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Abstract

This paper empirically investigates the propagation of business sentiment within the European Union (EU) and adds to the literature on shock absorption via a common market's real economy. To this end, we combine EU-wide official business sentiment indicators with world input-output (IO) data and information on indirect wage costs. Econometrically, we model interdependencies in economic activities via IO-linkages and apply space-time models. The resulting evidence provides indication for the existence of substantial spillovers in business sentiment formation. Accordingly, and highlighted by the estimated impacts of changes in indirect labor costs, policy reforms aiming at increasing the resilience of the European single market need to take these spillovers into account in order to increase its effectiveness.

JEL classification: C33; D84; E32; J32; L14.

Keywords: Business sentiment; propagation; economic fluctuations; input-output linkages; networks; space-time model; policy reforms.

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1 Introduction

With the outbreak of the global financial crisis and the subsequent European debt crisis, the question on potential contagion effects in financial markets received substantial policy attention. The discussion reinforced the necessity for a proper understanding of the propagation of shocks to economic activity within the European Union (EU) and especially among euro area member states. In particular, and based on both the traditional and recent literature on optimal currency areas (see e.g., Mundell 1961; Rey 2016), the question on the extent of prevailing asymmetries in the resilience to (negative) external shocks has been heavily debated. Furthermore, in borderless economic areas such as the EU and the euro area a proper understanding regarding the transmission of shocks across regions and economic activities is of specific policy relevance as effective common (or coordinated) policy measures need to account for the likely spillover effects occurring.

While the recent economic literature as well as policy makers devoted substantial interest on the transmission of negative shocks at the financial markets (see e.g. Yellen 2013; Acemoglu et al. 2015), the evidence on the propagation of expectations in the real economy is still limited.[1] This paper aims at filling this gap by analyzing the propagation of business sentiment within the EU. In particular, we are investigating how a shock to business sentiment in a certain industry in a member country, on average, affects business sentiment in other industries and member states both in the short- and long-run, respectively. Studying the formation of business expectations is important for many reasons. First, in the business cycle literature, business sentiments have been identified as important leading indicator for forecasting GDP growth (see e.g. Hansson et al. 2005; Pesaran and Weale 2006; Taylor and McNabb 2007). As a consequence, business sentiment data provides early and valuable information for designing short-run policy measures for counterbalancing (external) shocks. Second, changes in business sentiment result from inherently unobservable individual information gathering processes of firms and by studying potential spillover effects in the formation of business sentiment, this paper helps to foster our understanding on how firms react to changes in business expectations over European value chains. In case we are able to identify significant spillover effects, forecasting models might profit from incorporating this channel for shock transmission in order to increase their predictive power.

From a macroeconomic perspective, the paper is closely related to previous literature on the role of sentiments and their propagation for macroeconomic fluctuations. Angeletos and La'O (2013), for example, set up a business cycle model with (imperfect) communication between trading islands, where shifts in sentiments, formalized as shifts in expectations which are independent from changes in preferences and available technologies, may drive the business cycle. They show that communication can serve as transmission mechanism between agents, leading to contagion effects and the spread of rumors, which generate boom-and-bust cycles. Regarding the international transmission of business cycles, De Grauwe and Ji (2016) develop a two-country behavioral macroeconomic model where the main channel of synchronization takes place through waves of optimism and pessimism that become correlated internationally over time. Finally, Levchenko and Pandalai-Nayar (2015) investigate the international transmission of different kinds of shocks from the US to Canada, and find that shocks to sentiment are most important for generating short-run business cycle comovement between the two economies. The present paper adds to this literature by providing empirical evidence for the transmission of sentiment shocks via the channel of trade linkages within and across the EU member states.

We contribute to another recent strand in the literature demonstrating that idiosyncratic shocks taking place

[1] The literature on (global) value chains forms a notable exception and empirically assesses the spillovers induced by downstream demand shocks on suppliers located upstream in the value chain (see e.g. Bems et al. 2011).

on a disaggregated level may have important macroeconomic implications contradicting the view of Lucas (1977), who argued that individual shocks would average out at the aggregated level due to a law of large numbers. When studying the granularity in the firm size distribution, it turns out that its distribution is sufficiently heavy tailed implying an asymmetric impact of firms of different sizes on the evolution of macroeconomic aggregates (e.g. Gabaix 2011; di Giovanni et al. 2014). Furthermore, the existence of networks of input-output (IO) linkages due to the organization of production activities via (global) value chains induces a (positive) correlation in shock experiences translating into a comovement of individual firms or sectors over the business cycle (see e.g., Acemoglu et al. 2012, 2016). As a consequence of this sectoral heterogeneity in network relevance, macroeconomic tail risks might be substantial, such that deviations of aggregate variables from their trends cannot be approximated by a normal distribution at the tails since this distribution would underestimate the frequencies of economic downturns (Acemoglu et al. 2017). Concerning the international transmission of shocks originating at the firm level, trade linkages with a certain foreign country significantly increase the correlation of a firm and that country (di Giovanni et al. 2018). We explicitly model potential spillover effects via IO relationships in order to provide evidence for externalities resulting from this channel of shock transmission.

By studying the evolution of business sentiment over time we also contribute to the literature investigating the question how economic agents react to changes in available information which has been viewed as fundamental and is still highly debated.[2] With regard to the formation of expectations of firms, Hellwig and Veldkamp (2009) provide a nice microfoundation for expectation formation in which firms play a strategic game and can acquire information which, however, is costly. Consistent with this framework, Coibion et al. (2015) find a widespread dispersion of firm beliefs concerning relevant macroeconomic variables. Bachmann et al. (2013), in turn, investigate the impact of the resulting uncertainty on firms' economic activities and Bachmann and Elstner (2015) find systematic and non-negligible expectation biases of firms and are able to explain differences in these biases by observable firm characteristics. We add to this literature by providing systematic evidence on the propagation of sentiments based on interdependencies in economic activities.

Econometrically, we apply a space-time framework to model spillover effects in business sentiment within and across industries and countries and additionally allow for persistence of expectations over time. Following Badinger and Egger (2016) and based on the input-output network literature, we propose trade in intermediate goods as a measure for the magnitude of interactions between countries' industries. By further including time-specific exogenous demand-side variables and policy measures, we investigate how shocks to these affect business sentiment and are further transmitted to other industries and countries over time. The proposed space-time model also allows to disentangle direct from indirect effects and to calculate the short- versus long-run adjustment processes in business sentiment formation within the EU.

For empirically addressing our research question, we rely on business sentiment data provided by the European Commission. They are derived from harmonized surveys where national research institutes in the member states and candidate countries ask around 135,000 firms about their economic sentiment. From a subset of specific questions, the Commission then calculates a one-dimensional composite index called the business sentiment indicator (European Commission 2016). This information is available at the 2-digit NACE Rev.2 industry level from which we use the seasonally adjusted quarterly data spanning a time period from 2005 to 2014. Input-output linkages across industries and countries are empirically modeled by relying on data retrieved from the World Input Output Database (WIOD), release October 2016 (Timmer, Dietzen-

[2] A large body of research focuses on the formation of expectations of the general public, consumers and professional researchers/forecasters: Coibion and Gorodnichenko (2012), for example, find empirical evidence for serially correlated forecasting errors concerning the prediction of future inflation rates which indicates the existence of information rigidities. Such rigidities may point to an infrequent updating of available information (Mankiw and Reis 2002) or arise when agents are able to only acquire imperfect information (e.g. Woodford 2001; Sims 2003).

bacher, Los, Stehrer and de Vries 2015). The WIOD provides yearly inter-country input-output tables for mainly 2-digit (ISIC Rev.4) industries for the period from 2000-2014. In order to avoid potential endogeneity issues of the input-output relationships, we use the input-output table from 2004 when computing our linkage matrices. We draw on further data from WIOD in order to construct additional covariates. In particular, we split total production into production for (i) intermediate goods and (ii) final demand. Furthermore, we add quarterly data on indirect labor costs including social security contributions and payroll taxes retrieved from Eurostat (Eurostat 2017a). These data allow for an explorative analysis of the impact of policy reforms on business sentiment formation and the respective spillover effects induced by such reforms. The resulting data set covers 679 individual European industries per cross-section and the panel data set is balanced.

The results from our empirical analysis indicate high persistence in business expectations from quarter to quarter as well as cross-sectional autocorrelation of business sentiment formation resulting from trade dependencies. The latter implies that (exogenous) shocks will be multiplied due to repercussion effects. More explicitly, if a randomly chosen European industry experiences a positive and unitary shock, business sentiment in this particular industry will, on average, contemporaneously increase by 1.16 (net balance) index points. Due to confidence rigidities, the long-run effect of such a shock on business sentiment, on average, amounts to 4.15 index points. With regard to the explanatory variables of interest, positive average direct impacts of the growth rates of intermediate production and final demand are identified. The impacts decrease gradually over time, and are halved approximately two quarters after intermediate demand experiences a shock. The results also reveal positive spillovers related to intermediate production growth, while the spillovers of final demand growth are negative. Based on our estimates, we find that a reduction of social security contributions and payroll taxes in one particular industry located in one country leads to increases in business sentiments both in the affected industry as well as in all other industries and countries. With regard to the latter, the long-run effect suggests that a one standard deviation decline in the growth of indirect wage costs increases the business expectations in downstream industries by an average of 1.42 index points.

