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# The Propagation of Business Expectations within the European Union

## Abstract

This paper empirically investigates the propagation of fims' expectations within the European Union (EU). To this end, we combine EU-wide official business survey data with world input-output data. Econometrically, we model interdependencies in economic activities via input-output-linkages and apply space-time models with common factors. The resulting evidence provides indication for the existence of substantial spillovers in expectation formation. They are transmitted both upstream and downstream the European value chain, but the latter channel matters more.

JEL-Codes: C230, D840, E700, L140.

Keywords: business expectation formation, propagation, input-output linkages, spillovers, space-time model.

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# 1 Introduction

Expectations of firms play a crucial role in economics. They matter for decision making and thus impact investment, future employment and price setting. Taking theory to the data, recent literature has also shown empirically the relevance of firms' beliefs for economic outcome variables (Enders et al., 2019; Coibion et al., 2018; Boneva et al., 2019; Gennaioli et al., 2016). As a natural advancement, expectations themselves constitute an object of research interest and one may ask whether expectation formation is interdependent. When agents interact their views about future economic developments might be exchanged. While e.g. in the business cycle model by Angeletos and La'O (2013) coordination and communication can lead to contagion effects for sentiment formation – the "mood" part of expectations – research analyzing whether such interdependence of expectation formation can be found in actual expectations data is scarce.

In this paper, we fill this gap by empirically investigating the transmission of firms' expectations within the European Union. In particular, we study how changes of firms' expectations in a certain industry in a member country, on average, affect firms' expectations in other industries and member states both in the short- and in the long-run, respectively. Extensions of our empirical model allow to assess whether downstream or upstream linkages to other domestic versus same and/or other foreign industries are relatively more important in shaping expectations in European industries.

We are interested in exploiting and explaining cross-sectional and time dependence in the formation of business expectations within and across European industries. To this end, the paper relies on quarterly business survey data provided by the European Commission which are augmented by data on GDP, production, employment, labor costs, capital stocks and national stock price indices. We first estimate a simple dynamic panel data model for expectations with fixed effects for every European industry. As expected, the cross-sectional dependence (CD) test by Pesaran (2004) suggests strong cross-sectional dependence in expectation formation. Thus, in a next step we include European averages of expectations and past experience as common factors in the model. Since expectations are generally considered to be affected by fundamentals and news about them, we further add national total factor productivity (TFP) estimates and stock price indices (a measure for the arrival of news) as common factors and observe that the strong cross-sectional dependence in the residuals is effectively eliminated. The null hypothesis of this test is that the residuals are locally dependent, where "local" refers to some form of proximity, which is often spatial, or, as proposed in this paper, might stem from proximity of economic activities of industries.

With this finding at hand, we aim at further studying the structure of potential local spillover effects. For this purpose, the paper applies a powerful space-time framework similar to Halleck Vega and Elhorst (2016) to model spillover effects in business expectations within and across industries and countries and simultaneously account for common factors. Using the insights from the input-output (IO) network literature, we propose trade in intermediate goods as a measure for the magnitude of interactions between countries' industries. In the first set of space-time models, we only allow for a single transmission channel per regression, imposing that expectations are solely propagated either upstream or downstream the European value chain. After finding that both channels matter empirically, we include them simultaneously, which requires the estimation of higher-order dynamic space-time models. Since spillovers could further differ within and across countries (and industries), we make use of the additional dimensions in our network data, split up the network into domestic, foreign within- and across-industries networks and, by doing so, model the empirical diffusion process in a more flexible manner.

The results from the space-time models indicate significant spillover effects in business expectation formation over trade dependencies even when allowing for specific reactions of European industries to common factors. This suggests that changes in expectations will be multiplied due to repercussion effects. More explicitly, in case the expectation about future developments in a randomly chosen industry in one country increases by one index point, confidence in all European industries (including the one experiencing the initial expectation shift) will contemporaneously increase by 1.58 (net balance) index points in total. Due to expectation rigidities, the effect of such a change in expectations is amplified, creates additional spillovers in subsequent periods and, on average, amounts to 3.31 index points in the long-run. A closer investigation of the propagation channels reveals that while expectations are transmitted both upstream and downstream the value chain, the latter channel matters more. When comparing linkages within and across countries, the results show that domestic dependencies are generally associated with larger coefficients. Regarding the transmission to foreign industries, only linkages to the same industries across national borders are relevant, while linkages to other industries in foreign countries are not directly transmitting expectations.

Our paper is related to the literature studying expectations with actual survey data.[1] Regarding firms' expectations being an object of inquiry, Coibion et al. (2018) use expectations of firms in New Zealand about aggregate variables and particularly inflation. They show that firms are persistently inattentive, but when provided with new information, this is incorporated in their expectation formation and also in economic decision making. Related to this finding, Massenot and Pettinicchi (2018) present evidence for over-extrapolation by German firms, implying that they rely too much on past experience when forming their expectations. Concerning the types of information affecting expectations, Enders et al. (2019) investigate the impact of monetary policy shocks, and find evidence for non-linearities in this effect. Besides the response to aggregate information, Buchheim and Link (2017) present results showing that also disaggregate information is reflected in firms expectations, where aggregate and disaggregate information explain about equal shares of the variance of observed expectations.

With regard to cross-sectional dependence of expectational survey data, Nowzohour and Stracca (2017) and De Grauwe and Ji (2017) provide a more aggregate analysis and present statistics implying rather strong cross-country correlations of (business) confidence data. As Nowzohour and Stracca (2017) highlight, such cross-sectional correlations suggest either the existence of a common (global) factor or of substantial spillovers in expectation formation. In this paper, we exploit survey data at the country-industry level to combine the idea of common factors with the possibility that expectations create local spillover effects over the European value chain. To the best of our knowledge, this makes us the first to empirically address the

[1] See Bachmann (2019) for a discussion about the relevance and an excellent overview of the evolvement of this new expectations literature.

question whether the positive correlations purely emerge from (unobserved) common factors or also from expectations being transmitted via an economic network.

The relevance of networks is demonstrated in the literature showing that idiosyncratic shocks taking place on a disaggregated level may have important macroeconomic implications. This contradicts 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 linkages due to the organization of production activities via (global) value chains translates into a comovement of individual firms or sectors over the business cycle (see e.g., Acemoglu et al., 2012; Baqaee and Farhi, 2019). 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's performance and country growth (di Giovanni et al., 2018). Studying the relevance of foreign production networks for the international comovement of GDP, Huo et al. (2020) decompose the comovement into a component capturing correlated shocks and another one which accounts for transmission of shocks due to trade linkages. The authors find that in their preferred calibration, the transmission component accounts for one fifth of the GDP comovement. They conculde that shock transmission is therefore economically meaningful, but plays a smaller role than the shock correlation component for the international GDP comovement.

In contrast to Huo et al. (2020), this paper does not compare the contribution of these two components for international correlations of expectations, but aims at a better understanding of actual spillover effects for the formation of business expectations while controlling for correlated shocks by including common factors. When modeling potential (local) spillover effects via European input-output relationships, we explicitly explore and compare the relevance of various channels for the propagation of business expectations. To this end, we formulate higher-order spatial econometric models and differentiate between upstream and downstream, domestic and foreign, and intra- and inter-industry channels for the transmission of expectations. Apart from the general finding that networks matter in the formation of business expectations, our result on downstream linkages to be more relevant than upstream linkages is similar to previous findings by Carvalho et al. (2016) on the transmission of a natural disaster shock to firm sales in Japan. Furthermore and related to some results by Huo et al. (2020) for analyzing GDP responses to supply shocks in a multi-sector multi-country framework, we find that domestic intermediate trade relationships are more important for transmitting expectations than foreign ones.

