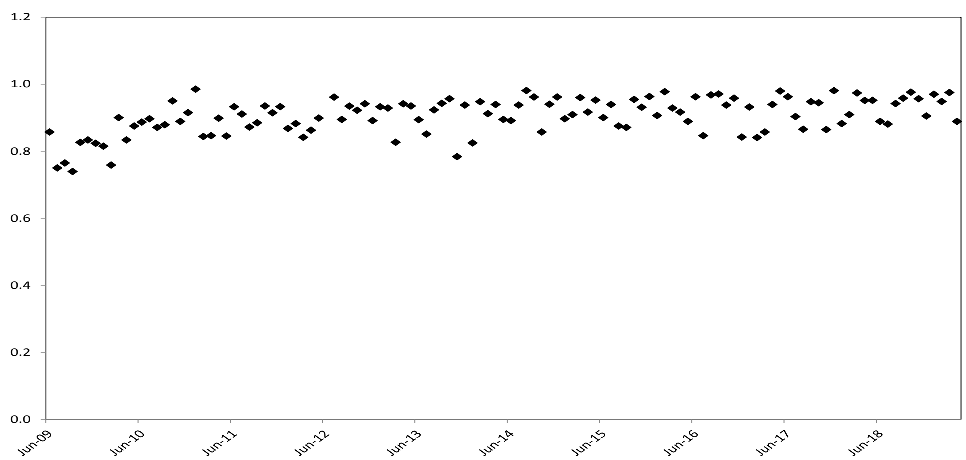
(b) The measure of multiplicity.



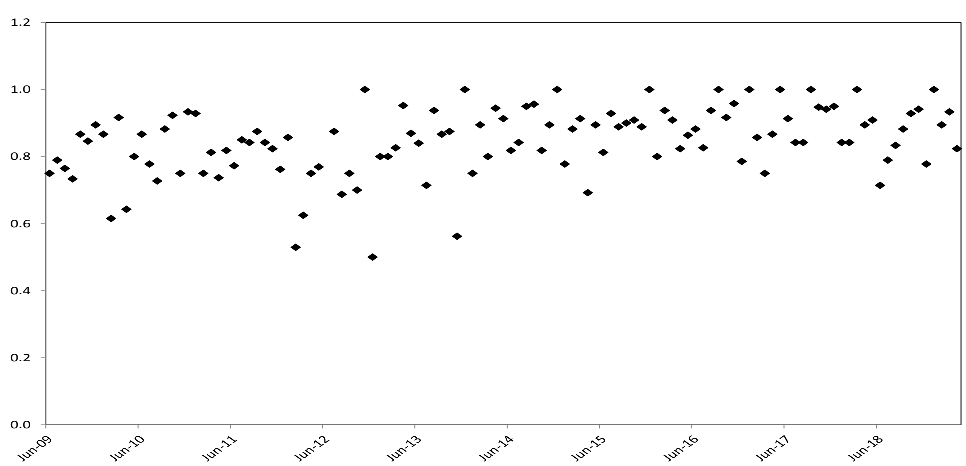
Note: The figure reports (a) the measure of commonality and (b) the measure of multiplicity defined in (9) and (11), respectively, for every month. In addition, the two dashed lines corresponds to [1-st, 99-th] centiles of the empirical distribution of Q_t and Q_t^{μ}, respectively, based on the 10,000 realizations of a Monte Carlo simulation, where the same number of price jump arrivals arrives independently.

Figure 3: The index and the grade of the co-arrival vectors on monthly basis.