From a policy point of view, our results confirm the view that idiosyncratic shocks will not cancel out in a macroeconomic perspective and, thus, spillover effects need to be taken into account when implementing public policies. A negative (and maybe external) shock to business sentiment in one specific industry and country will induce an externality to all other industries and countries in the common market and will be reinforced via feedback loops. Any attempt to increase the resilience of the European single market will thus only be successful when it increases the individual resilience of each and every industry which might be prone to negative external shocks. Accordingly, one size fits all policies might be very ineffective for increasing the resilience of the European economy and customized policy making, as proposed within the framework of the European Semester, might be most effective in supporting the member states in their efforts to prevent future economic downturns (see Oberhofer et al. 2016, for a similar discussion). The illustrative policy effects stemming from a hypothetical reduction in indirect wage costs, however, also document that such policies most likely also induce spillover effects in the formation of business sentiment within European value chains. For increasing the effectiveness of individual policy programs such effects should be taken into account.

Section 2 presents the econometric framework, provides a detailed discussion on the construction of the economic linkage matrices and discusses the transmission of shocks in the proposed model. Sections 3 and 4 present the utilized data sources and offer our empirical findings, respectively. In Section 5 we provide some concluding remarks and policy implications.

2 Model specification

2.1 Space-time model

We apply a space-time framework for modeling the interdependencies of business sentiment within and across industries and countries and to additionally allow for persistence in business expectation formation over time. For modeling cross-sectional dependence, we propose trade of intermediate goods as a measure for the magnitude of interactions between countries' industries. By further including time-varying covariates, we are able to investigate how shocks to these affect business sentiment and how these are transmitted over industries, countries and time.

Our baseline model for the formation of business sentiment takes the form of a dynamic Spatial Durbin Model (SDM) for a system with $i = 1, ..., N$ independent European industries (i.e, country-industry observations) and $t = 1, ...T$ time periods, which is given by

$$\boldsymbol{y}_t = \phi \boldsymbol{y}_{t-1} + \rho \boldsymbol{W} \boldsymbol{y}_t + \boldsymbol{X}_t \boldsymbol{\beta} + \boldsymbol{W} \boldsymbol{X}_t \boldsymbol{\theta} + \boldsymbol{v}_t, \tag{1}$$

with

$$\boldsymbol{v}_t = \boldsymbol{\mu} + \xi_t \boldsymbol{\iota}_N + \boldsymbol{\varepsilon}_t, \tag{2}$$

and

$$\boldsymbol{\varepsilon}_t \sim \mathcal{N}(0, \sigma^2 \boldsymbol{I}_N), \tag{3}$$

where $\boldsymbol{y}_t$ ($\boldsymbol{y}_{t-1}$) denotes an $N \times 1$ vector measuring business sentiment at period t ($t-1$). The $N \times N$ dimensional weights matrix $\boldsymbol{W}$ is non-negative with known constants. It gives a structure to the dependencies of country-industries and will be further explained in Subsection 2.2. For now, a vector or matrix pre-multiplied by $\boldsymbol{W}$ can be regarded as its lagged value when moving downstream the European production chain. The parameter ϕ denotes the serial correlation coefficient and the parameter ρ represents the cross-sectional autocorrelation coefficient. ϕ thus captures within-industry persistence in business sentiment while ρ measures the extent to which changes in business sentiment are transmitted via European value chains. $\boldsymbol{X}_t$ is a $N \times K$ matrix containing K explanatory variables for which we would like to test their respective impacts on the formation of business sentiment. The $K \times 1$ vectors $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ are response parameters associated with these variables. $\boldsymbol{v}_t$ is an $N \times 1$ vector describing the error term specification. It is composed of country-industry specific fixed effects, denoted by the $N \times 1$ vector $\boldsymbol{\mu}$, by time specific effects ξ_t and by the $N \times 1$ vector of disturbances $\boldsymbol{\varepsilon}_t$, which has zero mean and constant variance $\sigma \boldsymbol{I}_N$.

Elhorst (2008, 2014) shows that this type of a space-time model is stationary as long as the eigenvalues of the matrix $\phi(\boldsymbol{I}_N - \rho \boldsymbol{W})$ lie within the unit circle. This means that stationarity in time requires that $|\phi| < 1 - \rho\omega_{\max}$ if $\rho \geq 0$ or that $|\phi| < 1 - \rho\omega_{\min}$ if $\rho < 0$, where $\omega_{\max}$ and $\omega_{\min}$ denote the maximum and minimum eigenvalues of the weights matrix $\boldsymbol{W}$, accordingly.

2.2 Specification of the weights matrix

It is widely common to define the elements of the weights matrix $\boldsymbol{W}$ either as decreasing function of geographic distance or by means of binary entries giving information about some form of geographic neighbourhood of observations. However, in the light of the two-dimensional nature of our data (industry and country), such a specification would not fully take country-industry dependencies into account. In other words, a geographic distance-based measure would only allow to model spillovers across countries, while ignoring spillovers within countries as well as within and across industries.

For defining the elements of the $\boldsymbol{W}$ matrix to represent inter-country input-output linkages, we make use of both the dimensions of our data. The approach of investigating the transmission of shocks via trade of intermediate goods is related to the work by e.g., Carvalho (2010), Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi (2012), Acemoglu, Akcigit and Kerr (2016) and Acemoglu, Ozdaglar and Tahbaz-Salehi (2017), who study the impact of such sectoral networks on the macroeconomy by building on the multisector framework first developed by Long and Plosser (1983). Before standardization, a typical element of the weights matrix $\boldsymbol{W}$ is given by the share of intermediate production in total production:

$$w_{ik,jl} = \frac{\mathrm{IO}_{ik,jl}}{\mathrm{PROD}_{ik}}, \quad i \neq j \text{ if } k = l, \quad k \neq l \text{ if } i = j, \tag{4}$$

where $\mathrm{IO}_{ik,jl}$ denotes the sales of intermediate goods of industry k from country i to industry l in country j and PROD_{ik} is total production of industry k in country i. Thus, the weights matrix models the intensity of interactions between country-industries based on the sales of each country-specific industry to other country-industries relative to the industry's size. This approach is consistent with the definition of an upstream network presented in Acemoglu et al. (2016) for modeling the transmission of demand shocks. Moreover, the weights matrix strongly resembles the so-called allocation coefficient matrix from input-output analysis. The condition $i \neq j$ if $k = l$ and $k \neq l$ if $i = j$ reflects that the specification expressed in Equation (4) only applies to off-diagonal elements of the weights matrix $\boldsymbol{W}$. The main diagonal elements of $\boldsymbol{W}$ are set to zero such that contemporaneous self-influence of the dependent variable is avoided. The persistence in within-industry business sentiment is captured via $\phi \boldsymbol{y}_{t-1}$.

Concerning spillovers arising from changes in production costs via e.g., indirect wage costs, we impose the downstream instead of the upstream production network for modeling potential spillover effects. After an increase in social security payments and payroll taxes in industry ik, industries buying intermediates from ik are likely confronted with higher prices and therefore their sentiments might decline. Thus, for assessing the impact of this policy variable, we construct a weights matrix $\boldsymbol{W}_d$ which is based on input coefficients and therefore represents a downstream network. Before standardization, a typical element of $\boldsymbol{W}_d$ is defined as

$$w^d_{ik,jl} = \frac{\mathrm{IO}_{jl,ik}}{\mathrm{PROD}_{ik}}, \quad i \neq j \text{ if } k = l, \quad k \neq l \text{ if } i = j, \tag{5}$$

where $\mathrm{IO}_{jl,ik}$ denotes the sales of industry l from country j to industry k in country i which are the purchases of intermediate goods of industry k in country i from industry l from country j. In other words, the off-diagonal elements of $\boldsymbol{W}_d$ are the off-diagonal elements of the transpose of the input coefficient matrix from input-output analysis.

As an extension of the model, we want to exploit the two-dimensional nature of the weights matrix in order to distinguish between inter-industry versus intra-industry spillover effects. We split the weights matrix into two $N \times N$ matrices, which add up to the original weights matrix. The two matrices are denoted as $\boldsymbol{W}^{\text{inter}}$ and $\boldsymbol{W}^{\text{intra}}$, where the elements $w_{ik,jl}^{\text{inter}}$ of $\boldsymbol{W}^{\text{inter}}$ are non-zero for $k \neq l$, i.e. for all the industries different from k, and zero otherwise. The elements $w_{ik,jl}^{\text{intra}}$ of $\boldsymbol{W}^{\text{intra}}$ are non-zero for $k = l$, which captures the same industries in different countries, and zero otherwise. As mentioned above, $\boldsymbol{W}^{\text{inter}} + \boldsymbol{W}^{\text{intra}} = \boldsymbol{W}$. Analogously, we also compute $\boldsymbol{W}_d^{\text{inter}}$ and $\boldsymbol{W}_d^{\text{intra}}$ for the downstream network.