Section 2 presents the data sources and evidence from naive regressions. This is followed by Section 3 which elaborates on the suggested model for estimating local spillover effects and provides a detailed discussion on the construction of the economic linkage matrices. Section 4 discusses the empirical findings for different types of spillover effects in expectation formation. In Section 5 we provide some concluding remarks.

## 2 Data and naive regressions

### 2.1 Data sources, variables and sample

Data on business expectations in the European Union are provided by the European Commission on a monthly frequency (European Commission, 2016). They are derived from harmonized questionnaires where (economic) research institutes in the EU member states and candidate countries ask around 135,000 firms about their assessment of business opportunities. The questions address expectations concerning their business situation 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, and the answers are then aggregated as "balances": the difference between the percentages of respondents giving positive and negative replies. We choose the variable reflecting the forward looking question "How do you expect your production/demand/business activity/firm's employment to change over the next three months?" as our dependent variable, where the object of expectation is different for each sector (industry/services/retail/construction). Additional variables from this data set we include are based on questions addressing the firms' expectations concerning the prices they would charge as well as previous changes in their production/demand/business activity/employment. For simplicity reasons, from now on we will refer to the latter variable as past experience. Regarding the price variable, we use its quarterly lag, in particular because when including price expectations of suppliers in our model, we want to give their customers time to process information stemming from changes in expected charged prices by their suppliers. The data are 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 are seasonally adjusted and timely aggregated to a quarterly basis.

We further employ the Eurostat database to retrieve data on 2-digit industry-level labor costs for each country in the sample (Eurostat, 2019). 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 an index number 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 "total wages and salaries" (direct labor costs) and "labor costs other than wages and salaries" (indirect labor costs). The variable on direct labor costs appears to exhibit a unit root, so we only use its growth rate, whereas we can include the variable on indirect labor costs both in levels and as its growth rate.[2] For direct labor costs, we use the growth rate compared to the same quarter in the previous year (an annual growth rate on a quarterly frequency), for indirect labor costs we use the growth rate compared to the previous quarter, because this choice best fits the expectation data.

[2]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 these observations by interpolating applying a linear trend. This concerns nine observations in Greece, eleven observations in Ireland, six observations in Portugal and one in Cyprus.

In general, expectations are considered to react to changes in fundamentals as well as to the arrival of new information on these fundamentals (see e.g., Beaudry and Portier, 2006). Whether they are additionally (or instead) influenced by some (self-fulfilling) optimism or pessimism, often referred to as sentiment, and how this in turn influences actual output remains a question of debate in the literature.[3] As an attempt to control for fundamentals in our empirical model, we include country-level estimates of total factor productivity growth in addition to the variables on past experience and labor costs. To compute these estimates on a quarterly frequency, we retrieve quarterly GDP and employment data from the Eurostat database and linearly interpolate estimates of annual capital stocks from AMECO to obtain quarterly series. Using these variables, we estimate quarterly TFP as the Solow residual by assuming a constant labor share of 2/3. Moreover, we follow Beaudry and Portier (2006) and use stock price indices to represent news about future technological improvements. Quarterly data on the main national stock price indices are collected from Datastream.

Additionally to a firm's own assessment of its previous production or business situation, also *actual* production or turnover changes are likely to affect expectation formation. The Short Term Business Statistics by Eurostat provide this information on a quarterly frequency (seasonally adjusted) for European NACE Rev. 2 industries, with production data for the industry and construction sector, and turnover data for the retail and services sector. However, some sections of the NACE 2 classification are not covered, and adding actual production/turnover to our data set therefore makes us loose a substantial amount of observations per cross-section. Consequently, we will only include this variable in the robustness checks but not for the main analysis.

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. Despite the fact that the classifications NACE Rev. 2 and ISIC Rev. 4 are well compatible, the survey data need to be aggregated to a higher level in order to fit to the input-output data for some industries. Since the expectation index 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, 2017).

Merging the business survey data with the input-output data and further balancing the sample leaves us with a panel of 28,644 observations for the years 2005 to 2015. This implies that the sample covers in total 682 European industry observations per cross-section. These cross-sectional observations are based on 42 different industries located in 24 countries. We also build a smaller balanced sample (501 European industries per cross-section) where we include the actual production/turnover data from the Short Term Business statistics as additional variable. Concerning the economic network we construct, this should be exogenous, meaning that changes in production chains should not be driven by changes in expectation. For

[3] See e.g., Levchenko and Pandalai-Nayar (2020) for tracing back the impact of sentiment shocks on the business cycle, Böck and Zörner (2019) for the role of sentiment on credit cycle dynamics and Nowzohour and Stracca (2017) for a general review.

this purpose, we use the input-output table from 2004, one year before our data sample starts.

Table 1: Summary statistics

| Variable | Min | Max | Mean | Median | St. Dev. |
|---|---|---|---|---|---|
| Expectations | −99.00 | 99.00 | 7.92 | 8.23 | 23.52 |
| Past experience | −99.23 | 99.07 | 1.88 | 3.03 | 26.17 |
| Price expectations$_{t-1}$ | −100.00 | 98.20 | 2.99 | 2.57 | 19.91 |
| Production (growth) | −65.50 | 367.10 | 0.75 | 0.60 | 8.55 |
| Direct labor costs (growth) | −39.60 | 68.56 | 4.37 | 3.31 | 6.12 |
| Indirect labor costs (level) | 38.60 | 167.10 | 94.08 | 96.40 | 12.60 |
| Indirect labor costs (growth) | −40.16 | 62.40 | 0.93 | 0.81 | 3.49 |

*Notes* Growth rates are denoted in percent; statistics for production growth variable are computed from a smaller sample.

Table 1 reports the main summary statistics for the data sample at hand. Starting with the index for expectations, our sample exploits the whole distribution of potential realizations. There are several observations where 99% of firms expected a worsening for their economic activities. These are the British air and transport industry in the last quarter of 2008, an Italian retail industry, the Lithuanian automotive industry both in the first quarter of 2009, as well as two Greek manufacturing industries in 2005Q3, 2010Q4, and 2014Q2. In contrast, in the last quarter of 2014, 99% of Swedish firms in the manufacture of computer and electronic products expected enhanced business opportunities. On average, both the mean (7.92) and median (8.23) indicate that our sample period is characterized by improved business expectations as expressed by European firms. For the past experience measure and price expectations similar pictures emerge although the mean and median sample realizations for both variables are closer to zero. This might suggest that firms' expectations are over-optimistic in good times, which would be consistent with findings by Massenot and Pettinicchi (2018).

The descriptive statistics for the production growth figures are in line with the information for business expectations and past experience. As indicated by the mean and median growth rates across all industries and time periods, we observe quarterly growth rates amounting to 0.75% and 0.6%, respectively. The largest quarterly production decline (growth) is with −65.5% (367%) in a transport equipment industry in Lithuania (Belgium) in Q3 of 2013 (Q2 of 2009). 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 38.60 (167.10) for two retail industries in Romania (real estate activities in Portugal) in the first quarter of our sample (in the second quarter of 2010). The average growth rate of indirect labor costs exhibits 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 −40.16% (for Portuguese real estate activities in the third quarter of 2010) and 62.40% (for Portuguese telecommunication and computer programming activities in the first quarter of 2011), respectively. Yearly direct labor costs grew with mean and median realizations of 4.32% and 3.31%, respectively (this implies quarterly growth rates of 1.06% and 0.86%), and therefore increased only marginally stronger than indirect labor costs.

