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Financial Linkages and Sectoral Business Cycle Synchronisation: Evidence from Europe*

Abstract

We analyse whether financial integration between countries leads to converging or diverging business cycles using a dynamic spatial model. Our model allows for contemporaneous spillovers of shocks to GDP growth between countries that are financially integrated and delivers a scalar measure of the spillover intensity at each point in time. For a financial network of ten European countries from 1996-2017, we find that the spillover effects are positive on average but much larger during periods of financial stress, pointing towards stronger business cycle synchronisation. Dismantling GDP growth into value added growth of ten major industries, we observe that some sectors are strongly affected by positive spillovers (wholesale & retail trade, industrial production), others only to a weaker degree (agriculture, construction, finance), while more nationally influenced industries show no evidence for significant spillover effects (public administration, arts & entertainment, real estate).

Keywords: financial integration, business cycle synchronisation, industry dynamics, spatial model

JEL classification: E32, F44, G10

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1 Motivation

Countries with stronger economic, cultural and political ties tend to have more synchronized output fluctuations. However, whether financial integration is one of such synchronizing factors for international business cycles is unresolved in the literature. On the one hand, Kose et al. (2003), Imbs (2006) and Morgan et al. (2004) find a positive relationship between financial integration and business cycle synchronization. On the other hand, results by Kalemli-Ozcan et al. (2013a) and Kalemli-Ozcan et al. (2013b) suggest that a higher degree of financial integration entails diverging patterns of economic activity. Cesa-Bianchi et al. (2019) argue that the nature of the shock, common (negative effect) or country-specific (positive effect), is what matters for synchronization.

We contribute to this literature, first, by assessing the effect of financial integration on economic activity not only among country pairs but across a multilateral network of directly and indirectly linked countries. More specifically, we use a flexible spatial model recently developed by Blasques et al. (2016) that combines time-varying matrices of economic distances, reflecting financial linkages, with a dynamic parameter approach.[1] Our dynamic spatial model takes endogenous feedback and third-country effects into account.[2] In this way, we retrieve a scalar intensity parameter that reflects the extent of positive or negative business cycle co-movement over time. This set-up allows us to compare the extent of spillovers during recessions and tranquil periods. A static spatial model, in comparison, would only reveal the net effect of positive and negative spillovers. As a second contribution, we dismantle the business cycle into its main industrial sectors, similarly to Schnabel and Seckinger (2015). As different industries can be exposed by different extents to shocks transmitted through financial links, this decomposition can give further insights on the conflicting results above.[3]

The analysis is based on a sample of 10 European countries over the period from 1996 to 2017, for which gross domestic product (GDP) growth is dissected into the value-added by 10 industries. We find that financially more integrated countries tend to have on average positive business cycle synchronization. This finding means that shocks are transmitted across countries via their financial linkages resulting in positive co-movements of GDP growth. However,

[1](Static) spatial models have recently become popular in the empirical finance literature, see, e.g., Tonzer (2015), Herskovic et al. (2017), and Denbee et al. (2018).

[2]Acemoglu et al. (2012), for example, emphasize the relevance of the network structure for spillover effects between sectors.

[3]International co-movement through firms in one country and their cross-border links is analyzed by, for example, Di Giovanni et al. (2018) and Kleinert et al. (2015).

the effect depends crucially on time and industry. Positive synchronization effects of financial integration on GDP and industries with business-sensitive cycles such as industrial production or wholesale & retail trade are much larger during crisis periods, as in Kalemli-Ozcan et al. (2013a). Other industries are subject to small positive synchronization effects which are, interestingly, almost constant over both recessions and normal times (agriculture, construction). Cycle synchronization of a few industries is not subject to any positive or negative spillover effect stemming from financial integration, suggesting that these industries (public administration, real estate, arts & entertainment) are relatively closed-off and hardly affected by integrated financial markets. Therefore, time, industry-specification and feedback effects matter for the finance-business-cycle nexus.

The paper is structured as follows. In the next section, we describe the data and the empirical method. Results are presented in Section 3. The last section concludes the paper.

2 Empirical Strategy

2.1 Data

We proxy the degree of financial integration using data on direct bilateral cross-border claims of banks from the Bank for International Settlements (BIS). Similar to Kalemli-Ozcan et al. (2013a), Cesa-Bianchi et al. (2019) and many others, we make us of the locational banking statistics as they are well-suited for this task. Compared to the consolidated banking statistics, cross-border inter-office positions between banks of the same group are not netted out. Thus, the locational statistics deliver a clear picture on cross-border linkages with the potential of generating spillovers. From a theoretical perspective, this feature is important to consider as the activities of global banks matter for the transmission of shocks and effects on synchronization: Shocks in the real sector in one country should result in lower synchronization if global banks redirect their lending to unaffected countries. Shocks in the financial sector of some countries would induce global banks to retrench more globally, which in turn increases co-movement (Kalemli-Ozcan et al., 2013a).

For Europe, the BIS currently reports complete data for 10 countries since 1995.[4] Based on this data, we can span a sizeable network of European countries. A snapshots of the network can be seen in Figure 1 for 2017Q4. The graph reveals that some countries are more strongly

[4] Belgium, Denmark, Finland, France, Germany, Ireland, Netherlands, Sweden, Switzerland, UK.

interlinked than others, as reflected by the width of the links. The network overall shows a dense degree of interconnections. The sample period on which the estimations are based extends from 1996 until 2017 such that we can trace out whether the financial crisis starting in 2007/08 changes spillover dynamics permanently, or whether synchronization declines again, as one could hypothesize following the findings by Kalemli-Ozcan et al. (2013a) for the tranquil period before the financial crisis. In Tables 2 and 3, we show examples for the weighting matrix at different points in time. [5]

[Insert Figure 1 here]

[Insert Tables 2 and 3 here]

To capture the business cycle in a country and as our main dependent variable, we use quarterly GDP growth in constant prices drawn from the OECD. We then decompose GDP into quarterly gross value-added growth, also in constant prices, of 10 major industries downloaded from Eurostat.[6] All growth rates are winsorized at the 1st and 99th percentile. Figure 2 shows the average pattern of GDP growth and sectoral growth over time. Obviously, a sharp decline can be detected for aggregate GDP growth as well as for most sectors following the financial crisis starting in 2007/08. The growth path of some sectors closely resembles the one of aggregate GDP growth (e.g., industry (except construction) or wholesale & retail trade) while some sectors have notably different dynamics.

[Insert Figure 2 here]

In Tables 4-6, we show that GDP growth rates across countries are correlated to different extents. However, we take a purely bilateral perspective in this case. In the estimations, we explicitly account for the fact that also indirect links can contribute to business cycle synchronization. Still, such simple descriptive statistics reveal important facts. On average, there is less evidence for negative co-movements. Supporting the findings by Kalemli-Ozcan et al. (2013a), during the crisis period (Table 5), correlations go up, which does apply to most country pairs but excludes those with Ireland. Comparing the pre- and post-crisis period, no general pattern emerges. Partially, correlations are lower, while for some other country pairs they are still at a

[5] In the empirical analysis, we use row-normalized versions of these matrices.