(a) The index

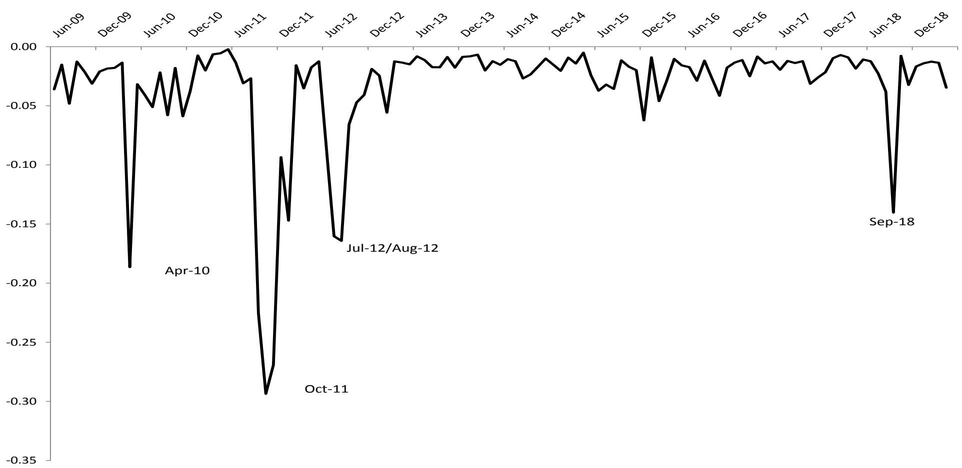


(b) The grade



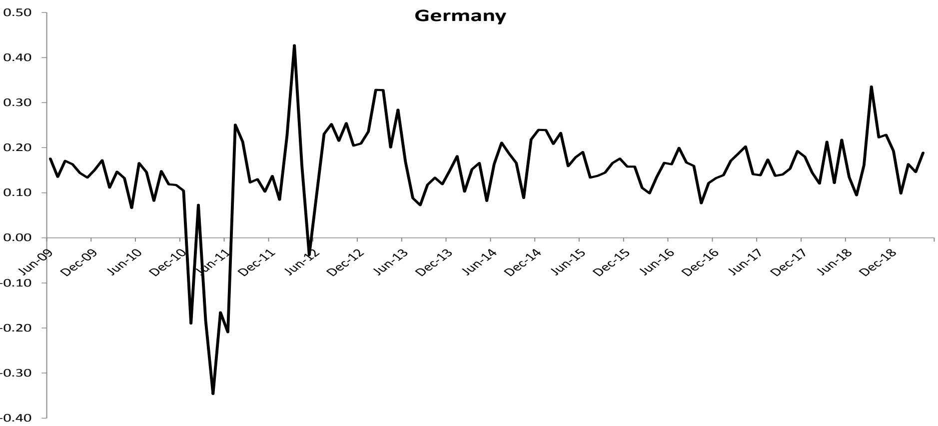
Note: The figure reports the index (a) and the grade (b) of the co-arrival vectors for every month as they are defined in (22) and (23), respectively.

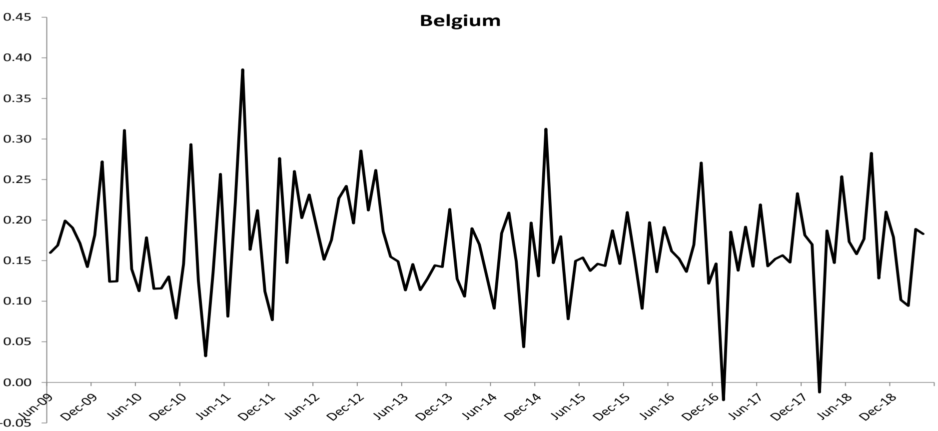
Figure 4: $G_n^{(w)}$-statistic monthly.

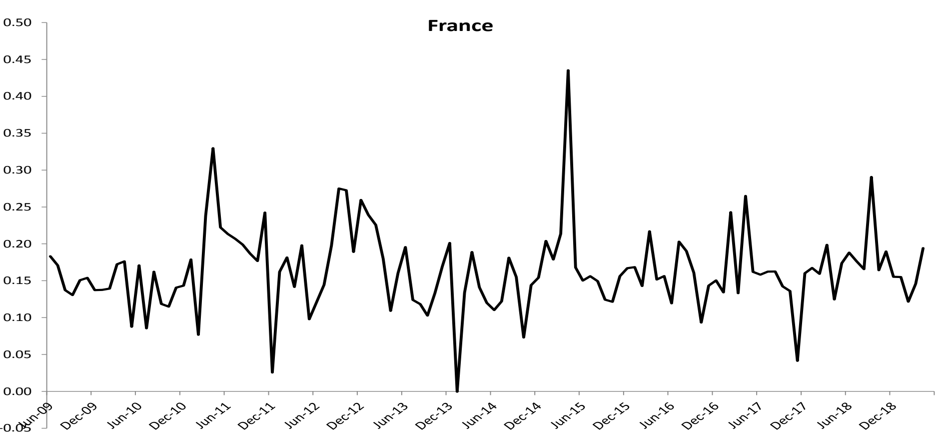


Note: The figure reports the $G_n^{(w)}$-statistic estimated for each month. The values on the y axis are multiplied by 1000. The 5% critical value to reject the null hypothesis of no jumps is equal to -2.11 and lies well below the plotted values.