### 2.2 Naive estimates

As an initial step we estimate a standard dynamic model where we regress business expectations on time-varying covariates which could potentially have an effect on the formation of business expectations. This model for $l = 1, ..., n$ (independent) industries in $i = 1, ..., C$ countries (i.e, a system with $N = n * C$ country-industry observations) and $t = 1, ...T$ time periods with fixed effects for each industry in a country is given by

$$\boldsymbol{exp}_t = \phi \boldsymbol{exp}_{t-1} + \boldsymbol{X}_t \boldsymbol{\beta} + \boldsymbol{\mu} + \varepsilon_t, \tag{1}$$

where $\boldsymbol{exp}_t$ denotes an $N \times 1$ vector measuring business expectations at period $t$ and $\boldsymbol{exp}_{t-1}$ represents its serially lagged values with the parameter $\phi$ for the corresponding serial correlation coefficient. $\boldsymbol{X}_t$ is a $N \times K$ matrix containing $K$ explanatory variables, which are firms' assessment of previous changes in the amount of their production/turnover (past experience), how they expected their charged prices to change in the previous quarter (price expectations), the growth of wages and salaries as well as the level and growth of payroll taxes and social security contributions. The $K \times 1$ vector $\boldsymbol{\beta}$ consists of response parameters associated with these variables. The error term is composed of country-industry specific fixed effects, denoted by the $N \times 1$ vector $\boldsymbol{\mu}$, and of the $N \times 1$ vector of disturbances $\boldsymbol{\varepsilon}_t$, which is normally distributed, has zero mean and constant variance $\sigma^2 \boldsymbol{I}_N$.

The initial estimates of this model are reported in column (I) of Table 2 and are obtained by applying the Least Squares Dummy Variable (LSDV) estimator, which we consider reasonable given the rather long time period available in our sample ($T = 42$). The results show that the estimates of the serial autocorrelation coefficient and of all the other parameters associated with the covariates in the model are highly statistically significant. They have the expected signs, where the positive effect of changes in direct labor costs on firms' confidence is likely to be attributed to positive effects of shifts in labor productivity (which are positively reflected by wages).

To test for cross-sectional dependence in expectation formation we employ the CD test by Pesaran (2004). It is based on pairwise correlation coefficients between the time series of each economic unit. We use the residuals and compute the statistic as $CD = \frac{2T}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \widehat{corr}_{ij}$, where $\widehat{corr}_{ij}$ denotes the estimated correlation coefficient between the residual of some European industry $i$ and the residual of another European industry $j$. The resulting test statistic is standard normally distributed. We obtain a value of $CD = 291.13$ which points to strong cross-sectional dependence in the residuals from this simple model for business expectations.

In an attempt to address the cross-sectional dependence, in a next step we include common factors. We follow Pesaran (2006) and Halleck Vega and Elhorst (2016) and define them as the cross-sectional averages of the dependent variable at times $t$ and $t-1$ and of the indepedent variables at time $t$, i.e. $\overline{exp}_t = \frac{1}{N}\sum_{i=1}^{N} exp_{it}$, $\overline{exp}_{t-1} = \frac{1}{N}\sum_{i=1}^{N} exp_{it-1}$, and $\overline{X}_{kt} = \frac{1}{N}\sum_{i=1}^{N} X_{ikt}$ where $k$ represents the $k^{\text{th}}$ explanatory variable in $\boldsymbol{X}_t$. As additional common factors we include country-specific changes in TFP and stock price indices, denoted by $tfp_{it}$ and $stockx_{it}$ . The respective model is

$$\begin{aligned} \boldsymbol{exp}_t = \phi \boldsymbol{exp}_{t-1} + \boldsymbol{X}_t \boldsymbol{\beta} + \boldsymbol{\Gamma}_1 \overline{exp}_t + \boldsymbol{\Gamma}_2 \overline{exp}_{t-1} \\ + \boldsymbol{\Gamma}_3 tfp_{it} + \boldsymbol{\Gamma}_4 stockx_{it} + \sum_{k=1}^{K} \boldsymbol{\Pi}_k \overline{X}_{kt} + \boldsymbol{\mu} + \boldsymbol{\varepsilon}_t, \end{aligned} \tag{2}$$

where individual responses of European industries to these common factors are stored in the $N \times 1$ vectors $\boldsymbol{\Gamma}_1$, $\boldsymbol{\Gamma}_2$, $\boldsymbol{\Gamma}_3$, $\boldsymbol{\Gamma}_4$ and $\boldsymbol{\Pi}_k$ for $k = 1, ...K$ and the remaining parameters and variables are defined as above.

The results for this model specification are depicted in column (III) of Table 2. Considering that each additional common factor increases the amount of parameters to be estimated by $N$, and that we already have to estimate $N$ country-industry fixed effects, from the set of explanatory variable we only include the cross-sectional average of the past experience variable as common factor in this estimation. In any case, extended regressions show that the averages of the other variables in $\boldsymbol{X}_t$ do not help to further reduce the $CD$ statistic.[4]

Not surprisingly, the parameter estimates of the coefficients decreased in magnitude and partly in significance when compared to the former specification since the common factors now pick up a substantial fraction of the variation in the data. Nonetheless, the strong relation between a firm's assessment of its previous business situation and its expectation concerning future developments remains. The serial correlation coefficient now shows a value of approximately 0.30. Referring to cross-sectional dependence, the $CD$ statistic is reduced drastically to $CD = -0.40$, which implies that this specification sufficiently accounts for common global factors. However, it should be noted that under the null hypothesis of this test, the series can still be "locally" interdependent (Pesaran, 2015). This means that when being close to each other, two European industries might still influence each other in the formation of expectations about future production potentials.

Specifications (I) and (III) do not comprise time fixed effects because in (III) they are perfectly multicollinear with common global factors. To provide a comparison, column (II) in Table 2 reports the results when including time fixed effects instead of common factors. Remarkably, the $CD$ statistic reveals that also time fixed effects control for the strong cross-sectional dependence of the expectation data ($CD = 0.67$). However, common factors with country-industry specific coefficients make the model much more flexible and allow us to explicitly disentangle the network effects from individual reactions to common shocks. For this reason, in the subsequent analysis we still include the particular common factors introduced above.

[4]Detailed results for a model with common factors based on all included covariates are available upon request.

Table 2: LSDV model estimates

| Model | (I) | (II) | (III) |
|---|---|---|---|
| $\phi \boldsymbol{exp}_{t-1}$ | $0.390^{***}$ | $0.395^{***}$ | $0.295^{***}$ |
| | (69.866) | (70.970) | (48.327) |
| Past experience | $0.350^{***}$ | $0.287^{***}$ | $0.280^{***}$ |
| | (74.796) | (58.725) | (51.186) |
| Price expectations | $-0.031^{***}$ | 0.001 | $0.017^{***}$ |
| | ($-5.544$) | (0.176) | (2.707) |
| Direct labor costs (growth) | $0.075^{***}$ | $0.113^{***}$ | 0.026 |
| | (4.039) | (5.788) | (1.126) |
| Indirect labor costs (level) | $-0.081^{***}$ | $-0.043^{***}$ | $-0.017^{*}$ |
| | ($-9.783$) | ($-3.439$) | ($-1.833$) |
| Indirect labor costs (growth) | $-0.108^{***}$ | $-0.081^{***}$ | $-0.067^{**}$ |
| | ($-4.065$) | ($-3.047$) | ($-2.538$) |
| Corrected $R^2$ | 0.518 | 0.547 | 0.630 |
| Time FE | NO | YES | NO |
| Common factors | NO | NO | YES |
| $CD$ | 291.134 | 0.672 | $-0.403$ |
| Nobs | 28644 | 28644 | 28644 |

*Notes* Common factors are $\overline{exp}_t$, $\overline{exp}_{t-1}$, $\overline{past}_t$, $tfp_{it}$, $stockx_{it}$; ***significant at 0.01 level, **significant at 0.05 level, *significant at 0.1. level; t-stastics in parenthesis; T=42.