[6] Agriculture, forestry and fishing. Arts, entertainment, recreation and other services. Construction. Financial and insurance activities. Industry (except construction). Information and communication. Professional, scientific and tech activities. Public administration, deference, education, human health and social work. Real estate activities. Wholesale and retail trade, transport, accommodation and food.

higher level (Tables 4 and 6). In sum, these patterns support the idea to control for time-varying spillover dynamics instead of taking a static view.

[Insert Tables 4-6 here]

To get a first glimpse on which sectors correlate most closely with aggregate growth, we show in Table 7 correlations between GDP growth and industrial sector growth rates. In line with the graphical evidence (Figure 2), correlations are highest between GDP growth and the industry (except construction) as well as the wholesale & retail trade sectors. The lowest correlation emerges with the agricultural sector. These differences highlight that economies' aggregate growth paths can be determined by diverging sectoral developments such that taking a more granular and sectoral view can provide useful insights.

[Insert Table 7 here]

We require further national and global control variables that might affect the finance-business-cycle nexus. On the country-level, we include quarterly growth rates of labor productivity, consumer confidence, labor force, gross fixed capital formation, government expenditure and credit to the non-financial sector (in percent of GDP). On the international level, we control for the quarterly change of the VIX and the Euro to U.S. Dollar exchange rate. More information on the variables can be found in the appendix. Summary statistics on the dependent and explanatory variables can be found in Table 8. We provide a correlation table between the dependent variable and the controls in Table 9.

[Insert Tables 8-9 here]

2.2 Method

Our empirical methodology comes from the literature on time-varying spatial dependence as established by Blasques et al. (2016). Compared to the related literature, we do not calculate bilateral correlations between countries' GDP growth and explain those correlations. Instead, we model each country's GDP growth as a weighted function of all financially interlinked countries' GDP growth. The spatial modelling approach has the advantage that interdependencies between a large set of countries can simultaneously be taken into account, and that the possibility of contemporaneous spillovers of shocks is incorporated.

Spatial models require the specification of a spatial weights matrix, which is typically chosen as a function of physical or economic distances between units. In our case, economic distance is defined by the cross-border bank claims two countries hold towards another, which is a measure of the degree of financial integration. We use a spatial lag model, which implies that each country's dependent variable may react to shocks to both the regressors and the disturbances of neighboring countries. Third-country and feedback effects are automatically taken into account. Additionally, we employ a time-varying spatial dependence parameter approach as suggested in Blasques et al. (2016). In this way, the magnitude of cross-sectional spillovers transmitted by financial integration can vary over time, allowing us to compare the effects during different stages of the economic and financial cycle.

The score-driven spatial lag model is given by

$$y_t = \rho_t W_t y_t + X_t \beta + e_t, \quad e_t \sim p_e(0; \Sigma, \nu), \quad t = 1, ..., T, \tag{1}$$

where y_t denotes an $N \times 1$- vector of country-specific growth rates of GDP or industrial value added at time t. $\beta = (\beta_1, ..., \beta_M)'$ is a vector of unknown coefficients, X_t is a matrix of country-specific and international regressors[7] and Σ is a positive definite covariance matrix. p_e denotes the density of the vector of disturbances e_t. We consider normally and Student's t-distributed disturbances. In the case of Student's t-distributed disturbances, p_e also depends on a degrees of freedom parameter ν.

The matrix W_t reflects the degree of financial integration between countries at time t and is assumed to be weakly exogenous.[8] The scalar spatial dependence parameter ρ_t measures the intensity of cross-country shock spillovers of real output, that are induced by financial links. To ensure stability, we specify $\rho_t = h(f_t)$ where $h(\cdot)$ is a monotone transformation such that $\rho_t \in (-1, 1)$. To describe the dynamics of f_t, we adopt the autoregressive score framework of Creal et al. (2011, 2013) and Harvey (2013).[9] The score framework centers around the use of the scaled score of the conditional density p_e to drive the time-variation in f_t. The updating equation for f_t is given by

$$f_{t+1} = \omega + A s_t + B f_t, \tag{2}$$

[7]The dependent variable and the explanatory variables are demeaned to control for country fixed effects. We control for time-varying dynamics affecting all countries alike by including global controls.

[8]See the data appendix for an example of a matrix for one point in time (Tables 2-3).

[9]See `www.gasmodel.com` for a more complete compilation of papers.

where ω, A, and B are fixed unknown parameters, and $s_t = S_t \nabla_t$ is the scaled score function, which serves as innovation term for the time-varying parameter.[10]

The spatial dependence coefficient ρ_t may be interpreted as an indicator of the degree of business cycle synchronization driven by financial links: A positive coefficient would reveal evidence for business cycle synchronization, while a negative coefficient would point towards desynchronization. Importantly, the modeling approach takes into account that in highly integrated markets, business cycle synchronization does not only occur between two countries in isolation. For example, shocks to country A can spill over to the directly linked country B but also affect country C, which has in turn financial links to country B.

Instead of imposing a particular model specification ex ante, we determine empirically whether GDP growth rates and industrial value added are indeed driven by shock spillovers from other countries. In particular, we estimate three versions of the model, each assuming either normally or Student's t distributed disturbances: (1) a baseline specification without any spillovers, i.e. $\rho_t = 0$, $t = 1, ..., T$, (2) a static version with $\rho_t = \rho$, $\forall t$ and (3) the dynamic specification given in equation (1). Model selection is conducted using the Akaike Information Criterion corrected for small sample sizes (AICc).

3 Estimation results

3.1 Results for overall output fluctuations (GDP)

Table 10 shows the results using quarterly GDP growth as the dependent variable for different specifications of the spatial model. Columns (1) and (2) report results obtained using a model without spillovers, columns (3) and (4) show findings allowing for spillovers with a static dependence coefficient, and columns (5) and (6) display results for a model with time-varying spillover effects of financial integration on GDP growth. The errors are assumed to be either normally or t-distributed. Values of the AICc indicate that the data favor the model using time-varying spillover effects and a t-distribution with the AICc being lower by 93 points than the no spillover model and by 20 points compared to the static model. Allowing for time-varying spillovers as introduced in Section 2.2 therefore seems to be the most appropriate way to measure the effect of financial integration on output fluctuations.

[10] The complete model specification including the expressions for s_t in the case of normal and Student's t distributed disturbances are given in the `online appendix`.