Since Equation (1) can only be solved if $\boldsymbol{I}_N - \rho \boldsymbol{W}$ is non-singular, the row- and column-sums of the weights matrix need to be uniformly bounded in absolute value (in addition to the already discussed necessary restrictions on the parameter space of ρ). This is usually achieved by normalizing the weights matrix in some way. Most applications apply row-normalization, where each element of the weights matrix is divided by the respective row sum. A less commonly applied method is maximum normalization, where the elements of the weights matrix are divided either by the maximum row sum or by the maximum column sum of the weights matrix, depending on which of the two is smaller, i.e. by $\min\{\text{sum}_{\max}^{\text{row}}, \text{sum}_{\max}^{\text{col}}\}$. Thus, when normalizing a matrix applying maximum normalization, each element is divided by the same scalar, while with row standardization, there are different normalization factors for each row. This is the advantage that lies in maximum normalization because the autoregressive parameter ρ can be multiplied by the single rescaling factor, which yields a specification corresponding to the un-normalized weights matrix (Kelejian and Prucha 2010). Further, as highlighted by Badinger and Egger (2016), and in contrast to row-normalization, maximum normalization does not destroy the notion of absolute distance.

For the research question at hand, this feature appears to be of particular importance for three reasons: First, the elements of the weights matrix should still denote the magnitude of sales of one country-industry observation to another relative to the total production of this industry, since the relevance of such a linkage depends not only on the industry's production for other industries and countries, but also on its production for all other final demand components. For example, let industry ik produce only for two other industries, il and im, in equal amounts and assume these sales are rather low. Moreover, let industry ik sell a large part of its total production to final consumption. Even though sales of industry ik to industry il amount to half of ik's sales in intermediate goods, the extent to which business sentiment in industry ik depend on sentiment in industry il should be rather low, because the linkage is not very relevant considering industry ik's total production. It is straightforward to show that when applying row-normalization to a matrix where the elements are defined as in Equation (4), total production cancels out as weighting factor, demonstrating the loss of absolute distance with row-normalization.[3]

Second, as Kelejian and Prucha (2010) emphasize, the possibility of computing an autoregressive parameter ρ which corresponds to the un-normalized model specification is beneficial since this parameter and its parameter space will not depend on N. Due to the fact that some European industries drop out from the sample due to missing observations, we consider a parameter independent of N to be preferable for our empirical application.

Another virtue of maximum-normalization is that when splitting the original weights matrix into multiple

[3]Let $w_{ik,il}^*$ be an element of the row-normalized weights matrix $\boldsymbol{W}^*$ for the previous example. Then $w_{ik,il}^* = \frac{w_{ik,il}}{w_{ik,il} + w_{ik,im}} = \frac{\frac{\text{IO}_{ik,il}}{\text{PROD}_{ik}}}{\frac{\text{IO}_{ik,il}}{\text{PROD}_{ik}} + \frac{\text{IO}_{ik,im}}{\text{PROD}_{ik}}} = \frac{\text{IO}_{ik,il}}{\text{IO}_{ik,il} + \text{IO}_{ik,im}}$.

matrices, it does not matter whether these matrices are normalized individually or jointly by using the row sums of their sum (Badinger and Egger 2016). To ensure comparability of the corresponding coefficients, they can easily be transformed by a certain rescaling factor. Another possibility is to rescale the weights matrices by this rescaling factor already prior to the estimation. This procedure is discussed below in more detail. Under row-normalization, however, the choice between independent or joint normalization can have strong implications and needs to be argued to fit to the particular application in economic terms.

In order to make the interpretation of the coefficient estimates of the lagged explanatory variables more comprehensible, we further rescale each maximum normalized weights matrix such that its average row sum is equal to one. In this way, the magnitude of the parameter estimates are not dependent on the entries in the corresponding weights matrix anymore but instead can be interpreted and compared directly with each other (Badinger and Egger 2016).

2.3 Transmission of Shocks

The space-time model allows to analyze the transmission of shocks in the EU real economy by taking on different perspectives. On the one hand, we can interpret the autoregressive parameter ρ and thereby learn how shocks to business sentiment propagate through the system. On the other hand, we can study how shocks to the explanatory variables affect business confidence and which repercussions they create. We first discuss the effects of shocks unrelated to the explanatory variables, and then introduce the impact measures associated with the included covariates.

The input-output dependencies in the space-time model imply that an idiosyncratic shock to business sentiment (i.e., the error term) in a certain European industry will not only have an effect on sentiment in that very industry, but also on business expectations in the other industries and countries which sell intermediate goods to the affected industry. If these in turn also purchase intermediate goods from the industry in which the shock initially occurred, the change in their business expectations will further exhibit an impact on the original industry's sentiment. Thus, the initial shock will be multiplied inducing a larger total effect on business sentiment formation. More formally, a uniform unitary shock to the error term at period t for a space-time model such as Equation (1) creates effects at period t given by $(\boldsymbol{I}_N - \rho \boldsymbol{W})^{-1}\boldsymbol{\iota}_N$, where $\boldsymbol{\iota}_N$ is a vector of ones denoting the uniform shock to all cross-sectional units. We will refer to this as the total effect, because it takes all feedback-loops caused by the endogenous lag of the dependent variable into account.[4] Considering the representation of the input-output multiplier as a Neumann series $(\boldsymbol{I}_N - \rho \boldsymbol{W})^{-1} = \boldsymbol{I}_N + \rho \boldsymbol{W} + \rho^2 \boldsymbol{W}^2 + ...$, shows that the total effect collapses to $\frac{1}{1-\rho}$ for each cross-sectional unit i when the weights matrix is row-normalized. However, this does not apply for maximum-normalized weights matrices, so we compute the average over the vector of individual effects (Badinger and Egger 2016). The reported average can thus be interpreted as the expected overall effect for a randomly drawn European industry which experiences an idiosyncratic shock.

For the calculation of the impacts of shocks to the explanatory variables, the input-output multiplier also has to be taken into account. LeSage and Pace (2009) provide specific impact measures in order to interpret the estimation coefficients of spatial models with endogenous spillover effects for a cross-sectional setting. Elhorst (2014) gives an overview about research extending this approach to a dynamic panel data setting. In general, the impact measures build on the matrix of partial derivatives, which is typically summarized in form of scalars to yield average direct and average indirect impacts.

[4] The general form for analyzing the effects of the shock over time can be denoted by the s-horizon impulse response $\partial \boldsymbol{y}_{t+s} = \phi^s (\boldsymbol{I}_N - \rho \boldsymbol{W})^{-1}\boldsymbol{\iota}_N$.

Following Debarsy et al. (2012), for a space-time model as given in Equation (1) the response of business sentiment at time $t+s$ to a transitory change in the k^{th} explanatory variable at time t is given by

$$\frac{\partial \boldsymbol{y}_{t+s}}{\partial \boldsymbol{x}_t^{(k)\prime}} = \phi^s (\boldsymbol{I}_N - \rho \boldsymbol{W})^{-1} (\boldsymbol{I}_N \beta_k + \boldsymbol{W} \theta_k), \quad s = 0, ..., S. \tag{6}$$

The $N \times N$ matrix denoted by Equation (6) includes all own- and cross-partial derivatives. The elements of the main diagonal reflect each observations' average response of the dependent variable when the explanatory variable k changes in the same European industry, therefore representing direct effects. This interpretation is similar to the interpretation of parameter estimates in classical linear models. The off-diagonal elements of the matrix are referred to as indirect effects and depict the spillovers to all other industries and countries. They show how the dependent variable responds when taking the partial derivative of covariate k in other industries, respectively. As proposed by LeSage and Pace (2009), the direct effects are summarized to a scalar measure by taking the average over the main diagonal elements, which gives the average direct impact. Accordingly, the average indirect impact is computed by taking the average over all off-diagonal elements. We can calculate the direct and the indirect impacts stemming from a shock to variable k in period t at any arbitrary time period $t+s$.

Similarly, we are able to compute the cumulative impacts over the whole period lasting from t to $t+S$ which arise from a change in the k^{th} explanatory variable at time t. The main and off diagonal elements of the corresponding matrix are given by

$$\frac{\partial \boldsymbol{y}_{t+S}}{\partial \boldsymbol{x}_t^{(k)\prime}} = \sum_{s=0}^{S} \phi^s (\boldsymbol{I}_N - \rho \boldsymbol{W})^{-1} (\boldsymbol{I}_N \beta_k + \boldsymbol{W} \theta_k). \tag{7}$$

3 Data and sample

Data on business sentiment in the European Union are provided by the European Commission on a monthly frequency. They are derived from harmonized surveys where (economic) research institutes in the member states and candidate countries ask around 135,000 firms about their assessment of business opportunities. The questions address production and turnover expectations for the next three months as well as developments in business situations over the past three months. The respondents answer the questions by +, − or =, for increased, decreased or unchanged business expectations. These answers are then aggregated as "balances": the difference between the percentages of respondents giving positive and negative replies. From a subset of specific questions (the questions differ between the surveyed sectors and are presented in Table A1 in the Appendix), the European Commission then calculates a one-dimensional composite index called the confidence indicator, or business sentiment indicator (European Commission 2016). It is available for 66 2-digit NACE Rev.2 industries from the year 1985 onwards. However, we choose 2005 as the starting year of our sample, since in the publicly available data set, a substantial amount of observations is missing for the first 20 years. The data we use is seasonally adjusted and timely aggregated to a quarterly basis.