## 3 Modeling local spillover effects: The dynamic Spatial Durbin Model

The naive regression results indicated substantial cross-sectional dependence in the expectations data. While common factors take care of so-called "strong" cross-sectional dependence, firms' expectations might still be locally dependent on each other. Thus, we apply a powerful space-time framework for modeling the interdependencies of firms' expectations within and across industries and countries which also allows for persistence in expectation formation over time. As a measure for the magnitude of interactions between countries' industries we propose trade of intermediate goods. Concerning the time-varying covariates introduced in Section 2, we do not only allow them have an impact on expectations in the respective European industry, but also to directly affect expectations in upstream/downstream industries.

This model for the formation of firm expectations takes the form of a dynamic Spatial Durbin Model (SDM) which reads as:

$$\begin{aligned} \boldsymbol{exp}_t &= \phi \boldsymbol{exp}_{t-1} + \rho \boldsymbol{W} \boldsymbol{exp}_t + \eta \boldsymbol{W} \boldsymbol{exp}_{t-1} + \boldsymbol{X}_t \boldsymbol{\beta} + \boldsymbol{W} \boldsymbol{X}_t \boldsymbol{\theta} \\ &\quad + \boldsymbol{\Gamma}_1 \overline{exp}_t + \boldsymbol{\Gamma}_2 \overline{exp}_{t-1} + \boldsymbol{\Gamma}_3 tfp_{it} + \boldsymbol{\Gamma}_4 stockx_{it} + \sum_{k=1}^{K} \boldsymbol{\Pi}_k \overline{X}_{kt} + \boldsymbol{\mu} + \boldsymbol{\varepsilon}_t, \end{aligned} \tag{3}$$

where $\boldsymbol{W}$ is a $N \times N$ dimensional weights matrix, which has non-negative and known constants. It models the interdependencies of European industries and will be further explained in Subsection 3.1. For now, a vector or matrix pre-multiplied by $\boldsymbol{W}$ can be regarded as its lagged value when moving downstream or upstream the European production chain. The parameter $\phi$ again denotes the serial correlation coefficient, the parameters $\rho$ and $\eta$ are the response parameters corresponding to $\boldsymbol{Wexp}_t$ and $\boldsymbol{Wexp}_{t-1}$, respectively. $\phi$ thus captures within-industry persistence in business expectations while $\rho$ measures the extent to which changes in business expectations are transmitted via European value chains. $\boldsymbol{\theta}$ is $K \times 1$ vector which stores the response parameters associated with $\boldsymbol{WX}_t$. The common factors are defined as in Equation 2. Note that in contrast to the common factors having unit-specific effects on expectation formation, the variables representing dependence over the value chain enter with common coefficients. The remaining variables, parameters and the error term are specified as in Equation 1 and 2, where the error term again does not include any time-specific effects, since they are already covered by the more general form of unit-specific coefficients corresponding to the common factors.

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

### 3.1 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 economic units. 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 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), Carvalho, Nirei, Saito and Tahbaz-Salehi (2016) and Acemoglu, Ozdaglar and Tahbaz-Salehi (2017), who study the impact of sectoral networks on the macroeconomy by building on the multisector framework first developed by Long and Plosser (1983).[5]

[5]Other examples which rely on spatial econometrics in combination with interdependence of industries included e.g. Cohen and Morrison Paul (2005), Badinger and Egger (2016) and Ozdagli and Weber (2017). Cohen and Morrison Paul (2005) study the importance of spatial and industrial spillovers for agglomeration and location decisions in the US food manufacturing industry across states. Badinger and Egger (2016) investigate inter- and intra-industry spillovers of productivity for a panel of 12 OECD countries and Ozdagli and Weber (2017) examine the role of production networks for the transmission of monetary policy in the US.

Since business expectations might be transmitted both upstream and downstream the European value chain, we use the input-output information to construct two matrices $\boldsymbol{W}_{\text{up}}$ and $\boldsymbol{W}_{\text{down}}$ where each represents one of these transmission mechanisms. Before standardization, a typical element of the upstream weights matrix $\boldsymbol{W}_{\text{up}}$ is given by the share of intermediate production in total production:

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

where $\text{IO}_{ik,jl}$ denotes the sales of intermediate goods of industry $k$ from country $i$ to industry $l$ in country $j$ and $\text{PROD}_{ik}$ 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 industry to other 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.

For the specification of the downstream network, we define a typical element of $\boldsymbol{W}_{\text{down}}$ before standardization as:

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

where $\text{IO}_{jl,ik}$ 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 $\boldsymbol{W}_{\text{down}}$ are the off-diagonal elements of the transpose of the input coefficient matrix from input-output analysis.

The condition $i \neq j$ if $k = l$ and $k \neq l$ if $i = j$ reflects that the formulas for the calculation of the weights expressed in Equations (4) and (5) only apply to off-diagonal elements of the respective matrices. The main diagonal elements of $\boldsymbol{W}_{\text{up}}$ and $\boldsymbol{W}_{\text{down}}$ are set to zero such that contemporaneous self-influence of the dependent variable is avoided. The persistence in within-industry business expectations is captured via $\phi \boldsymbol{y}_{t-1}$.

In the durbin term of the space-time model ($\boldsymbol{W}\boldsymbol{X}_t$) the downstream matrix $\boldsymbol{W}_{\text{down}}$ will be used for the pre-multiplication of the independent variables representing prices and labor costs, since they can be interpreted as something similar to supply shock variables. As an example, consider the spillover effects of an increase in social security payments and payroll taxes in industry $ik$: this would lead to higher input prices for industries buying intermediates from $ik$ and therefore these downstream industries might adjust their expectations downwards. In contrast, the upstream matrix will be used for the pre-multiplication of the variables associated with output.

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

Since Equation (3) 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 $\rho$). 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 $\min\{\text{sum}_{\text{max}}^{\text{row}}, \text{sum}_{\text{max}}^{\text{col}}\}$. 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 an advantage that lies in maximum normalization because the autoregressive parameter $\rho$ can be multiplied by the single rescaling factor, which yields a specification corresponding to the un-normalized weights matrix. As Kelejian and Prucha (2010) emphasize, this can be beneficial since the parameter corresponding to the un-normalized weights matrix 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. 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.[6] Another virtue of maximum-normalization is that when estimating a higher-order model (a spatial model with several weights matrices) it does not matter whether the 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 or can be rescaled already prior to the estimation.

[6]Consider the upstream matrix where the elements of the weights matrix should still denote the magnitude of sales of one industry to another relative to the total production of the former 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 expectations in industry $ik$ depends on expectations 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: Let $w_{ik,il}^{*}$ be an element of the row-normalized weights matrix $\boldsymbol{W}^{*}$ for the previous example. Then $w_{ik,il}^{*} = \frac{w_{ik,il}}{w_{ik,il}+w_{ik,im}} = \frac{\frac{\text{IO}_{ik,il}}{\text{PROD}_{ik}}}{\frac{\text{IO}_{ik,il}}{\text{PROD}_{ik}}+\frac{\text{IO}_{ik,im}}{\text{PROD}_{ik}}} = \frac{\text{IO}_{ik,il}}{\text{IO}_{ik,il}+\text{IO}_{ik,im}}$.

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.

### 3.2 Transmission of expectations

The space-time model allows to analyze the transmission of expectations in the EU real economy by taking on different perspectives. On the one hand, we can interpret the autoregressive parameters $\rho$ and $\eta$ and thereby learn how changes in the unexplained part of expectations propagate through the system. On the other hand, we can study how changes in the explanatory variables affect business confidence and which repercussions they create. We first discuss the effects of shifts in expectations orthogonal to the covariates, and then introduce the impact measures associated with the explanatory variables.