[Insert Table 10 here]

Turning to the coefficients, we find strong evidence for spatial dependence both in the static and the dynamic model, with ρ as well as A and B, the parameters entering the dynamic updating equation (2), being large and statistically highly significant. This result thus supports that, from a regional perspective, business cycles should not be considered in isolation in financially integrated countries as dynamics can propagate via financial links towards a country's own GDP growth.

All other coefficients enter with largely expected signs in all models. For example, productivity growth enters with a positive and economically and statistically highly significant coefficient. In our preferred specification, that features dynamic spillovers and t-distributed errors (column (6)), we obtain that rising consumer confidence, labor force, government expenditure and a depreciating Euro towards the U.S. Dollar are positively and statistically significantly associated with higher GDP growth. Gross fixed capital formation growth also enters with a positive coefficient that is, however, not significant on a 10% level. Changes in the volatility index VIX enter with a positive sign while increasing credit ratios carry a negative sign, but both coefficients are statistically insignificant.[11]

Having established that dynamic spillover effects from financial integration matter for European countries' GDP growth, we now turn to the evolution of the spillover intensity parameter over time, see Figure 3. We observe a strong cyclical component. While the parameter is positive on average, it peaks during times of financial stress, in particular the dotcom bubble (around 2000), the financial crisis (around 2008) and the European debt crisis (2011-2013). In calmer times (mid 1990s or mid 2000s), the spillover strength is lower, whereas in the recent time period (mid 2010s) characterized by financial disintegration, the spillover strength even becomes negative. This result is broadly in line with Kalemli-Ozcan et al. (2013a) who identify that financial integration has stronger effects on business cycle synchronization in times of crisis.

[Insert Figure 3 here]

3.2 Results for industrial output flucations

We now apply the analysis to individual industrial sectors. This dissection can shed light on the components that drive the aggregated effects on GDP we discussed in the previous section. Note

[11] The results are robust towards employing an alternative model specification using OLS regressions with country and year fixed effects.

that certain sectors are highly sensitive towards the business cycle, such as industrial output or wholesale and retail trade. For these sectors, we therefore expect similar patterns, both in terms of the best-fitting model and for the graph of the time-varying spillovers, compared to GDP growth. For other industrial sectors, we do not expect the same sensitivity towards growth shocks from other countries. An example is public administration, a largely nationally determined sector that should not vary much with business cycle spillovers due to international financial integration.

As before, we estimate six versions of each model (no spillovers, constant and dynamic dependence parameter, and both normal and t-errors), but for brevity, we only show the respective best model in Table 11 according to the AICc.[12] The results in Table 11 can be summarized as follows. Time-varying spillover dynamics fit the data best for four out of ten industrial sectors: industry (excluding construction); information & communication; professional, scientific and tech activities; wholesale & retail trade. Four different sectors show the best fit for a model that allows for spillovers, which are, however, driven by a constant instead of a time-varying parameter: agriculture, forestry and fishing; arts, entertainment, recreation and other services; construction; financial and insurance activities. Finally, there are two cases, public administration and real estate, for which we do not find evidence for any spatial dependence.

[Insert Table 11 here]

Figure 4 depicts the time-varying dependence parameters for the four industries, for which the time-varying model turned out to be the best fit.

[Insert Figure 4 here]

The patterns of three industrial sectors' spillover parameters are similar to the graph for GDP, see Figure 3. The resemblance is most obvious for the wholesale & retail trade sector, but it is also present for industry (excluding construction) as well as for professional, scientific and tech activities.[13] These three industries have in common that they strongly depend on the current business cycle, making them similarly affected towards spillovers from financial integration as overall GDP. Hence, both our estimation results and the graphs suggest that

[12] In the `online appendix`, we provide tables containing results from all model specifications for each sector (Tables A1-A10).

[13] This sector comprises mostly legal, management or engineering activities, see: `https://ec.europa.eu/eurostat/statistics-explained/index.php?title=File:F1_Sectoral_analysis_of_Professional,_scientific_and_technical_activities_(NACE_Section_M),_EU-28,_2016.png`.

interlinked countries specializing in these sectors are very likely to face a higher extent of business cycle synchronization, which relates to the results by Imbs (2004).

We also observe strong, time-varying spillovers across European countries' IT sectors (information & communication). However, the pattern differs from the ones for the other three sectors. Our interpretation of this finding is that IT sectors do face growth spillovers driven by financial interconnections, but in a more idiosyncratic way, potentially reflecting the more volatile and disruptive nature of this sector.

There is no evidence for spatial dependence for the public administration sector.[14] Similar results can be observed for the sector arts & entertainment and the real estate sector, which makes sense as both are largely nationally influenced. In the estimation results, these sectors showed the best fit for a no-spillover or static spillover model, suggesting that they are largely unaffected by spillover effects stemming from financial market integration.

We observe positive but rather small spillover effects for the agricultural, construction and financial sectors. Furthermore, the data for all these sectors favor a model with static spillover coefficient.[15] These results may indicate that the mentioned sectors are exposed to spillovers due to financial integration, but not as prime candidates or in a cyclical manner.

4 Conclusions

Whether financial integration between countries leads to diverging or converging patterns of GDP growth is still not fully resolved in the literature. We shed new light on this issue by modeling a group of financially developed European countries as a financial network, thereby extending the pure bilateral framework used in the literature, and taking dynamic feedback effects within the network into account. We arrive at two major results.

First, spillover effects via the channel of financial integration on business cycles vary over time and are much stronger during periods of financial turmoil. Second, business-sensitive sectors like industrial production, wholesale & retail trade, or professional, scientific & tech activities are strongly exposed to spillover effects from financial integration, with time-variation following a similar cyclical pattern as for overall GDP. Industrial sectors such as agriculture, construction or finance also feature positive spillover effects, but are less affected, and the spillover intensity

[14] This is also visible in the respective plot in the `online appendix`, where the spillover parameter fluctuates around zero (Figure A1).

[15] The time-varying spillover coefficients are also almost constant throughout our estimation period, as can be seen in the `online appendix`.

does not vary over time. Nationally influenced sectors such as public administration, arts & entertainment and real estate are not subject to relevant spillovers, positive or negative, due to financial integration.

Our results bear important policy implications. As we consistently find evidence for positive spillover dynamics across European countries and over time, our results show that in a densely financially integrated network of countries, business cycles are co-moving. Consequently, focusing only on national approaches to stabilize business cycles is likely to have limited effects, especially during times of crisis. In contrast, national measures should be accompanied by supranational actions mitigating spillovers of shocks via cross-border links among banking system, which supports policy measures such as the establishment of a European Banking Union. Furthermore, we show that industries are exposed to growth spillovers at different extents. This finding implies that in order to evaluate the exposure of a country's economy to business cycle synchronization and to mitigate negative effects during crisis times, sectoral specializations have to be taken into account. Only then can policy rescue programs be more effectively designed to support the sectors in distress.