We retrieve input-output data from the World Input Output Database (WIOD), release October 2016 (Timmer et al. 2015). The platform provides yearly inter-country input-output tables for 56 industries (mainly 2-digit, ISIC Rev. 4) for the period from 2000-2014. In order to avoid endogeneity stemming from (sentiment driven) changes in input-output linkages, we use the input-output table from 2004 when computing the weights matrices. We draw further data from the WIOD to construct variables on the industry level assumed to have an influence on the formation of business sentiment. In particular, we compute measures for production of intermediate goods (sales to all other industries in all countries) and for production for final demand (summing up production for all domestic and foreign demand categories including private consumption, consumption by non-profit organization, government consumption, investment and changes in inventories) and calculate their yearly growth rates.[5] Final demand thus also incorporates changes in demand stemming from non-included economies such as, e.g., China. WIOD captures the demand components from non-included countries in its rest of the world aggregated. These realized demand components should further control for information stemming from past developments which are partly used for constructing the composite business sentiment indicator (see Table A1 in the Appendix).

Despite the fact that the classifications NACE Rev. 2 and ISIC Rev. 4 are well compatible, for some industries the confidence indicators need to be aggregated to a higher level in order to fit to the input-output data. Since the business sentiment indicator represents a percentage balance, we use the number of enterprises per industry as weights for the averages in this aggregation which are extracted from the Structural Business Statistics in the Eurostat database (Eurostat 2017b).

We further employ the Eurostat database to retrieve data on 2-digit industry-level labor costs for each country in the sample (Eurostat 2017a). The Labour Cost Index (LCI) is available on a quarterly frequency and in seasonally adjusted form and reflects average hourly labor costs. It is constructed as index numbers with reference year 2012, such that the average over the four 2012 quarters for every industry in each country equals 100. From the different labor cost categories provided by Eurostat, we choose "labour costs other than wages and salaries" (instead of total labor costs) for two reasons: First, an increase in wages and salaries can stem from an increase in labor productivity (arising either from productivity increases of the existing labor force in the industry or from changes in the composition of employment in the industry)[6], which most likely not affect business sentiment as real production costs might not change. In contrast, a change in employers' social security contributions and payroll taxes (minus subsidies) is likely to be considered as a change in real production costs which could make business sentiment to react. Second, the index related to wages and salaries appears to have a unit root when taken in levels, which is not the case for social security contributions and payroll taxes. As explanatory variables we use the one year lagged level of indirect wage costs, as well as its one quarter lagged growth rate. This induced time pattern allows the firms to process the new information stemming from (changes in) indirect labor costs when expressing their business expectations.[7] The quarterly frequency of the LCI makes this data source especially suitable for studying the impact of (some type of) policy reforms for the formation of business sentiment in European industries.

Merging the business sentiment indicators with the input-output data and further balancing the sample leaves us with a panel of 26,481 observations for the years 2005 to 2014. This implies that the sample covers in total 679 European industry observations per cross-section. The business sentiment indicators and indirect labor costs are measured on a quarterly frequency, while the country-industry characteristics retrieved from

[5] Since the variables for investment and changes in inventories can take on negative values, final demand can also be lower than zero. This is the case for manufacturing of chemical products as well as of computer products in Malta at several years. We exclude these two Maltese industries from our sample in order to avoid problems when computing the final demand growth rates.

[6] The LCI does not discount changes in the composition of employment in each industry.

[7] It shall be noted that for some observations, a sharp increase (decrease) from one quarter to the next is followed by a substantial decrease (increase) in indirect labor costs. Since the changes seem disproportionately large in magnitude and are considered to result from measurement error, we clean this data by interpolating applying a linear trend. This concerns five observations in Greece and three observations in Portugal.

the WIOD are provided as annual data.[8]

Table 1 reports the main summary statistics for the data sample at hand. Starting with the business sentiment indicator, our sample almost fully exploits the whole distribution of potential realizations. In net balance, at the second quarter of 2014, 97% of firms in the Greek transport equipment other than motor vehicles and trailers manufacturing industry expected a worsening for their economic activities while in the last quarter of 2007 98% of the Italian postal services and courier activities providers expected enhanced future business opportunities.

Table 1: Summary statistics

Variable	Min	Max	Mean	Median	Standard Deviation
Business Sentiment Indicator	−96.97	97.97	−2.80	−2.17	20.48
Intermediate production growth	−86.12	349.47	6.78	5.48	22.07
Final demand growth	−86.14	62.40	6.04	4.62	23.48
Indirect labor costs	37.90	152.10	90.58	93.10	13.38
Indirect labor cost growth	−35.68	62.40	0.95	0.84	3.48

Notes: Growth rates are depicted in percent.

Our measure for growth of production for intermediate consumption documents the increasing importance of global value chains over time. On average, intermediate production grew by an annual rate of 6.78% with minimum and maximum values amounting to -86.12% (for air transport in Slovakia in 2009) and 349.47% (for scientific research and development in Lithuania in 2008). The reported decline in intermediate production by about 86% impressively highlights the severity of the economic downturn induced by the Great depression, while the increase by about 350% seems to be related to a substantial R&D tax relief policy program implemented in Lithuania in April 2008 (see Ministry of Finance of Lithuania 2015). The level of indirect labor costs shows substantial variation both over time and across European industries where its (lagged) realizations show a minimum (maximum) value amounting to 37.90 (152.10) for professional, scientific and technical activities (accommodation and food service activities) in Romania (Greece) in the second quarter of 2005 (last quarter of 2010). The average growth rate of indirect labor costs shows a quarterly increase by approximately 1% across all country-industry observations. This average, however, hides substantial variation as documented by the minimum and maximum values amounting to -35.68% (for Hungarian real estate activities in quarter three of 2013) and 62.40% (for Portuguese telecommunication and computer programming activities in the first quarter of 2011), respectively.

4 Estimation results

This section first presents the regression results for the baseline model introduced in Section 2.1. Followed by this, we expand the model to investigate whether the spillovers originating from the explanatory variables differ within and across industries. In order to provide a proper interpretation of the estimates, we compute direct and indirect impacts as discussed in Section 2.3 and analyze how they evolve over time. The results are obtained via the bias-corrected quasi maximum likelihood estimator suggested by Lee and Yu (2010), applying MATLAB codes from Elhorst et al. (2013). It should be noted that the approach by Lee and Yu (2010) conditions on the initial period observation and assumes that this period is only subject to input-

[8]Table A2 in the Appendix reports on the 24 EU member countries included and number of industries per country captured in the final sample.

output dependence. Given the rather long time period available in our sample with $T = 39$ and the imposed bias correcting procedure, we consider it reasonable to treat the initial period as (conditionally) exogenous.

4.1 Main results

Table 2 reports the coefficient estimates and corresponding t-statistics of the baseline space-time model including country-industry and time fixed effects. In order to test for the stability of the model we perform a Wald test with $H_0 : \phi + \rho\omega_{\max} = 1$. The value of $\phi + \rho\omega_{\max} = 0.844$ and the Wald statistic takes a value of 473.45, which implies that the H_0 is rejected and therefore ensures that the model is not explosive.[9]

Concerning the parameter estimates, we find strong persistence in business sentiment from quarter to quarter, as indicated by the estimate of ϕ which takes on a value of 0.72 and is statistically highly significant. Accordingly, firms tend to only sporadically adjust their business expectations. This finding is well in line with the previous literature and can be explained by the costs involved for acquiring new information (Hellwig and Veldkamp 2009).

Table 2: Estimates of the baseline space-time model

Variables	Coefficient	t-stat
β_1 Intermediate production growth	0.013^{***}	3.674
β_2 Final demand growth	0.017^{***}	5.301
β_3 Indirect labor costs	-0.015	-1.257
β_4 Indirect labor cost growth	0.033	1.535
θ_1 $\boldsymbol{W}$ Intermediate production growth	0.021^{**}	2.453
θ_2 $\boldsymbol{W}$ Final demand growth	-0.031^{***}	-3.946
θ_3 $\boldsymbol{W}_d$ Indirect labor costs	-0.013	-0.909
θ_4 $\boldsymbol{W}_d$ Indirect labor cost growth	-0.101^{**}	-2.320
$\phi\boldsymbol{y}_{t-1}$	0.720^{***}	159.490
$\rho\boldsymbol{W}\boldsymbol{y}_t$	0.141^{***}	18.664
Input-output multiplier$_{\text{SR}}$	1.161	
Input-output multiplier$_{\text{LR}}$	4.147	
Corr. R^2	0.509	
σ^2	94.083	
Log-Likelihood	$-95,272$	
Number of observations	$26,481$	

Notes: Dynamic spatial panel data model with country-industry and time period fixed effects; ***significant at 0.01 level, **significant at 0.05 level, *significant at 0.1. level; N=679, T=39.