The input-output dependencies in the space-time model imply that an idiosyncratic shock to business expectations (i.e., the error term) in a certain European industry in period $t$ will not only have an effect on expectations in that very industry, but also on business expectation formation in the other industries and countries which are related through trade in intermediates to the affected industry. If this relationship goes both ways, the resulting changes in beliefs will further have an impact on the original industry's expectation. Thus, the initial shift in expectations will be multiplied inducing a larger total effect. In period $t$ these feedback effects are stored in the matrix $(\boldsymbol{I}_N - \rho \boldsymbol{W})^{-1}$. Following Debarsy et al. (2012), we can further compute the $s$-horizon impulse-response of such a transitory change by:

$$(-1)^s(\boldsymbol{B}^{-1}\boldsymbol{A})^s\boldsymbol{B}^{-1}, \quad s = 0, ..., S \tag{6}$$

where $\boldsymbol{A} = -(\phi \boldsymbol{I}_N + \eta \boldsymbol{W})$ and $\boldsymbol{B} = (\boldsymbol{I}_N - \rho \boldsymbol{W})$. Taking the infinite sum over time yields the long-run effects matrix, which is given by $\big((1-\phi)\boldsymbol{I}_N - (\rho + \eta)\boldsymbol{W}\big)^{-1}$ (Elhorst, 2014). Since we apply maximum-normalization and the estimates of $\rho$ and $\eta$ will thus depend on the size of the elements in $\boldsymbol{W}$, we use these feedback matrices to compute some statistics which should better demonstrate the magnitude of expectation propagation over the input-output network. Taking the average over the row sums of the feedback matrix can be interpreted as the total effect generated by a unitary increase in the the net-balance of expectations in a randomly chosen European industry on this industry itself (direct effect) as well as on all other European industries together (indirect effect). We will call this average of the total effect the input-output multiplier, and compute it for the short-run (the total effect of an idiosyncratic increase of expectations the period of the shift) and for the long-run based on the respective feedback matrices.

For the calculation of the impacts associated with the explanatory variables, the repercussion effects also have 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.

Similar to expression (6), for a space-time model as given in equation (3) the response of business expectations at time $t+s$ to a transitory change in the $k^{\text{th}}$ explanatory variable at time $t$ is given by:

$$\frac{\partial \boldsymbol{exp}_{t+s}}{\partial \boldsymbol{x}_t^{(k)\prime}} = \boldsymbol{D}_s(\boldsymbol{I}_N \beta_k + \boldsymbol{W}\theta_k) \tag{7}$$

with

$$\boldsymbol{D}_s = (-1)^s(\boldsymbol{B}^{-1}\boldsymbol{A})^s\boldsymbol{B}^{-1}, \quad s = 0, ..., S \tag{8}$$

where $\boldsymbol{A}$ and $\boldsymbol{B}$ are defined as above. The $N \times N$ matrix denoted by expression (7) 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. 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 change of variable $k$ in period $t$ at any time period $t+s$.

## 4 Estimation results

In order to investigate whether firms' expectations depend on each other via a network, we estimate the dynamic Spatial Durbin Model introduced in Section 3. The first set of results is obtained from the bias-corrected quasi maximum likelihood estimator suggested by Lee and Yu (2010), applying MATLAB codes from Elhorst et al. (2013). The approach by Lee and Yu (2010) conditions on the initial period observation and assumes that this period is only subject to input-output dependence. In our view this estimator is suitable since the time period available in our sample is rather long and the approach further imposes a bias correcting procedure for estimating $\phi$.

Columns (IV) and (V) in Table 3 report the results when using the upstream matrix $\boldsymbol{W}_{\text{up}}$ as the weighting matrix for the autocorrelation of expectations, while column (VI) and (VII) depict the results from an estimation with $\boldsymbol{W}_{\text{down}}$ instead.[7] As discussed in Section 3, the models are stationary if $\phi + (\rho + \eta)\omega_{\max} < 1$, where $\omega_{\max}$ refers to the largest eigenvalue of the corresponding weighting matrix. This condition is fulfilled for all four models.

Concerning the parameter estimates, the estimate of the serial autocorrelation coefficient remains similar

[7]For the pre-multiplication of the variables in $\boldsymbol{X}_t$, the matrices are used as explained in Section 3.1.

to its counterpart in the specification without input-output dependence. Though highly significant, it is relatively small considering the quarterly frequency of the data. This implies that firms tend to adjust their business expectations rather regularly. The low coefficient can partly be explained by the inclusion of common factors (see the results in columns (I) and (III) in Table 2), and partly by the the fact that expectations are regressed on the firms' answers about previous production or sales developments, which to some extent already control for past developments. In a model without common factors and the past experience variable, the estimated serial autocorrelation coefficient is substantially larger and amounts to 0.60.

Studying 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 their transmission. Column (IV) in Table 3 reports a positive and statistically highly significant parameter estimate of $\rho$. Accordingly, an increase in firms' expectations in an industry induces positive expectation adjustments in upstream industries, i.e., in the industries from which it purchases intermediate goods. The estimate for $\eta$, in contrast, is small and not statistically significant. Thus, we also present the results for a model excluding the term which lags the dependent variable both in time and over the network ($\boldsymbol{Wexp}_{t-1}$). Column (V) shows that the parameters estimates for this restricted model remain very similar. When interpreting the magnitude of $\rho$, the normalization method of the weights matrix $\boldsymbol{W}$ should be kept in mind, since the size of the elements in $\boldsymbol{W}$ matter for the size of the coefficient. Due to the fact that we rescaled the weights matrix such that its maximum row sum is equal to one (see Section 3.1)(and the average element of $\boldsymbol{W}$ is thus smaller than the average element of a row normalized matrix), the estimated $\rho$ will be larger than an autocorrelation coefficient from a model with a row-normalized matrix. However, we can rescale the parameter estimate by using the rescaling coefficient that would make the average row sums of the weights matrix to equal one. The transformed parameter estimate then amounts to a value of $\rho^* = 0.16$.

Using the estimate of $\rho$, we further compute the input-output multiplier to better demonstrate the size of spillover effects stemming from idiosyncratic changes in expectations (see Section 3.2). This measure denotes how a unitary change of the error term in one European industry, on average, affects business expectations in the same industry and in all other industries incorporating all induced feedback effects. Since we control for fundamentals such as past experience (the firms' own assessment of previous changes in a fundamental), labor productivity, indirect labor costs, and country-level estimates of technology, as well as for new information on the country-level, the unexplained part of expectations can be interpreted as country-industry specific information and/or some form of mood, i.e. sentiment. Although we cannot disentangle these two components of the error term, we emphasize that the model allows unit-specific reactions to changes in the national stock price indices as our attempt to filter out the "news" effect.

That being said, in response to a positive unitary shift in the net balance of this unexplained part of firms' expectations in period $t$, the net balance of expectations will increase by 1.19 in the same period, taking all repercussions across European industries into account. In contrast, in a situation where no network spillovers were to be found, the effect would just amount to 1. Due to expectation rigidities, the rise of confidence in all industries will have further effects in period $t+1$, which again induces additional spillovers over the network.