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6 Tables and Figures

Table 1: Description and sources of variables

Variable	Description	Source
Dependent Variables		
ΔGDP	Quarter-to-quarter growth rate of GDP in constant 2010 prices, seasonally adjusted.	OECD
ΔIndustry Sector	Quarter-to-quarter growth rates of gross value added in constant 2010 prices, season and calendar adjusted. Industries according to Eurostat's A*10 industry breakdown are: Agriculture, forestry and fishing. Arts, entertainment, recreation and other services. Construction. Financial and insurance activities. Industry (except construction). Information and communication. Professional, scientific and tech activities. Public administration, defence, education, human health and social work. Real estate activities. Wholesale and retail trade, transport, accommodation and food.	Eurostat
Spatial Matrix		
Spatial Matrix Weights	BIS locational banking statistics, total claims of all reporting banks (in all currencies and instruments) towards all sectors in counterparty country.	BIS
Control Variables		
ΔProductivity	Labour productivity, growth rate, seasonally adjusted.	OECD
ΔConsumer Confidence	Consumer confidence indicator, growth rate, seasonally adjusted.	OECD
ΔGross Fixed Capital Formation (GFCF)	Gross fixed capital formation, growth rate, constant prices, seasonally adjusted.	OECD
ΔLabour Force	Labour force, growth rate, seasonally adjusted.	OECD
ΔGovernment Expenditure	Government final consumption expenditure, growth rate, constant prices, seasonally adjusted.	OECD
ΔCredit to Non-Financial Sector	Credit to private non-financial sector, growth rate, provided by all sectors, in percent of GDP.	BIS
ΔVIX	Volatility VIX, growth rate.	CBOE
ΔEuro-to-Dollar Exchange Rate	Euro to U.S. Dollar exchange rate, growth rate.	Thomson Reuters

Table 2: Network matrix of banking systems' cross-border claims for 1996:Q1

	Belgium	Denmark	Finland	France	Germany	Ireland	Netherlands	Sweden	Switzerland	UK
Belgium		1374	1526	28657	10514	5974	14907	3855	5348	47685
Denmark	2038		1341	3136	1533	2533	850	5507	969	15507
Finland	617	470		786	372	17	316	3914	233	3916
France	29439	6380	2241		39688	3529	15750	4918	16766	146083
Germany	13509	5466	4576	28134		11273	21636	6820	13429	116563
Ireland	1126	650	794	2400	8621		1647	1474	479	12090
Netherlands	21963	2280	703	14368	21862	6041		3768	7602	40884
Sweden	1351	1594	1656	897	1746	277	2117		778	17531
Switzerland	36673	1475	927	31597	23261	1868	34426	2498		173198
UK	41960	9614	9224	96405	161291	17703	33092	25833	39088	

Notes: This table shows the network matrix based on BIS locational banking statistics for 1996:Q1. Data on a country's banking system claims (from row-country towards column-country) in millions of US dollars is depicted.

Table 3: Network matrix of banking systems' cross-border claims for 2017:Q4

	Belgium	Denmark	Finland	France	Germany	Ireland	Netherlands	Sweden	Switzerland	UK
Belgium		2423	1150	71463	52457	20012	72993	2444	14870	72486
Denmark	1998		7661	12851	47964	2114	3039	83375	3520	31498
Finland	1318	12614		5858	8170	496	2583	21551	143	8985
France	122957	10260	7133		118875	67037	108142	18416	76632	372761
Germany	36694	20771	22328	216641		34132	173043	41449	79548	322777
Ireland	6312	4006	908	19655	16158		26158	2445	2416	94892
Netherlands	61170	4268	10620	85493	81552			6724	29611	318205
Sweden	2930	104404	96840	12968	29685	1102	9286		5897	64214
Switzerland	9654	5510	1109	57596	49264	8158	23053	4374		148994
UK	56175	22008	17182	507496	439557	163186	315718	44461	199079	

Notes: This table shows the network matrix based on BIS locational banking statistics for 2017:Q4. Data on a country's banking system claims (from row-country towards column-country) in millions of US dollars is depicted.

Table 4: Correlation of ΔGDP between countries (pre-crisis)

	Belgium	Denmark	Finland	France	Germany	Ireland	Netherlands	Sweden	Switzerland	UK
Belgium	1.000									
Denmark	0.175	1.000								
Finland	0.214	-0.141	1.000							
France	0.432	0.303	0.315	1.000						
Germany	0.365	0.274	0.133	0.368	1.000					
Ireland	0.339	0.234	0.144	0.176	0.095	1.000				
Netherlands	0.425	0.424	0.136	0.507	0.448	0.218	1.000			
Sweden	0.222	0.121	0.141	0.411	0.094	0.074	0.348	1.000		
Switzerland	0.462	0.060	0.233	0.469	0.345	0.202	0.348	0.307	1.000	
UK	0.006	-0.064	-0.009	0.104	-0.007	0.214	0.082	-0.005	0.160	1.000

Notes: This table shows correlations of GDP growth rates (ΔGDP) between countries before 2008 (pre-crisis). GDP growth rates are winsorized at the 1st and 99th percentile. Data is obtained from the OECD.

Table 5: Correlation of ΔGDP between countries (during the crisis)

	Belgium	Denmark	Finland	France	Germany	Ireland	Netherlands	Sweden	Switzerland	UK
Belgium	1.000									
Denmark	0.846	1.000								
Finland	0.830	0.743	1.000							
France	0.889	0.751	0.849	1.000						
Germany	0.918	0.752	0.875	0.991	1.000					
Ireland	0.152	-0.081	0.148	0.137	0.109	1.000				
Netherlands	0.721	0.546	0.811	0.860	0.873	-0.111	1.000			
Sweden	0.764	0.510	0.794	0.748	0.762	0.433	0.780	1.000		
Switzerland	0.925	0.775	0.874	0.860	0.912	0.005	0.811	0.761	1.000	
UK	0.922	0.680	0.685	0.891	0.907	0.139	0.684	0.619	0.805	1.000

Notes: This table shows correlations of GDP growth rates (ΔGDP) between countries 2008:Q1-2009:Q4 (during the crisis). GDP growth rates are winsorized at the 1st and 99th percentile. Data is obtained from the OECD.

Table 6: Correlation of ΔGDP between countries (post-crisis)

	Belgium	Denmark	Finland	France	Germany	Ireland	Netherlands	Sweden	Switzerland	UK
Belgium	1.000									
Denmark	0.369	1.000								
Finland	0.551	0.188	1.000							
France	0.399	0.018	0.423	1.000						
Germany	0.626	0.082	0.450	0.564	1.000					
Ireland	0.181	-0.318	-0.140	0.381	0.205	1.000				
Netherlands	0.338	0.026	0.446	0.441	0.327	0.265	1.000			
Sweden	0.062	-0.229	-0.038	-0.118	0.008	0.094	0.534	1.000		
Switzerland	0.088	0.072	0.136	0.187	0.302	0.170	0.134	-0.102	1.000	
UK	0.137	0.045	0.192	0.132	0.325	0.155	0.189	0.237	0.220	1.000

Notes: This table shows correlations of GDP growth rates (ΔGDP) between countries after 2009 (post-crisis). GDP growth rates are winsorized at the 1st and 99th percentile. Data is obtained from the OECD.