Referring to input-output linkages as a potential source for spillover effects in business expectations, our estimates suggest that European value chains constitute an important channel for shock transmission. Table 2 reports a positive and statistically highly significant parameter estimate for ρ. Accordingly, an increase in business sentiment in an industry induces positive business sentiment adjustments in upstream industries, i.e. in the industries from which it buys intermediate goods. Hence, our result is in line with the model set up in Angeletos and La'O (2013), where a shock hitting only a few agents in the beginning, can spread endogenously

[9] We further test for the alternative and more restrictive stationarity condition $|\phi| + |\rho| < 1$ put forward by Yu et al. (2008). The corresponding test results reveal that our model for business sentiment is stationary in the both relevant dimensions, space and time.

over the rest of the economy as agents trade and communicate with each other. When interpreting the magnitude of ρ, the normalization method of the weights matrix $\boldsymbol{W}$ should be kept in mind. Since we rescaled the maximum normalized weights matrix such that its average row sum is equal to one (see Section 2.2), the estimated ρ presented in Table 2 can be compared to an autocorrelation coefficient corresponding to a model with a row-normalized matrix. Furthermore, we can rescale the estimate of ρ in order to get an estimate which relates to a model where the weights matrix is not normalized. The transformed parameter estimate amounts to $\rho^* = 0.47$, which indicates considerable correlation via input-output linkages also in quantitative terms. This result further implies that an attempt trying to accurately model and forecast the evolution of the business sentiment indicator over time would likely benefit from accounting for this channel of shock transmission.

The estimate of ρ is used to compute the input-output multiplier presented in Table 2. This measure denotes how a common unitary shock to the error term, on average, affects business sentiment in the period of the shock. For this reason, the input-output multiplier can also be interpreted as the expected overall effect (incorporating all feedback effects) stemming from an exogenous shock to a randomly chosen European industry on this industry itself. Our results reveal that, on average and in case of a positive unitary shock, business sentiment will increase contemporaneously by 1.16, taking all the repercussions across all European industries into account. Even though this may appear as a moderate response, considering the strong rigidities in expectation formation, this leads to an increase of 3.34 index points after one year and to a long-run effect of 4.15 index points (see Figure A1 in the Appendix).[10] In general, a short-run input-output multiplier larger than one indicates that part of the interdependence between countries and industries cannot be traced back to spillovers stemming from the included covariates, but instead originate from the unexplained component of the business sentiment indicator. Business sentiment is formed based on an inherently unobservable information gathering process within firms and our input-output multiplier estimate suggests that these unobserved components are indeed economically relevant for shaping business sentiment across European industries.

Apart from looking at the average input-output multiplier over all European industries, we can also use the matrix $(\boldsymbol{I} - \rho\boldsymbol{W})^{-1}$ to analyze how a shock to a specific industry in a particular country is transmitted through the system. In the light of the 2015 Volkswagen emissions scandal, we choose the German industry "manufacture of motor vehicles, trailers and semi-trailers" as an illustrative example.[11] According to our model, we find that a decrease of business sentiment by one net balance index point in the German automotive industry creates only minor feedback effects for this particular industry itself, such that the total effect (taking all repercussions into account) in the period of the shock amounts to -1.0016. Naturally, this result depends on the structure of the value chain of the German automotive industry. We further compute the average externalities of this negative shock for the sentiments of motor vehicle manufacturers in the other countries in the sample. The results indicate that when business sentiment in the German automotive industry decreases by one index point, sentiments in all other European automotive industries decrease on average by -0.03 index points in the same quarter. The strongest reaction is denoted in Hungary, with a decline of -0.12 net balance points.

As discussed in Section 2.3, the estimated coefficients associated with the explanatory variables cannot be interpreted directly. Hence, we compute average direct and average indirect impacts in order to take repercussions arising from the input-output linkages into account. Based on 1,000 sampled parameter estimates from a multivariate normal distribution, we calculate the average impacts as well as the corresponding 0.025 lower and 0.975 upper bound estimates from the distribution of possible effects. The results are reported in

[10] The long-run effect is computed as the sum of a geometric series where the time periods go to infinity.

[11] In a recent paper, Bachmann et al. (2017) investigate the impact of the Volkswagen emissions scandal on the sales of the other German car producers and identify economically significant negative exertnalities for BMW, Mercedes-Benz and Smart.

Table 3. In general, the impacts in period zero only incorporate the input-output effect, while the impacts of the following periods capture both, the input-output dependence as well as the time dependence. The column to the right of the 0.975 upper bound estimated effects documents the accumulated impacts over time. Figure 1 further graphically illustrates the evolution of the average direct and average indirect impacts over time, respectively, where the mean impacts are illustrated by the (blue) solid line and the confidence intervals are displayed by the (red) dashed lines.

Table 3: Direct and indirect impact estimates, baseline model

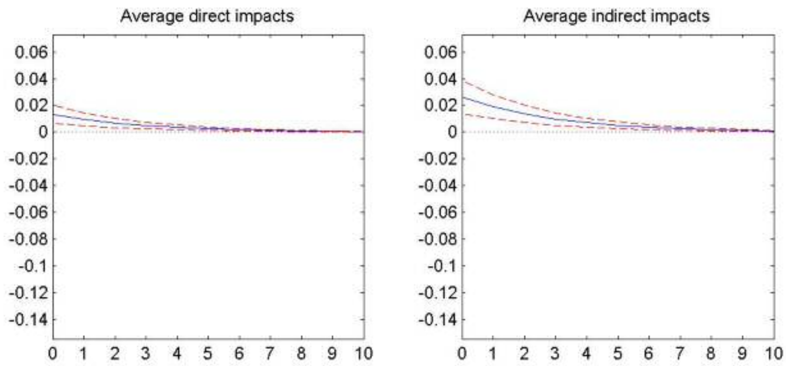
Period	Average direct impacts				Average indirect impacts			
	Lower 0.025	Mean	Upper 0.975	Cumulative	Lower 0.025	Mean	Upper 0.975	Cumulative
Intermediate production growth								
0	0.0066	0.0133	0.0201	0.0133	0.0139	0.0265	0.0387	0.0265
1	0.0047	0.0096	0.0144	0.0229	0.0100	0.0191	0.0280	0.0455
2	0.0034	0.0069	0.0104	0.0297	0.0072	0.0137	0.0202	0.0592
3	0.0024	0.0050	0.0075	0.0347	0.0052	0.0099	0.0146	0.0691
4	0.0018	0.0036	0.0054	0.0383	0.0037	0.0071	0.0105	0.0762
10	0.0002	0.0005	0.0008	0.0462	0.0005	0.0010	0.0015	0.0920
Final demand growth								
0	0.0110	0.0171	0.0231	0.0171	−0.0450	−0.0330	−0.0207	−0.0330
1	0.0080	0.0123	0.0166	0.0294	−0.0324	−0.0237	−0.0149	−0.0567
2	0.0058	0.0089	0.0119	0.0383	−0.0234	−0.0171	−0.0107	−0.0738
3	0.0042	0.0064	0.0086	0.0447	−0.0169	−0.0123	−0.0077	−0.0861
4	0.0030	0.0046	0.0062	0.0493	−0.0121	−0.0089	−0.0055	−0.0950
10	0.0004	0.0006	0.0009	0.0594	−0.0017	−0.0012	−0.0008	−0.1146
Indirect labor costs								
0	−0.0377	−0.0151	0.0075	−0.0151	−0.0186	−0.0174	−0.0169	−0.0174
1	−0.0271	−0.0108	0.0054	−0.0259	−0.0135	−0.0125	−0.0121	−0.0299
2	−0.0192	−0.0078	0.0039	−0.0337	−0.0100	−0.0090	−0.0087	−0.0389
3	−0.0137	−0.0056	0.0028	−0.0393	−0.0073	−0.0065	−0.0062	−0.0454
4	−0.0099	−0.0040	0.0020	−0.0433	−0.0053	−0.0047	−0.0045	−0.0501
10	−0.0014	−0.0006	0.0003	−0.0523	−0.0007	−0.0007	−0.0006	−0.0604
Indirect labor cost growth								
0	−0.0117	0.0318	0.0731	0.0318	−0.1547	−0.1141	−0.0730	−0.1141
1	−0.0085	0.0229	0.0527	0.0547	−0.1112	−0.0821	−0.0527	−0.1962
2	−0.0061	0.0165	0.0381	0.0711	−0.0799	−0.0591	−0.0381	−0.2553
3	−0.0044	0.0119	0.0275	0.0830	−0.0576	−0.0426	−0.0275	−0.2978
4	−0.0032	0.0085	0.0199	0.0915	−0.0415	−0.0306	−0.0199	−0.3285
10	−0.0005	0.0012	0.0028	0.1105	−0.0058	−0.0043	−0.0028	−0.3963

Notes: Impacts computed according to Equations (6) and (7) and based on 1,000 sampled parameter estimates.

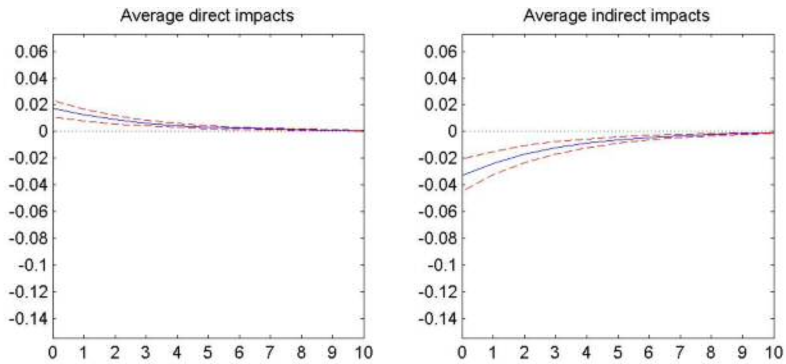
Focusing first on the demand variables included in the model, we find that the yearly growth rates of intermediate goods production and production for final demand exhibit positive direct impacts on business sentiment in European industries. Both impacts are statistically significant and similar in magnitude. A one standard deviation increase of intermediate production growth (final demand growth) increases business sentiment by 0.30 (0.40) index points in the period of the shock, and by 1.04 (1.44) index points in the long-run. Concerning the average effect on all other industries and countries, we find significant positive spillover effects associated to the growth rate of intermediate production, while the spillovers induced by changes in final demand growth exhibit a negative impact.[12] Note, that ceteris paribus increases in intermediate

[12] We also estimate the model when splitting final demand into domestic and foreign demand. However, for both variables this yields direct and indirect impacts which are negligible both in terms of statistical significance and economic relevance, respectively.