Table 3: Dynamic Spatial Durbin Model estimates

| Model | (IV) | (V) | (VI) | (VII) |
|---|---|---|---|---|
| $\phi \boldsymbol{exp}_{t-1}$ | $0.316^{***}$ | $0.316^{***}$ | $0.309^{***}$ | $0.310^{***}$ |
| | (50.248) | (50.466) | (48.930) | (49.524) |
| $\rho \boldsymbol{W} \boldsymbol{exp}_t$ | $0.494^{***}$ | $0.497^{***}$ | $0.514^{***}$ | $0.549^{***}$ |
| | (13.324) | (14.028) | (14.863) | (18.133) |
| $\eta \boldsymbol{W} \boldsymbol{exp}_{t-1}$ | $-0.006$ | | $0.061^{**}$ | |
| | (0.275) | | (2.083) | |
| $\beta_1$ Past experience | $0.260^{***}$ | $0.260^{***}$ | $0.254^{***}$ | $0.254^{***}$ |
| | (53.358) | (53.356) | (52.061) | (52.168) |
| $\beta_2$ Price expectations$_{\text{t-1}}$ | 0.005 | 0.005 | $0.007^{*}$ | $0.007^{*}$ |
| | (1.579) | (1.580) | (1.940) | (1.913) |
| $\beta_3$ Direct labor costs (growth) | 0.006 | 0.005 | 0.019 | 0.019 |
| | (0.249) | (0.255) | (0.728) | (0.721) |
| $\beta_4$ Indirect labor costs (level) | $-0.041^{**}$ | $-0.041^{**}$ | $-0.050^{***}$ | $-0.050^{***}$ |
| | $(-2.384)$ | $(-2.384)$ | $(-2.899)$ | $(-2.907)$ |
| $\beta_5$ Indirect labor costs (growth) | $-0.088^{***}$ | $-0.088^{***}$ | $-0.090^{***}$ | $-0.090^{***}$ |
| | $(-2.865)$ | $(-2.868)$ | $(-2.941)$ | $(-2.955)$ |
| $\theta_1 \boldsymbol{W}_{\text{up}}$ Past experience | $-0.025$ | $-0.031$ | $0.115^{***}$ | $0.121^{***}$ |
| | $(-0.576)$ | $(-0.599)$ | (4.245) | (4.714) |
| $\theta_2 \boldsymbol{W}_{\text{down}}$ Price expectations$_{\text{t-1}}$ | $0.062^{**}$ | $0.061^{**}$ | $-0.008$ | 0.003 |
| | (2.052) | (2.080) | $(-0.327)$ | (0.153) |
| $\theta_3 \boldsymbol{W}_{\text{down}}$ Direct labor costs (growth) | $-0.059$ | $-0.060$ | $-0.075$ | $-0.070$ |
| | $(-0.472)$ | $(-0.461)$ | $(-0.617)$ | $(-0.555)$ |
| $\theta_4 \boldsymbol{W}_{\text{down}}$ Indirect labor costs (level) | $0.083^{*}$ | $0.083^{*}$ | $0.108^{**}$ | $0.113^{***}$ |
| | (1.941) | (1.954) | (2.493) | (2.627) |
| $\theta_5 \boldsymbol{W}_{\text{down}}$ Indirect labor costs (growth) | 0.127 | 0.127 | 0.156 | 0.158 |
| | (0.942) | (0.944) | (1.165) | (1.187) |
| Input-output multiplier$_{\text{SR}}$ | 1.186 | 1.187 | 1.288 | 1.314 |
| Input-output multiplier$_{\text{LR}}$ | 1.885 | 1.895 | 2.266 | 2.215 |
| $\phi + (\rho + \eta)\omega_{\max}$ | 0.455 | 0.457 | 0.548 | 0.539 |
| $CD$ | 0.320 | 0.317 | 0.595 | 0.459 |
| Common factors | YES | YES | YES | YES |
| Loglik | $-112758$ | $-112758$ | $-112700$ | $-112702$ |
| Nobs | 28644 | 28644 | 28644 | 28644 |

*Notes* Common factors are $\overline{exp}_t$, $\overline{exp}_{t-1}$, $\overline{past}_t$, $tfp_{it}$, $stockx_{it}$; ***significant at 0.01 level, **significant at 0.05 level, *significant at 0.1. level; assymptotic z-statstics in parenthesis; T=42.

Taking the infinite sum over time (and over input-output repercussions) yields the long-run input-output multiplier, amounting to 1.90 in this specification. This suggests that the contagion effects of expectations cannot only be traced back to believes in a European industry reacting to changes of fundamentals in other European industries, but that also the arrival of specific new information or/and changes in confidence will create spillovers over the network.

The previously presented results referred to specifications where we assumed that increases in expectations were propagated upstream the value chain, based on the idea that such shifts make suppliers expect rising demand for their intermediate goods. However, similar to supply shocks, if a business expects to produce more in the subsequent quarter, this belief may also be transmitted to its customers as they might assume their input prices to decrease accordingly. The respective results based on the downstream matrix are reported in Table 3, Column (VI) and Column (VII), where the latter corresponds to a model with the restriction $\eta = 0$. In both cases, positive and statistically significant estimates of $\rho$ are reported, suggesting that this channel of shock transmission also matters for expectation formation. Comparing the input-output autocorrelation coefficients across specifications with different (maximum-normalized) weights matrices is only sensible when rescaling the coefficients as explained above. Alternatively, drawing on the input-output multipliers indicates that spillovers originating from the downstream channel are even larger than from the upstream channel. However, in order to thoroughly compare the two channels, a higher-order model needs to be estimated where both spillover matrices are simultaneously included. This allows us to investigate whether and to what extent one specific channel matters while holding the effect from the other channel constant.

The estimated positive coefficient associated with the past experience variable remains large and highly statistically significant over all four models estimated. We further find negative immediate effects of indirect labor costs and their growth rate on expectations, which are statistically significant but moderate in size. Also the parameter estimates corresponding to the durbin term of the model are relatively low. We compute likelihood ratio tests to evaluate whether the model can be reduced to a model without lagging the explanatory variables over the network (dynamic Spatial Autoregressive (SAR) model)). While for specifications (IV) and (V), taking twice the difference of likelihoods between the full and the restricted model does not exceed the 99% critical value of a $\chi^2(5)$ distribution (15.09), for the specifications based on the downstream network, this value is exceeded and so the test provides no evidence that a SAR specification is favored over the SDM specification. Thus, the subsequent analysis is based on the more general model allowing the covariates to directly affect expectations in upstream/downstream industries.

## 4.1 Upstream and downstream transmission

The results from the above analysis suggested that expectations could be transmitted both upstream and downstream over the value chain. Yet, these channels are likely to be correlated, and thus mistakenly imposing a model where only one of them is included can lead to biased and inconsistent estimates because the dependence will only be attributed to a single channel (Badinger and Egger, 2011). Consequently, we extend the model to a second order additive process where we simultaneously allow for upstream and downstream spillover effects. For the sake of simplicity and because the coefficient estimates of $\eta$ were very low and partly insignificant when estimating the first order processes, we do not include the terms lagging the dependent variable both in time and over the upstream and downstream network. The estimation is based on the Two Stage Least Squares (TSLS) approach with many instruments by Lee and Yu (2014), since maximum likelihood is computationally very demanding in the case of several spatial lags. In order to eliminate the individual fixed effects, the variables are first transformed by the forward orthogonal difference (FOD) transformation, where $\boldsymbol{exp}_t^*$ and $\boldsymbol{exp}_{t-1}^{*-1}$ denote the transformed $\boldsymbol{exp}_t$ and $\boldsymbol{exp}_{t-1}$ respectively.[8][9] We instrument the endogenous variables $\boldsymbol{W}_{\text{up}}\boldsymbol{exp}_t^*$, $\boldsymbol{W}_{\text{down}}\boldsymbol{exp}_t^*$ and $\boldsymbol{exp}_{t-1}^*$ and use the IV matrix