Table 7: Correlations between GDP and industrial sector growth rates

	ΔGDP	ΔAgriculture, Forestry and Fishing	ΔArts, Entertainment and Recreation	ΔConstruction	ΔFinancial and Insurance Activities	ΔIndustry	ΔInformation and Communication	ΔProfessional, Scientific and Tech Activities	ΔPublic Administration	ΔReal Estate Activities	ΔWholesale and Retail Trade, Transport
ΔGDP	1.000										
ΔAgriculture, Forestry and Fishing	0.133	1.000									
ΔArts, Entertainment and Recreation	0.150	-0.002	1.000								
ΔConstruction	0.385	-0.022	0.127	1.000							
ΔFinancial and Insurance Activities	0.264	0.086	0.053	0.053	1.000						
ΔIndustry	0.662	0.047	0.065	0.114	0.081	1.000					
ΔInformation and Communication	0.337	0.043	0.043	0.085	0.021	0.129	1.000				
ΔProfessional, Scientific and Tech Activities	0.347	0.048	0.091	0.144	0.044	0.168	0.097	1.000			
ΔPublic Administration	0.199	0.004	0.047	0.077	0.061	0.015	0.120	0.033	1.000		
ΔReal Estate Activities	0.232	0.013	0.019	0.069	-0.015	0.093	0.033	0.025	0.060	1.000	
ΔWholesale and Retail Trade, Transport	0.535	0.020	0.167	0.278	0.073	0.191	0.170	0.281	0.042	0.119	1.000

Notes: This table shows correlations between GDP and industrial growth rates for the period 1996-2017. All variables are in quarterly growth rates. GDP and industrial sector growth rates are winsorized at the 1st and 99th percentile. Data is obtained from the OECD and Eurostat.

Table 8: Summary statistics of dependent and independent variables

	(1) N	(2) mean	(3) p50	(4) sd	(5) min	(6) max
ΔGDP	910	0.553	0.532	0.897	-2.275	4.004
ΔAgriculture, Forestry and Fishing	906	0.178	0.128	5.205	-19.24	19.72
ΔArts, Entertainment and Recreation	906	0.320	0.295	1.756	-5.420	5.914
Δ Construction	906	0.279	0.296	2.468	-8.088	7.895
ΔFinancial and Insurance Activities	906	0.636	0.538	3.019	-9.018	10.46
ΔIndustry	906	0.445	0.429	2.699	-9.753	11.16
ΔInformation and Communication	898	1.488	1.236	2.667	-6.968	12.06
ΔProfessional, Scientific and Tech Activities	906	0.835	0.784	1.828	-4.825	6.882
ΔPublic Administration	906	0.312	0.305	0.624	-1.486	2.267
Δ Real Estate Activities	906	0.405	0.336	1.089	-2.785	3.901
ΔWholesale and Retail Trade, Transport	898	0.521	0.592	1.274	-4.337	4.053
Δ Productivity	916	0.313	0.270	1.197	-5.830	21.71
ΔCredit to Non-Financial Sector	910	0.482	0.374	1.912	-9.325	28.86
ΔLabourForce	910	0.202	0.179	0.533	-1.650	7.990
ΔConsumer Confidence	907	0.0159	0.0413	0.562	-2.327	2.274
ΔGFCF	910	0.867	0.674	7.326	-46.95	161.1
ΔGovernment Expenditure	910	0.410	0.388	0.926	-4.893	6.657
ΔEuro-to-Dollar Exchange Rate	910	0.000484	0.00282	0.0490	-0.116	0.118
ΔVIX	910	-0.00367	-0.0120	0.274	-0.664	1.052

Notes: This table shows summary statistics of dependent and independent variables for the period 1996-2017. All variables are in quarterly growth rates. GDP and industrial sector growth rates are winsorized at the 1st and 99th percentile. See the data description for more information on data sources.

Table 9: Correlations between dependent and independent variables

	Δ GDP	ΔAgriculture, Forestry and Fishing	ΔArts, Entertainment and Recreation	ΔConstruction	ΔFinancial and Insurance Activities	ΔIndustry	ΔInformation and Communication	ΔProfessional, Scientific and Tech Activities	ΔPublic Administration	ΔReal Estate Activities	ΔWholesale and Retail Trade, Transport
ΔProductivity	0.739	0.032	0.101	0.209	0.216	0.590	0.282	0.180	0.070	0.115	0.352
ΔConsumer Confidence	0.229	0.057	-0.011	0.075	0.075	0.166	0.007	0.093	-0.034	-0.059	0.188
ΔLabourForce	0.110	-0.073	0.089	0.145	0.007	-0.020	0.027	0.069	0.078	0.058	0.110
ΔGFCF	0.198	0.012	0.084	0.239	0.022	0.068	0.010	0.032	0.002	0.009	0.124
ΔGovernment Expenditure	0.150	0.030	0.032	0.106	0.027	0.083	0.013	0.082	0.256	0.083	0.056
ΔCredit to Non-Financial Sector	-0.000	-0.052	0.049	-0.037	0.085	0.023	0.056	-0.058	0.030	-0.015	-0.066
ΔEuro-to-Dollar Exchange Rate	-0.001	0.003	-0.041	0.076	0.002	-0.051	0.037	0.047	-0.026	-0.011	-0.036
ΔVIX	-0.112	0.026	-0.038	-0.029	-0.028	-0.127	0.041	-0.048	-0.002	-0.002	-0.058

Notes: This table shows correlations between dependent and independent variables for the period 1996-2017. All variables are in quarterly growth rates. GDP and industrial sector growth rates are winsorized at the 1st and 99th percentile. See the data description for more information on data sources.