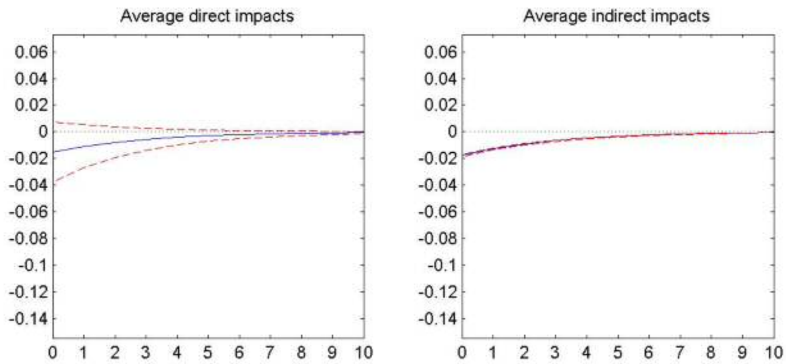
Figure 1: Impacts estimates of explanatory variables over time



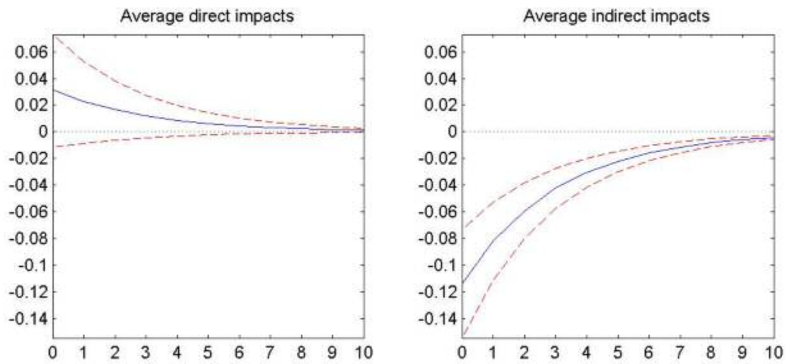
(a) intermediate production growth



(b) domestic demand growth



(c) indirect labor costs



(d) indirect labor cost growth

Notes Graphs obtained by applying MATLAB codes provided by Piribauer and Wanzenböck (2016).

production could be interpreted as structural changes in production processes, and firms might expect these changes in European value chains to be persistent, since input-output relations are fairly time-invariant in general (Badinger and Egger 2016). The expected lasting nature of such an increase could therefore contribute to a firm's optimism related to intermediate production growth in downstream industries. In contrast, the fact that business sentiment reacts negatively when final demand growth for the production of the competing industries surges, might reflect firms' concerns about some setbacks for its competitiveness in the single market or adverse shifts in consumer preferences. We will further investigate this hypothesis below when distinguishing between intra- and inter-industry spillover effects.

With regard to the effect of indirect labor costs, we find that a reduction of social security contributions and payroll taxes in one European industry leads to increases in business sentiment both in this industry (direct impact), as well as in all other industries on average (indirect impact). In contrast to the average direct impact, the average indirect impact for this variable is rather precisely estimated. However, when using the original data on labor costs without interpolating for the suspected outlying observations (see Section 3), also the direct impact is statistically significantly different from zero at the five percent confidence level.

We further find relatively strong positive spillovers arising from decreases in the growth rate of social security contributions and payroll taxes. Any policy measure which reduces (the increase in) indirect wage costs is identified to positively stimulate business sentiment in European industries. More precisely, a one standard deviation decline in the quarterly growth rate of indirect wage costs (i.e., 3.48 percentage points) in industry ik immediately increases the business sentiment in all other industries by an average amount of 0.40 index points, taking all cross-sectional repercussion effects into account. The long-run spillover effect, which is the cumulative effect over the infinite amount of time periods, takes a value of 1.42 index points. The results from this exercise reveal that the space-time econometric approach proposed might be helpful for studying economic policy effects within the European single market because it additionally allows to analyze the policy induced spillover effects for other industries and countries.

4.2 Intra-industry versus inter-industry spillover effects

In Tables 4 and 5 we further investigate the nature of the spillover effects stemming from the demand-side covariates and or policy variable of interest. For this purpose, we separate the input-output relationships into intra- and inter-industry linkages as discussed in Section 2.2. Table 4 reports the corresponding quasi maximum likelihood based estimation results. We disentangle the effects of the explanatory variables by pre-multiplying them with $\boldsymbol{W}^{\text{intra}}$ and $\boldsymbol{W}^{\text{inter}}$ (or $\boldsymbol{W}_d^{\text{intra}}$ and $\boldsymbol{W}_d^{\text{inter}}$), respectively. With regard to the spillover effect directly originating from changes in business sentiment, we do not differentiate between the autoregressive spillover parameters for within and across industries, since we are mainly interested in the differing channels regarding the impact of the explanatory variables. Furthermore, the inclusion of two different weighting matrices for the temporal and spatially lagged dependent variable would increase the complexity of the model in an unnecessary manner.

Table 4: Estimates of space-time model with differing intra- and inter-industry spillovers

Variable	Coefficient	t-stat
β_1 Intermediate production growth	0.014^{***}	3.915
β_2 Final demand growth	0.017^{***}	5.373
β_3 Indirect labor costs	-0.011	-0.970
β_4 Indirect labor cost growth	0.034	1.566
θ_1^{intra} $\boldsymbol{W}^{\text{intra}}$ Intermediate production growth	0.003	0.537
θ_2^{intra} $\boldsymbol{W}^{\text{intra}}$ Final demand growth	-0.015^{***}	-2.688
θ_3^{intra} $\boldsymbol{W}_d^{\text{intra}}$ Indirect labor costs	0.006	1.067
θ_4^{intra} $\boldsymbol{W}_d^{\text{intra}}$ Indirect labor cost growth	-0.016	-0.475
θ_1^{inter} $\boldsymbol{W}^{\text{inter}}$ Intermediate production growth	0.023^{***}	2.882
θ_2^{inter} $\boldsymbol{W}^{\text{inter}}$ Final demand growth	-0.023^{***}	-3.228
θ_3^{inter} $\boldsymbol{W}_d^{\text{inter}}$ Indirect labor costs	-0.015	-1.137
θ_4^{inter} $\boldsymbol{W}_d^{\text{inter}}$ Indirect labor cost growth	-0.095^{**}	-2.421
$\phi \boldsymbol{y}_{t-1}$	0.720	159.231
$\rho \boldsymbol{W} \boldsymbol{y}_t$	0.137	18.111
Input-output multiplier$_{\text{SR}}$	1.156	
Input-output multiplier$_{\text{LR}}$	4.131	
Corr. R^2	0.510	
σ^2	93.996	
Log-Likelihood	$-95,260$	
Number of observations	$26,481$	

Notes: Dynamic spatial panel data model with country-industry and time period fixed effects; ***significant at 0.01 level, **significant at 0.05 level, *significant at 0.1. level; N=679, T=39.

Table 5: Direct and indirect impact estimates with differing intra- and inter-industry spillovers

Period	Average direct impacts				Average indirect impacts			
	Lower 0.025	Mean	Upper 0.975	Cumulative	Lower 0.025	Mean	Upper 0.975	Cumulative
Intermediate production growth								
0	0.0072	0.0143	0.0218	0.0143	0.0168	0.0317	0.0469	0.0317
1	0.0052	0.0103	0.0157	0.0246	0.0122	0.0229	0.0341	0.0546
2	0.0037	0.0074	0.0113	0.0320	0.0088	0.0165	0.0246	0.0711
3	0.0027	0.0053	0.0081	0.0373	0.0063	0.0119	0.0179	0.0829
4	0.0019	0.0038	0.0058	0.0412	0.0046	0.0085	0.0129	0.0915
10	0.0003	0.0005	0.0008	0.0497	0.0007	0.0012	0.0018	0.1104
Final demand growth								
0	0.0113	0.0174	0.0238	0.0174	−0.0564	−0.0405	−0.0252	−0.0405
1	0.0081	0.0125	0.0171	0.0298	−0.0405	−0.0292	−0.0182	−0.0696
2	0.0058	0.0090	0.0124	0.0388	−0.0292	−0.0210	−0.0131	−0.0906
3	0.0042	0.0065	0.0089	0.0453	−0.0209	−0.0151	−0.0094	−0.1057
4	0.0030	0.0047	0.0064	0.0500	−0.0150	−0.0109	−0.0068	−0.1166
10	0.0004	0.0007	0.0009	0.0604	−0.0021	−0.0015	−0.0010	−0.1408
Indirect labor costs								
0	−0.0362	−0.0117	0.0125	−0.0117	−0.0139	−0.0121	−0.0114	−0.0121
1	−0.0260	−0.0084	0.0090	−0.0201	−0.0102	−0.0087	−0.0083	−0.0209
2	−0.0188	−0.0061	0.0065	−0.0262	−0.0073	−0.0063	−0.0060	−0.0271
3	−0.0135	−0.0044	0.0047	−0.0306	−0.0052	−0.0045	−0.0043	−0.0317
4	−0.0098	−0.0032	0.0034	−0.0337	−0.0039	−0.0033	−0.0031	−0.0349
10	−0.0014	−0.0004	0.0005	−0.0407	−0.0005	−0.0005	−0.0004	−0.0422
Indirect labor cost growth								
0	−0.0086	0.0327	0.0721	0.0327	−0.1928	−0.1254	−0.0557	−0.1254
1	−0.0062	0.0236	0.0518	0.0563	−0.1386	−0.0903	−0.0399	−0.2157
2	−0.0045	0.0170	0.0373	0.0732	−0.1000	−0.0651	−0.0287	−0.2808
3	−0.0032	0.0122	0.0269	0.0855	−0.0722	−0.0469	−0.0208	−0.3277
4	−0.0023	0.0088	0.0194	0.0943	−0.0519	−0.0338	−0.0150	−0.3614
10	−0.0003	0.0012	0.0027	0.1138	−0.0074	−0.0047	−0.0021	−0.4362