$$[\boldsymbol{Q}_\tau, \boldsymbol{\mathcal{W}}\boldsymbol{Q}_\tau, \boldsymbol{\mathcal{W}}^2\boldsymbol{Q}_\tau, \boldsymbol{R}_\tau]$$

where $\boldsymbol{\mathcal{W}}\boldsymbol{Q}_\tau = [\boldsymbol{W}_{\text{up}}\boldsymbol{Q}_\tau, \boldsymbol{W}_{\text{down}}\boldsymbol{Q}_\tau]$ and $\boldsymbol{\mathcal{W}}^2\boldsymbol{Q}_\tau = [\boldsymbol{W}_{\text{up}}^2\boldsymbol{Q}_\tau, \boldsymbol{W}_{\text{down}}^2\boldsymbol{Q}_\tau, \boldsymbol{W}_{\text{up}}\boldsymbol{W}_{\text{down}}\boldsymbol{Q}_\tau, \boldsymbol{W}_{\text{down}}\boldsymbol{W}_{\text{up}}\boldsymbol{Q}_\tau]$, with $\boldsymbol{Q}_\tau = [\boldsymbol{exp}_{t-1}, \boldsymbol{exp}_{t-2}, \boldsymbol{exp}_{t-3}, \boldsymbol{W}\boldsymbol{X}_t^*, \boldsymbol{W}\boldsymbol{X}_{t-1}^*, \boldsymbol{W}\boldsymbol{X}_{t-2}^*]$, and where $\boldsymbol{R}_\tau = [\boldsymbol{X}_t^*, \boldsymbol{X}_{t-1}^*, \boldsymbol{X}_{t-2}^*, \boldsymbol{F}_t^*, \boldsymbol{F}_{t-1}^*, \boldsymbol{F}_{t-2}^*]$. $\boldsymbol{W}\boldsymbol{X}_t^*$ generalizes the spatial durbin term and refers to the same choice of weights matrices for pre-multiplication of the explanatory variables as described in Section 3.1. $\boldsymbol{F}_t^*$ is a matrix containing the FOD transformed common factors and cannot be pre-multiplied by $\boldsymbol{\mathcal{W}}$ due to multicollinearity. We only include two lags to instrument the time lagged dependent variable because the number of instruments quickly increases with further lags due to the inclusion of common factors. In contrast to Lee and Yu (2014), we use the transformed exogenous variables $\boldsymbol{X}_t^*$ (and their lags) instead of the untransformed $\boldsymbol{X}_t$ in the IV matrix, because then the results of estimating a first order process best resemble the estimates when employing the bias-corrected quasi maximum likelihood approach.

We first check for the consistency of the estimates from the two different methods applied and replicate the results of Table 3 by means of TSLS with many instruments for first order processes (see Lee and Yu, 2014), where we use two time lags and the transformed exogenous variables $\boldsymbol{X}_t^*$ in the IV matrix as explained above. The results in Table A2 affirm that the coefficient estimates for the explanatory variables and also for the serial autocorrelation term are rather similar to the results from the quasi maximum likelihood estimation, where the persistence is generally slightly stronger according to the TSLS estimation. The most striking difference is observed regarding the estimate of $\rho$, which is considerably larger when estimated by TSLS and thereby also affects the estimate of the input-output multiplier in the same direction, though to a mitigated extent because the elements in the weights matrices are relatively small. The deviation between the estimated multipliers is less pronounced for the restricted models (V) and (VII) and amounts to 0.05 in the upstream and to 0.12 in the downstream specification, respectively.

The results for models incorporating both the upstream and downstream transmission channels are reported in Table 4. The short-run and the long-run input-output multipliers of higher-order spatial models of order $S$ are computed as the average row sums of $\left(\boldsymbol{I}_N - \sum_{s=1}^S \rho_s \boldsymbol{W}_s\right)^{-1}$ and $\left((1-\phi)\boldsymbol{I}_N - \sum_{s=1}^S \rho_s \boldsymbol{W}_s\right)^{-1}$ respectively. The models are stable if the condition $\phi + \sum_{s=1}^S \rho_s \omega_{s\max} < 1$ is satisfied, which again is the

[8]The FOD transformation makes us loose the observations of the last period.

[9]$\boldsymbol{exp}_{t-1}^*$ and $\boldsymbol{exp}_{t-1}^{*-1}$ are not the same.

case for all specifications estimated. $\boldsymbol{W}_1$ in model (VIII) represents the upstream weights matrix, and $\boldsymbol{W}_2$ the downstream weights matrix. They are both separately maximum normalized. Since the estimates of $\rho_1$ and $\rho_2$ are both significantly different from zero, the results indicate that a shift in expectations in an European industry affects expectation formation of the industry's suppliers as well as of its customers. We can easily rescale these two estimates by the average row sums of the respective weights matrix in order to obtain autocorrelation coefficients corresponding to matrices where the average row sum is equal to one. The rescaled estimates are directly comparable and allow us to determine which channel is more important for the propagation of expectations. Rescaling yields values of $\rho_1^* = 0.134$ and $\rho_2^* = 0.275$, indicating that the downstream channel matters more for shock transmission. Testing the null hypothesis $\rho_1^* - \rho_2^* = 0$ confirms that the difference is statistically significant. This finding for spillover effects in expectation formation is consistent with results reported by Carvalho et al. (2016) on the propagation effects of a natural disaster shock for changes in firms' sales. They find that the shock of the Great Japanese earthquake 2011 is transmitted both downstream and upstream the Japanese value chain, but that the upstream effect is quantitatively weaker.

Despite the fact that we can assess the relevance of the alternative transmission channels connected to the first-round spillovers, a higher-order additive autoregressive process such as model (VIII) does not allow an additive (or multiplicative) decomposition of the overall spillover effects, incorporating all feedback effects. This means that we cannot split up the multiplier into average spillover effects stemming from the upstream versus the downstream channel. Instead, the model imposes that the spillovers interact with each other, which we consider more plausible anyway.

### 4.1.1 Differentiating between domestic and foreign transmission

In the previously presented specifications, a single autocorrelation coefficient is estimated for all downstream and for all upstream industries, disregarding whether two industries are located in the same country or not. Differences between domestic and foreign transmissions are to some extent already controlled for by using trade in intermediates, which is typically more pronounced within than across countries, to determine the strength of linkages. Nevertheless, border effects might play an additional role in the decay function of expectations across the value chain. Thus, we make the specification more flexible and disentangle the two previously discussed transmission channels in terms of national and international linkages. For this purpose, we separate the upstream and the downstream weights matrices each in a domestic and a foreign matrix as discussed in Section 3.1.

Column (IX) in Table 4 reports the corresponding TSLS based estimates for such a fourth order model, where $\boldsymbol{W}_1 = \boldsymbol{W}_{\text{up}}^{\text{dom}}$, $\boldsymbol{W}_2 = \boldsymbol{W}_{\text{up}}^{\text{for}}$, $\boldsymbol{W}_3 = \boldsymbol{W}_{\text{down}}^{\text{dom}}$ and $\boldsymbol{W}_4 = \boldsymbol{W}_{\text{down}}^{\text{for}}$.[10] The matrices are all separately maximum normalized. While the estimate of the serial correlation coefficient remains almost identical to the previous specification, the autoregressive coefficients associated to the input-output network reveal

[10] The extension of the above introduced TSLS approach from the second order model to a fourth order model is straightforward and therefore not discussed in detail.

interesting findings. Firstly, the upstream network has statistically significant coefficients both for the domestic and foreign linkages, whereas for the downstream network, only domestic input-output relations are relevant. Secondly, rescaling the coefficients to make them comparable gives $\rho_1^* = 0.092$, $\rho_2^* = 0.087$, $\rho_3^* = 0.215$ and $\rho_4^* = 0.029$, suggesting that first-round spillovers to upstream industries (weighted by trade in intermediates) are not additionally impacted by border effects. On the one hand, this highlights the intensity of economic integration prevalent in the European economy. On the other hand, domestic first-round spillovers in this model setting can only occur across industries, while foreign spillovers can arise both within and across industries (since domestic within industry spillovers would imply regressing the dependent variable on itself). In order to investigate to what extent the this argument plays a role for the underlying findings, we proceed by splitting the foreign linkages into within- and across-industry linkages.