Table 10: Estimation results – Gross domestic product

	no spillovers		static spillovers		dynamic spillovers	
	normal	t	normal	t	normal	t
ρ			0.436	0.309		
			(0.026)	(0.032)		
ω					0.168	0.037
					(0.102)	(0.034)
A					0.007	0.042
					(0.002)	(0.007)
B					0.553	0.806
					(0.248)	(0.084)
$\ln(\sigma^2)$	-0.630	-1.388	-0.916	-1.411	-0.922	-1.428
	(0.048)	(0.096)	(0.048)	(0.088)	(0.048)	(0.087)
constant	-0.165	-0.218	-0.135	-0.221	-0.119	-0.219
	(0.029)	(0.025)	(0.025)	(0.023)	(0.026)	(0.022)
ΔVIX	-0.002	0.165	-0.002	0.110	-0.031	0.073
	(0.092)	(0.080)	(0.080)	(0.070)	(0.080)	(0.063)
ΔEuroToDollar	-0.022	1.243	0.149	0.687	0.121	1.159
	(0.505)	(0.415)	(0.438)	(0.385)	(0.432)	(0.358)
ΔProductivity	0.519	0.722	0.447	0.682	0.441	0.672
	(0.022)	(0.026)	(0.020)	(0.025)	(0.020)	(0.025)
ΔCreditToNonFinancialSector	-0.118	-0.011	-0.094	-0.018	-0.089	-0.017
	(0.013)	(0.012)	(0.012)	(0.011)	(0.012)	(0.011)
ΔConsumerConfidence	0.273	0.160	0.117	0.104	0.114	0.117
	(0.046)	(0.039)	(0.041)	(0.037)	(0.042)	(0.035)
ΔGFCF	0.008	0.004	0.005	0.004	0.005	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
ΔLabourForce	0.136	0.146	0.090	0.120	0.086	0.108
	(0.046)	(0.038)	(0.040)	(0.037)	(0.040)	(0.035)
ΔGovernmentExpenditure	0.061	0.062	0.059	0.059	0.062	0.054
	(0.027)	(0.020)	(0.023)	(0.019)	(0.023)	(0.019)
ν		4.122		5.290		5.616
		(0.734)		(1.029)		(1.123)
logLik	-971.264	-812.141	-862.333	-774.284	-854.227	-761.522
AICc	1965.385	1649.755	1750.139	1576.727	1739.373	**1556.797**

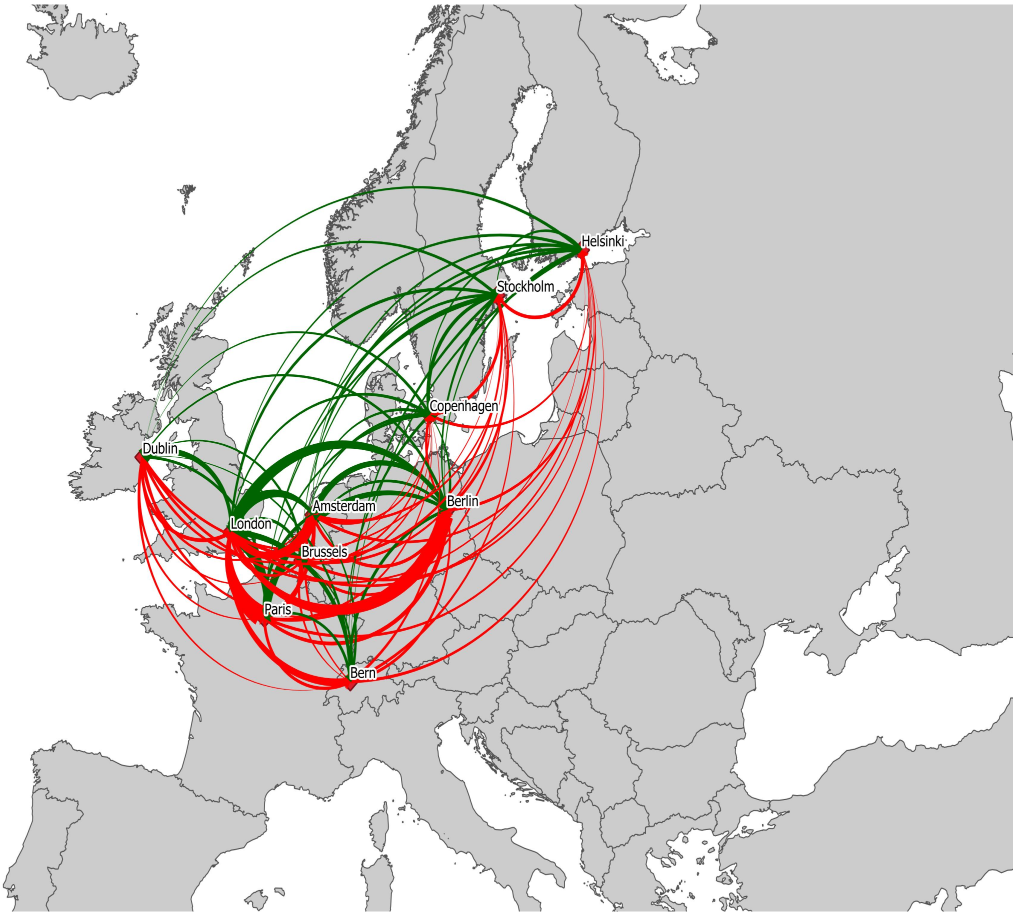
Notes: This table shows estimation results for different model specifications (no spillovers, static spillovers, dynamic spillovers) based on normal or t-distribution as indicated in the column header. Standard errors are reported in brackets below coefficient estimates. The Akaike information criterion (AICc) is depicted in bold for the model with the best fit (smallest value). The dependent variable is quarterly GDP growth. The sample period spans 1996-2017. All variables are in quarterly growth rates. GDP and industrial sector growth rates are winsorized at the 1st and 99th percentile. See the data description for more information on data sources.

Table 11: Estimation results – Industrial sectors (best model fit)