Figure 5: Co-jump vectors w.

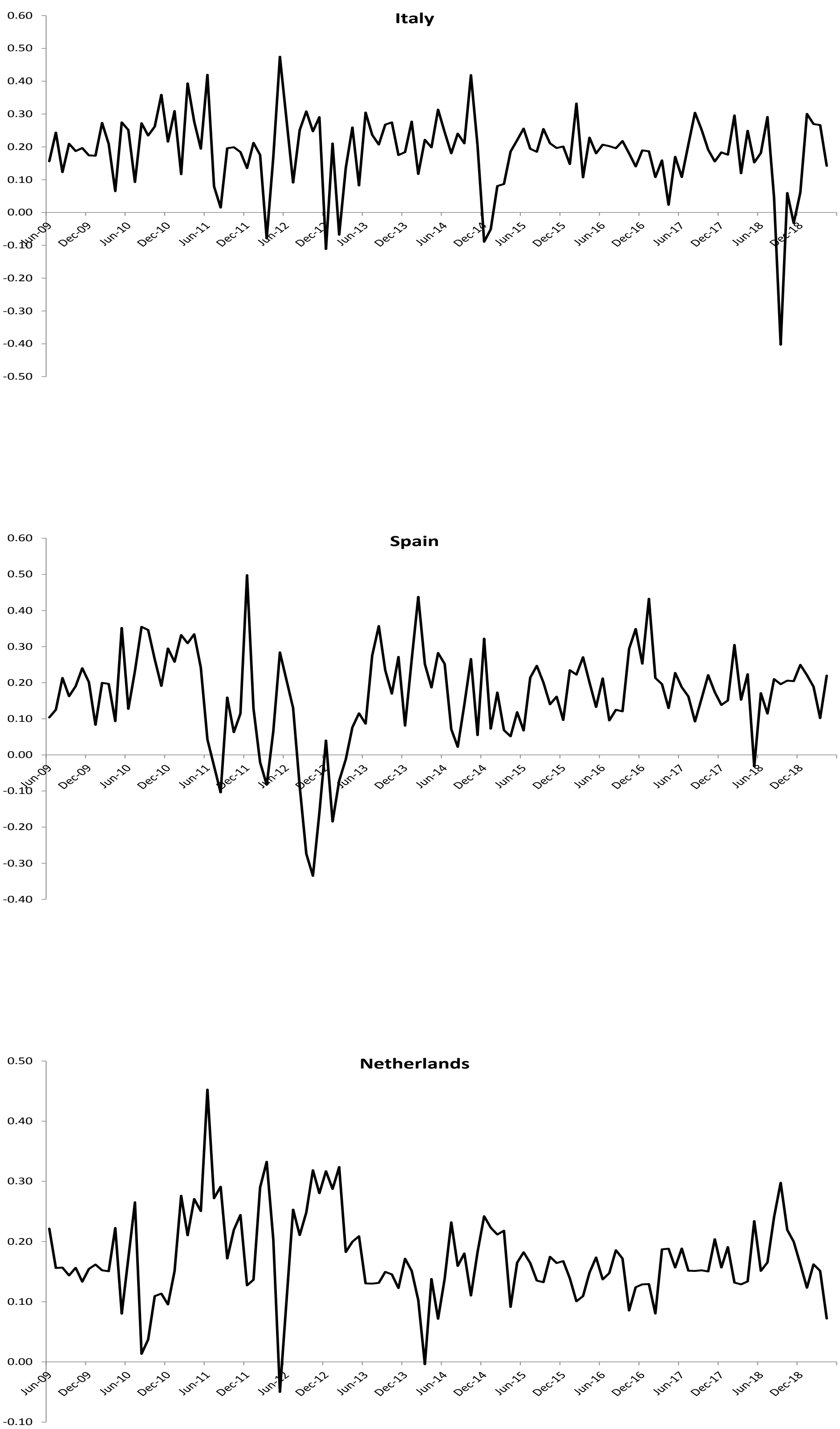






Note: The figure reports the country components of the co-jump vectors for each month.

Figure 6: Co-jump vectors w – continuation.



Note: The figure reports the country components of the co-jump vectors for each month.