Notes Impacts computed according to Equations (6) and (7) and based on 1,000 sampled parameter estimates.

Focusing first on the demand variables gathered from the WIOD database, we find positive first-round spillovers for intermediate production growth both within and across industries, however, the spillovers across industries are substantially larger in magnitude and statistically significant. In other the words, the positive effect of increasing production of intermediate goods on business sentiment in upstream industries is mainly due to spillovers *across* industries, rather than to spillovers *within* industries (apart from the repercussion effects captured by the autocorrelation coefficient ρ). Concerning the negative indirect impact of final demand growth, we observe that this relates to significantly negative intra- as well as inter-industry spillover effects. A potential explanation for the negative effect *within* industries can be offered by likely intensified competition perceived by some European industries within the single market. As discussed in Hellwig and Veldkamp (2009), within industries firms are likely to play a game with each other. Rising growth rates of final demand for some firms might thus result from a competitive advantage as compared to other firms in the very same industry but different country. As a consequence, the latter firms might expect their business opportunities to decline whenever other firms – ceteris paribus – increase their production for final demand. Referring to the negative effect *across* industries, a possible reason for firms becoming pessimistic when final demand growth for production of other firms rises, is given by be the fact that firms might assume the presence of some (temporal) budget constraint, combined with a shift in preferences. Therefore, firms may expect that increased consumption of other goods must be compensated by (future) demand reduction for the goods produced by the own industry.

The estimates for the impact of indirect labor costs show that the negative first-round spillover effects both in quantitative size and statistical significance matter more *across* than *within* industries. In this setting intra-industry spillovers can only arise across countries and thus firms might simply lack information on changes in labor costs in the same industries located in other EU member countries. Furthermore, the results for inter-industry spillover effects reveal that business sentiment formation tends to be increasingly shaped by European and within-country value chains. According to our estimates, firms take into account recent changes in indirect labor costs of their suppliers when forming their respective business sentiment. This implies that shocks related to changes in indirect labor costs are transmitted downstream the production chain, while they are accelerated by the input-output autocorrelation of business sentiment, which are then propagated upstream.

The overall impacts of the explanatory variables when distinguishing between intra- and inter-industry spillovers are presented in Table 5. The results do not differ substantially from the impact estimates from the simpler baseline specification discussed in Section 4.1.

4.3 Robustness analysis: A placebo test

In Sections 4.1 and 4.2 we identified significant spillover effects in the formation of business sentiment. Now, we address the potential concern that this finding might result from some mechanical process in the econometric model set up instead of reflecting the interdependence of expectations based on production networks. To this end, we follow Ozdagli and Weber (2017) and construct a random input-output weights matrix to see whether the regression results based on random weights will still show a similar input-output multiplier as with the original weights matrix. If this is the case, the estimator for our cross-sectional autocorrelation coefficient would actually be biased and non-informative.

For the construction of the random weights matrix, Ozdagli and Weber (2017) consider the features of the empirical weights matrix, which is rather sparse and shows that few sectors are suppliers to the rest of the industries in the economy. Following their approach, we therefore condition on the amount of non-zero entries in the empirical weights matrix and draw from a generalized Pareto distribution. We choose the corresponding parameters such that the distribution best fits the data of the un-normalized empirical weights matrix (a tail index parameter of 1.36714866 and a scale parameter of 0.00000699). We repeat the same procedure for the empirical weights matrix representing a downstream network (tail index parameter 1.39089448 and scale index parameter 0.00000699). We then maximum normalize these matrices and rescale them such that their average row sum is equal to zero.

Table 6: Estimates of space-time model based on pseudo weights matrices

Variables	Coefficient	t-stat
β_1 Intermediate production growth	0.019^{***}	5.211
β_2 Final demand growth	0.018^{***}	5.622
β_3 Indirect labor costs	-0.024^{***}	-2.732
β_4 Indirect labor cost growth	0.015	0.796
θ_1 $\boldsymbol{W}$ Intermediate production growth	0.000	-0.058
θ_2 $\boldsymbol{W}$ Final demand growth	0.000	-0.045
θ_3 $\boldsymbol{W}_d$ Indirect labor costs	0.000	0.026
θ_4 $\boldsymbol{W}_d$ Indirect labor cost growth	0.001	0.403
$\phi\boldsymbol{y}_{t-1}$	0.749^{***}	169.654
$\rho\boldsymbol{W}\boldsymbol{y}_t$	0.000	0.952
Input-output multiplier$_{\mathrm{SR}}$	1.000	
Input-output multiplier$_{\mathrm{LR}}$	3.982	
Corr. R^2	0.507	
σ^2	95.908	
Log-Likelihood	$-95,523$	
Number of observations	$26,481$	

Notes: Dynamic spatial panel data model with country-industry and time period fixed effects; ***significant at 0.01 level, **significant at 0.05 level, *significant at 0.1. level; N=679, T=39.

The estimation results reported in Table 6 suggest that the repercussion effects identified in the previous sections do not arise due to the econometric model framework and thus they highlight the importance of the European value chain as a channel for the transmission of business sentiments across European industries. Based on a (pseudo) random weights matrix, the estimate for the cross-sectional autocorrelation coefficient ρ takes a value of 0.0002, and is statistically not different from a zero-effect. Hence, a shock of one unit to the error term immediately increases sentiments by only one unit on average, since no feedback effects are created. Nevertheless, due to the strong rigidities of sentiments from quarter to quarter, the long-run effect of such a shock still takes a value of 3.98. In any case, note that the estimate for the serial autocorrelation coefficient ϕ is larger than when estimating the model using the empirical input-output matrix – conditional on the baseline estimate for ϕ, the long-run effect using the pseudo matrix only amounts to 3.57 index points.

We neither find any significant spillover effects concerning the explanatory variables, as their indirect impacts are not different from zero (see Figure A2 in the Appendix). In brief, the results indicate that it is the specific structure of the input-output network which matters for the transmission of business sentiments within the European economy.

5 Discussion and conclusion

Business sentiment is typically viewed as important and informative leading indicator for the economic development of countries. In order to provide a sensible picture of the state of the EU-wide economy, the European Commission provides harmonized business sentiment indicators at the country-industry-level of disaggregation. These data are typically gathered by (economic) research institutes located in the member states which incorporate them into their economic forecasts. In this paper, we make use of the time variation in these data for studying how business sentiment is formed and propagated within the EU and across industries and national borders. To this end, we rely on space-time econometric models and set-up a unique dataset which combines business sentiment data with information on input-output relationships within the EU.

Our empirical investigation reveals non-negligible within-industry persistence in business sentiment over time but, at the same time, our estimates also provide evidence for substantial spillover effects stemming from EU-wide value chains. As a consequence, business sentiment in one industry is estimated to contemporaneously increase by 1.16, on average, after a positive unitary shock hits this industry, implying a long-run impact of 4.15 index points. Unexpected changes in business sentiment, maybe due to the arrival of new information, are thus multiplied due to repercussion effects and amplify reactions in expectation formation within the EU common market, generating waves of optimism and pessimism across European industries. This new insight can be of help for increasing the accuracy of business sentiment forecasts and for predicting business cycles in GDP growth as business sentiments are important leading indicators for changes in overall economic development.

Furthermore and ceteris paribus, we identify positive direct impacts of the growth rates of intermediate production and final demand which decrease gradually over time, and are halved approximately two quarters after the change has taken place. We also provide evidence for firms' sentiments to rise when their buyers exhibit increases in intermediate production growth. This result is in line with previous findings by Acemoglu et al. (2016), who show that demand related shocks are mainly propagated upstream the production network. Given the relatively strong persistence in input-output relationships, firms might expect that demand growth for intermediates has a long-lasting impact and thus expectation formation might be positively affected by such relationships. In contrast, the average spillovers related to final demand growth show a negative and statistically significant effect. This might represent firms being concerned about shifts in consumer preferences or becoming pessimistic due to expected losses in their competitiveness.