	Agriculture	Arts & Entertainment	Construction	Finance & Insurance	Industry	Information & Communication	Professional, Scientific & Tech Activities	Public Administration	Real Estate	Wholesale & Retail Trade
ρ	0.182	0.063	0.224	0.174						
	(0.050)	(0.051)	(0.043)	(0.047)						
ω					0.054	0.113	0.127			0.054
					(0.050)	(0.088)	(0.063)			(0.040)
A					0.03	0.044	0.046			0.044)
					(0.009)	(0.019)	(0.013)			(0.011)
B					0.718	0.542	0.543			0.694
					(0.218)	(0.317)	(0.174)			(0.161)
$\ln(\sigma^2)$	-0.488	-0.378	-0.32	-0.209	-0.873	-0.438	-0.378	-0.25	-0.182	-0.552
	(0.094)	(0.086)	(0.072)	(0.071)	(0.081)	(0.082)	(0.073)	(0.074)	(0.072)	(0.078)
constant	-0.004	-0.068	-0.062	-0.043	-0.081	-0.104	0.02	-0.150	-0.061	-0.03
	(0.035)	(0.036)	(0.036)	(0.038)	(0.030)	(0.037)	(0.036)	(0.037)	(0.039)	(0.033)
ΔVIX	0.097	-0.100	0.001	-0.019	-0.113	0.076	0.017	-0.072	0.067	0.138
	(0.099)	(0.102)	(0.114)	(0.120)	(0.082)	(0.104)	(0.108)	(0.115)	(0.124)	(0.101)
ΔEuroToDollar	-0.498	-0.974	1.298	0.137	-0.186	0.911	0.568	-0.920	0	0.452
	(0.549)	(0.605)	(0.617)	(0.653)	(0.465)	(0.599)	(0.586)	(0.616)	(0.655)	(0.562)
ΔProductivity	0.079	0.055	0.127	0.119	0.425	0.188	0.111	0.032	0.099	0.216
	(0.033)	(0.029)	(0.028)	(0.029)	(0.030)	(0.030)	(0.026)	(0.029)	(0.031)	(0.029)
ΔCreditTo NonFinancialSector	-0.012	-0.011	-0.045	0.003	-0.030	-0.004	-0.05	-0.000	-0.015	-0.051
	(0.017)	(0.016)	(0.016)	(0.017)	(0.015)	(0.017)	(0.016)	(0.018)	(0.018)	(0.016)
ΔConsumer Confidence	0.020	-0.029	0.100	0.082	0.059	-0.098	0.087	-0.033	-0.1	0.148
	(0.052)	(0.054)	(0.057)	(0.060)	(0.045)	(0.055)	(0.056)	(0.058)	(0.062)	(0.052)
ΔGFCF	0.001	0.007	0.016	-0.002	-0.002	-0.006	-0.002	0.000	-0.003	0.001
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
ΔLabourForce	-0.087	0.143	0.140	0.009	0.011	0.009	0.021	0.087	0.039	0.128
	(0.056)	(0.061)	(0.058)	(0.058)	(0.046)	(0.059)	(0.054)	(0.063)	(0.061)	(0.050)
ΔGovernment Expenditure	-0.012	0.035	0.053	0.006	0.034	-0.013	0.049	0.284	0.028	0.036
	(0.032)	(0.034)	(0.033)	(0.035)	(0.026)	(0.034)	(0.032)	(0.037)	(0.036)	(0.030)
ν	4.931	6.39	12.747	14.733	7.253	7.221	13.31	12.330	13.702	9.222
	(1.020)	(1.453)	(3.904)	(5.283)	(1.607)	(1.645)	(4.613)	(4.004)	(4.729)	(2.485)
logLik	-1184.578	-1199.272	-1173.394	-1213.112	-972.731	-1165.378	-1149.99	-1202.457	-1226.363	-1092.829
AICc	2397.316	2426.704	2374.949	2454.385	1979.216	2364.509	2333.733	2430.388	2478.200	2219.412

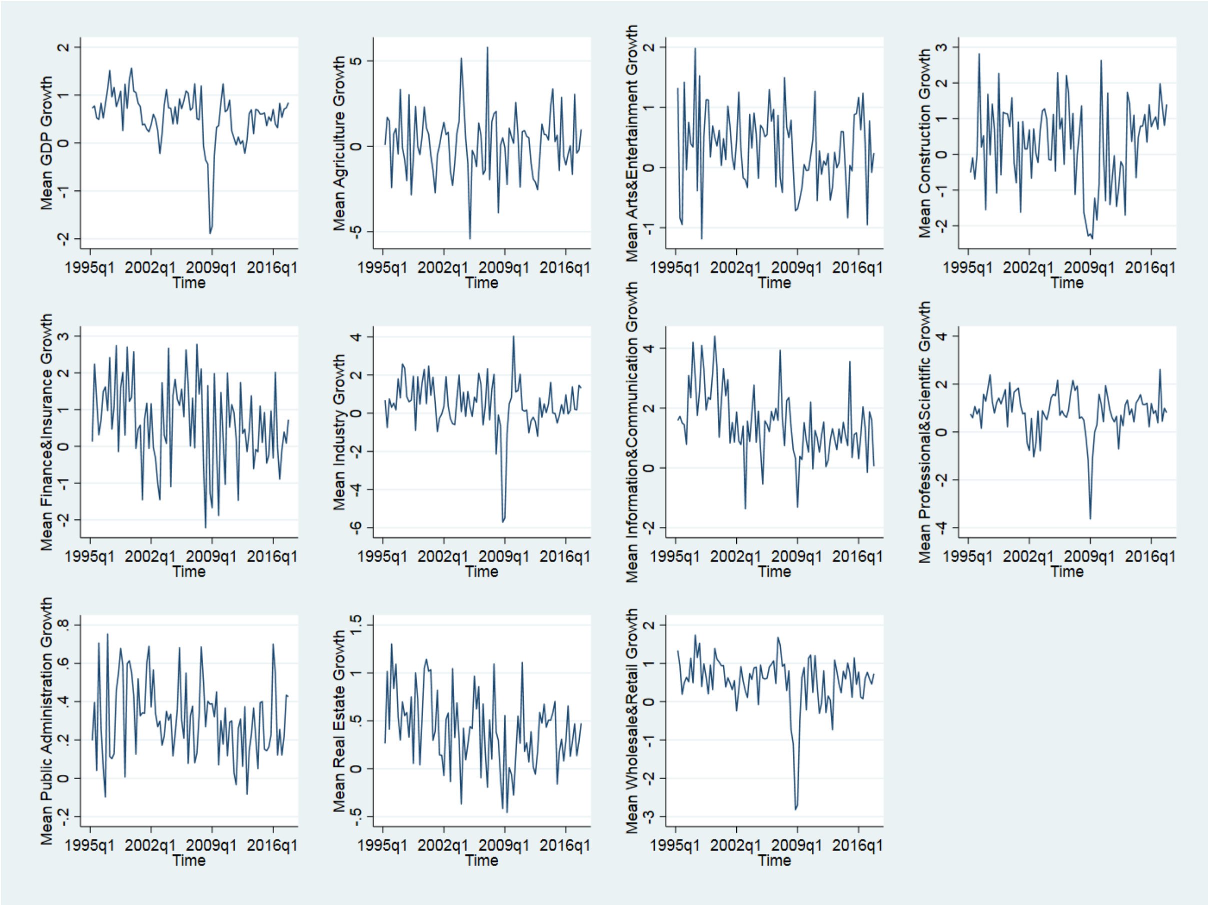
Notes: This table shows estimation results for the different industrial sectors whereas the model specification with the best fit is shown (see online appendix, Tables A1-A10, for all specifications per sector). All estimates are based on a t-distribution. Standard errors are reported in brackets below coefficient estimates. The dependent variable is the quarterly growth of the sector as indicated in the column header. The sample period spans 1996-2017. All variables are in quarterly growth rates. GDP and industrial sector growth rates are winsorized at the 1st and 99th percentile. See the data description for more information on data sources.