In addition we also utilize the proposed space-time econometric framework for studying the impact of economic policy reforms for business sentiment formation. In this exercise, we rely on data capturing information on social security contributions and payroll taxes. These indirect labor costs are highly debated in the European economy and often suggested for policy reforms. Furthermore, data on these are available at a sufficiently high frequency which allows to incorporate them into our framework. Based on our estimates, we find that a reduction of social security contributions and payroll taxes in a particular industry leads to increases in business sentiment both in the affected industry as well as in all other industries which directly or indirectly demand intermediates from the affected industry. With regard to the latter, the long-run effect identified from the proposed model suggests that a one standard deviation decline in the growth of social security contributions and payroll taxes (i.e., 3.48 percentage points) over time increases the business expectations in downstream industries by an average of 1.42 index points.

From a policy point of view, the paper provides evidence for non-negligible spillover effects in business sentiment formation within the European single market. As a consequence, a negative shock to business sentiment, for example, will be transmitted and amplified via European value chains and in the long-run also shapes expectations in all other countries and industries located inside EU borders. For increasing the resilience of the European economy as a whole, the absorptive capacity of shocks in each and every member state and industry thus seems to be pivotal for strengthening the overall EU-wide resilience as idiosyncratic shocks will not cancel out in a (EU-wide) macroeconomic perspective.

In order to strengthen individual industry's and country's capabilities for dealing with negative shocks, one size fits all policies are thus likely to be not very effective. Rather than that individual and tailormade policy programs might be best suited for addressing structural problems in different countries and industries. The European Commission's approach taken within the framework of the European Semester thus seems to be most suitable for effectively reducing asymmetries across the different member states. However, coordinated policy making will still be essential as without such an integrated approach the likely spillover effects in business sentiment indicators across industries and EU countries would most probably be neglected or insufficiently considered which, in the worst case, could even worsen the overall resilience of the whole EU economy.

The latter point is illustrated by empirically investigating the impact of reforms taking social security contributions and payroll taxes as an example. A reduction in indirect labor costs would not only boost business expectations in the targeted industries and countries but would also generate positive spillover effects on business sentiment in downstream industries within the European value-added chain.

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Appendix: Additional tables and figures

Table A1: Questions to construct the composite sentiment indicator

Industrial confidence indicator		
Q2	Do you consider your current overall order books to be...?	
	+	more than sufficient (above normal)
	=	sufficient (normal for the season)
	−	not sufficient (below normal)
Q4	Do you consider your current stock of finished products to be...?	
	+	too large (above normal)
	=	adequate (normal for the season)
	−	too small (below normal)
Q5	How do you expect your production to develop over the next 3 months? It will...	
	+	increase
	=	remain unchanged
	−	decrease
Services confidence indicator		
Q1	How has your business situation developed over the past 3 months? It has...	
	+	improved
	=	remained unchanged
	−	detoriated
Q2	How has demand (turnover) for your company's services changed over the past 3 months? It has...	
	+	increased
	=	remained unchanged
	−	decreased
Q3	How do you expect the demand (turnover) for your company's services to change over the next 3 months? It will...	
	+	increase
	=	remain unchanged
	−	decreasd
Retail trade confidence indicator		
Q1	How has (have) your business activity (sales) developed over the past 3 months? It has (They have)...	
	+	improved (increased)
	=	remained unchanged
	−	deteriorated (decreased)
Q2	Do you consider the volume of stock currently hold to be...?	
	+	too large (above normal)
	=	adequate (normal for the season)
	−	too small (below normal)
Q4	How do you expect your business activity (sales) to change over the next 3 months? It (They) will...	
	+	improve (increase)
	=	remain unchanged
	−	deteriorate (decrease)
Construction confidence indicator		
Q3	Do you consider your current overall order books to be...?	
	+	more than sufficient (above normal)
	=	sufficient (normal for the season)
	−	not sufficient (below normal)
Q4	How do you expect your firm's total employment to change over the next 3 months? It will...	
	+	increased
	=	remained unchanged
	−	decreased

Notes: Table adapted from European Commission (2016).

Table A2: Number of industries per country

Country	Number of industries in sample
Austria	28
Belgium	33
Bulgaria	36
Czech Republic	33
Germany	25
Denmark	19
Spain	20
Finland	21
France	27
Great Britain	33
Greece	35
Hungary	25
Italy	33
Lithuania	33
Luxembourg	13
Lativa	32
Malta	12
Netherlands	22
Poland	41
Portugal	32
Romania	33
Slovakia	35
Slovenia	30
Sweden	28
Total	679

Figure A2: Cumulative input-output multiplier over time

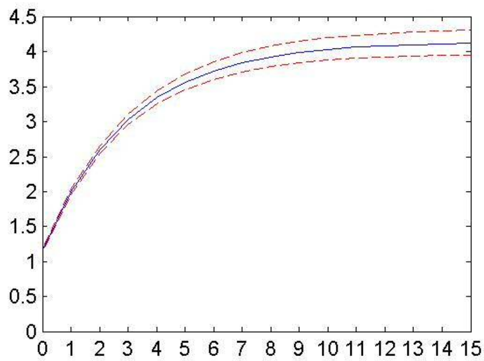
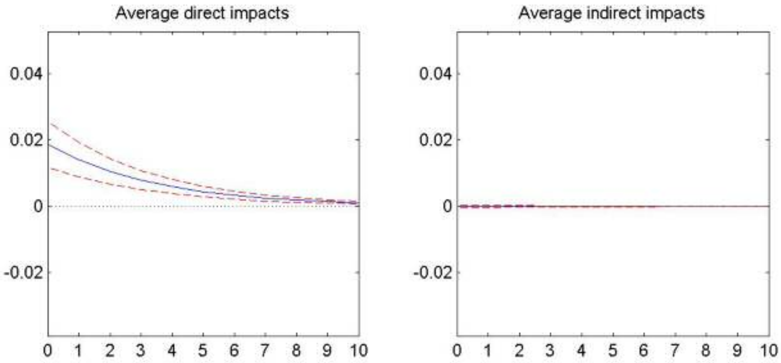
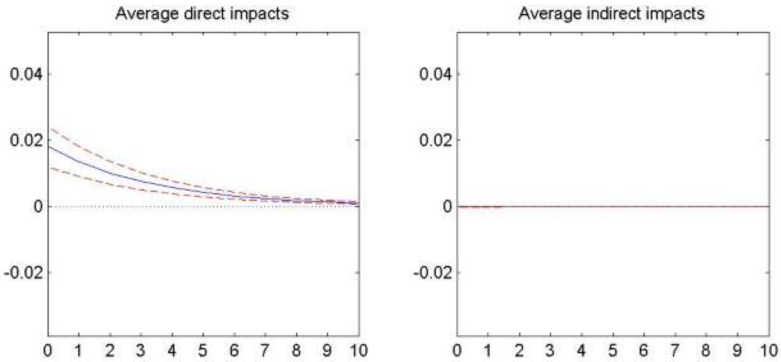


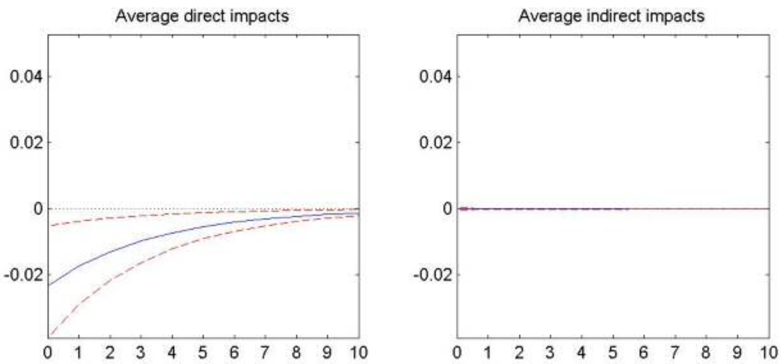
Figure A2: Impact estimates of explanatory variables over time, based on pseudo weights matrices



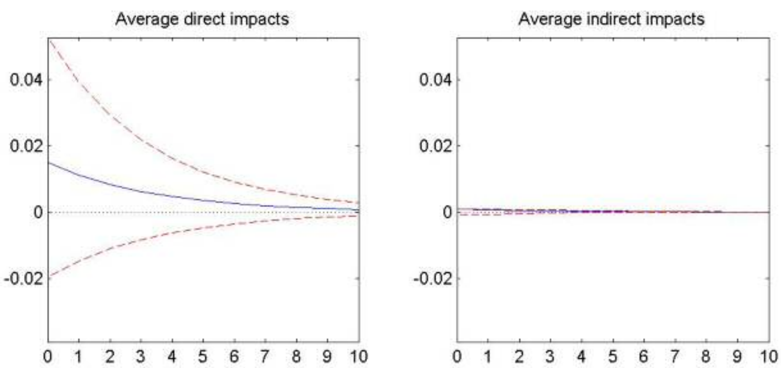
(a) intermediate production growth



(b) domestic demand growth



(c) indirect labor costs



(d) indirect labor cost growth

Notes Graphs obtained by applying MATLAB codes provided by Piribauer and Wanzenböck (2016).