Figure 1: Bilateral banking network, 2017Q4



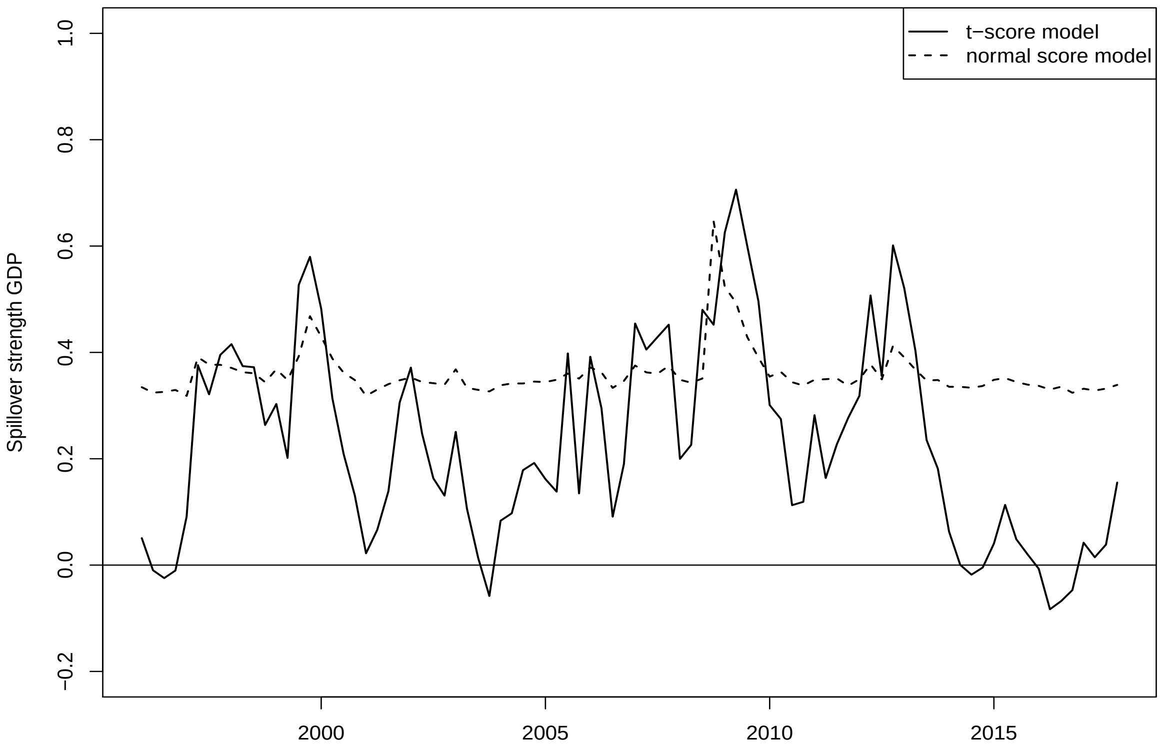
Notes: The graph shows bilateral cross-border claims of countries' banking systems for 2017Q7. Data is obtained from the Locational Banking Statistics of the Bank for International Settlements.

Figure 2: Growth rates of GDP and all industrial sectors.



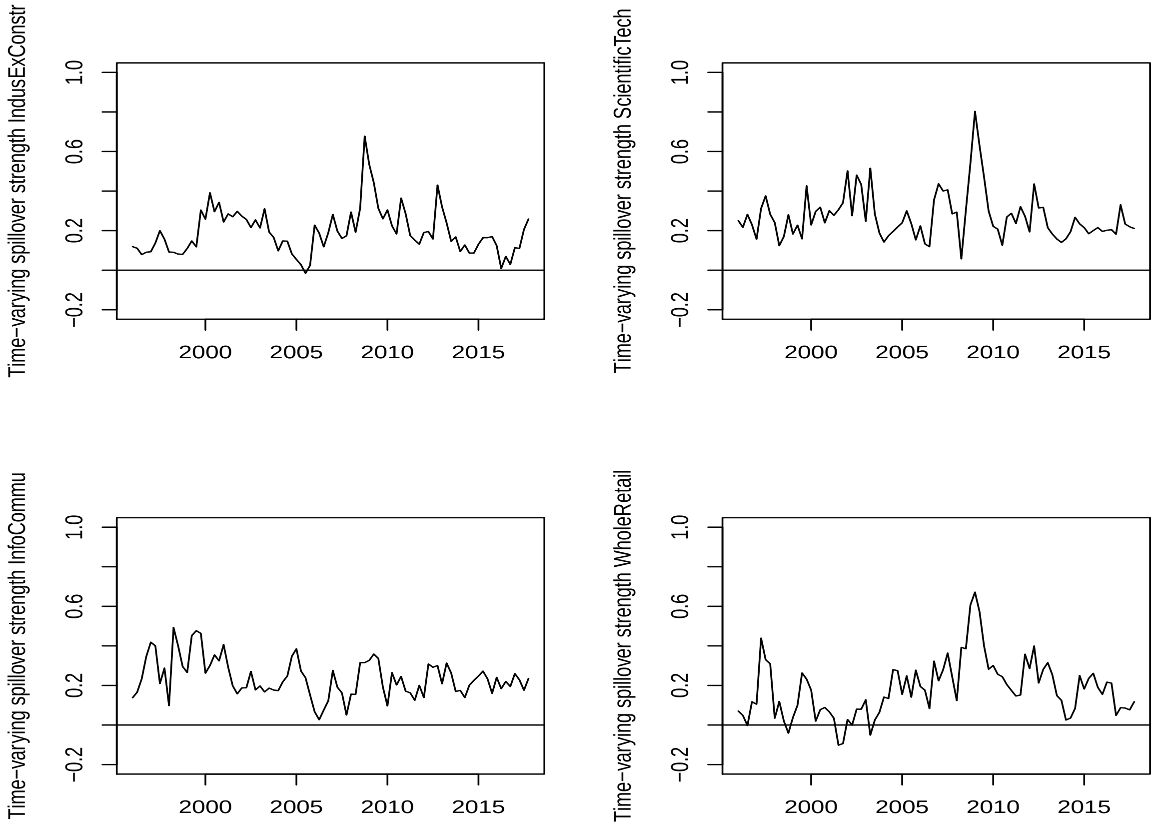
Notes: The graph shows quarterly growth rates of GDP and the industrial sectors. The sample period spans 1996-2017. Data is obtained from the OECD and Eurostat.

Figure 3: Time-varying spillover strength for gross domestic product



Notes: The graph shows the time-varying spillover strength for the model with quarterly GDP growth as the dependent variable and the sample period 1996-2017. The model is estimated based on a score-driven model with Student's t-distributed (solid line) and normally distributed (dashed line) disturbances.

Figure 4: Time-varying spillover strength for four industrial sectors



Notes: The graph shows the time-varying spillover strength for the four industrial sectors for which the time-varying model is the best. The dependent variable is the quarterly sectoral growth rate and the sample period spans 1996-2017. The sectors comprise: Upper left: Industry (except construction); Upper right: Professional, scientific and tech activities; Lower left: Information and Communication; Lower right: Wholesale and retail trade, transport, accommodation and food). The model is estimated based on score-driven model with Student's t-distributed disturbances.

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