### 4.1.2 Differentiating between intra-industry and inter-industry transmission

When interpreting the input-output multiplier, we are agnostic about whether what is propagated is information that is only available in a specific industry in some country (unit-specific "news", since we already control for country-specific "news"), or whether this is some mood part of expectations. In both cases, industries are likely to react stronger to "news" or moods stemming from the *same* foreign industry than from *different* foreign industries, since firms could expect similar developments in their home market as abroad. Thus, in a next step we allow the foreign diffusion process to carry different coefficients within and across industries. The corresponding results are reported in the last three columns of Table 4. We construct the matrices $\boldsymbol{W}_{\text{up}}^{\text{for,intra}}$ and $\boldsymbol{W}_{\text{up}}^{\text{for,inter}}$ which sum up to $\boldsymbol{W}_{\text{up}}^{\text{for}}$, and where an element $w_{ik,jl}^{\text{for,intra,up}}$ of $\boldsymbol{W}_{\text{up}}^{\text{for,intra}}$ is non-zero for $i \neq j$ and $k = l$ and zero otherwise, and an element $w_{ik,jl}^{\text{for,inter}}$ of $\boldsymbol{W}^{\text{for,inter}}$ is non-zero for $i \neq j$ and $k \neq l$ and zero otherwise. We again compute the downstream networks $\boldsymbol{W}_{\text{down}}^{\text{for,intra}}$ and $\boldsymbol{W}_{\text{down}}^{\text{for,inter}}$ accordingly. Column (X) refers to a model where we use $\boldsymbol{W}_1 = \boldsymbol{W}_{\text{up}}^{\text{dom}}$, $\boldsymbol{W}_2 = \boldsymbol{W}_{\text{up}}^{\text{for, intra}}$, $\boldsymbol{W}_3 = \boldsymbol{W}_{\text{up}}^{\text{for, inter}}$ and where we control for the downstream network by setting $\boldsymbol{W}_4 = \boldsymbol{W}_{\text{down}}$.[11] Column (XI) reports the estimates for a model in which the downstream network is split up – the order of the matrices is the same as in the upstream case – and controlling for the upstream matrix $\boldsymbol{W}_4$. We do not distinguish between foreign intra- and inter-industry transmission for upstream and downstream networks simultaneously because this would require the estimation of a sixth-order process, and the numbers of instruments increases quickly with higher orders.

The insignificant estimates of $\rho_3$ in columns (X) and (XI) reveal that foreign first-round spillovers across industries are neither significant in the upstream, nor in the downstream case. Foreign downstream within-industry transmission, in contrast, matters as indicated by the significant parameter estimate. Rescaling the coefficients gives $\rho_1^* = 0.098$ ($\rho_1^* = 0.214$) and $\rho_2^* = 0.017$ ($\rho_2^* = 0.035$) for the upstream (downstream) transmission channel, suggesting that domestic first-round spillovers across industries are larger than foreign first-round spillovers within industries.

[11] Note that $\boldsymbol{W}_{\text{up}}^{\text{dom}}$ is in fact $\boldsymbol{W}_{\text{up}}^{\text{dom, inter}}$.

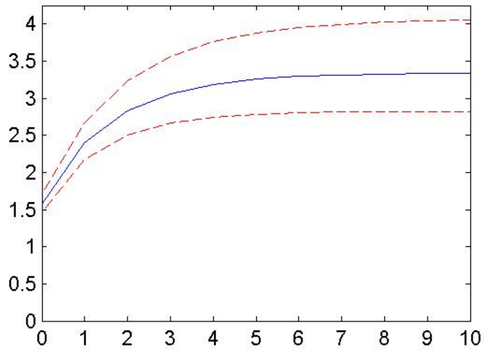
Table 4: Dynamic higher-order Spatial Durbin Model estimates, TSLS estimates

| Model | (VIII) | (IX) | (X) | (XI) | (XII) |
|---|---|---|---|---|---|
| $\phi \boldsymbol{exp}_{t-1}$ | $0.329^{***}$ | $0.327^{***}$ | $0.330^{***}$ | $0.330^{***}$ | $0.325^{***}$ |
| | (28.996) | (29.798) | (30.032) | (29.950) | (29.512) |
| $\rho_1 \boldsymbol{W}_1 \boldsymbol{exp}_t$ | $0.414^{***}$ | $0.408^{***}$ | $0.435^{***}$ | $0.666^{***}$ | $0.393^{***}$ |
| | (5.700) | (5.952) | (6.384) | (12.567) | (5.690) |
| $\rho_2 \boldsymbol{W}_2 \boldsymbol{exp}_t$ | $0.628^{***}$ | $0.655^{***}$ | $0.211^{**}$ | $0.317^{***}$ | $0.237^{**}$ |
| | (10.903) | (4.515) | (2.320) | (3.820) | (2.261) |
| $\rho_3 \boldsymbol{W}_3 \boldsymbol{exp}_t$ | | $0.669^{***}$ | 0.080 | $-0.095$ | $0.653^{***}$ |
| | | (12.507) | (0.522) | $(-0.828)$ | (12.129) |
| $\rho_4 \boldsymbol{W}_4 \boldsymbol{exp}_t$ | | 0.124 | $0.675^{***}$ | $0.386^{***}$ | $0.342^{***}$ |
| | | (1.291) | (12.106) | (5.587) | (3.479) |
| $\beta_1$ Past experience | $0.244^{***}$ | $0.243^{***}$ | $0.243^{***}$ | $0.243^{***}$ | $0.244^{***}$ |
| | (38.961) | (39.428) | (39.239) | (39.276) | (39.488) |
| $\beta_2$ Price expectations$_{\text{t-1}}$ | 0.004 | 0.004 | 0.004 | 0.003 | 0.004 |
| | (0.597) | (0.649) | (0.566) | (0.465) | (0.599) |
| $\beta_3$ Direct labor costs (growth) | 0.011 | 0.012 | 0.010 | 0.012 | 0.011 |
| | (0.354) | (0.381) | (0.339) | (0.382) | (0.379) |
| $\beta_4$ Indirect labor costs (level) | $-0.052^{***}$ | $-0.056^{***}$ | $-0.052^{***}$ | $-0.054^{***}$ | $-0.052^{***}$ |
| | $(-2.901)$ | $(-3.152)$ | $(-2.902)$ | $(-3.016)$ | $(-2.939)$ |
| $\beta_5$ Indirect labor costs (growth) | $-0.088^{***}$ | $-0.091^{***}$ | $-0.088^{***}$ | $-0.091^{***}$ | $-0.089^{***}$ |
| | $(-2.886)$ | $(-2.970)$ | $(-2.866)$ | $(-2.964)$ | $(-2.917)$ |
| $\theta_1 \boldsymbol{W}_{\text{up}}$ Past experience | $-0.161^{***}$ | $-0.198^{***}$ | $-0.187^{***}$ | $-0.168^{***}$ | $-0.171^{***}$ |
| | $(-3.171)$ | $(-4.118)$ | $(-3.859)$ | $(-3.470)$ | $(-3.577)$ |
| $\theta_2 \boldsymbol{W}_{\text{down}}$ Price expectations$_{\text{t-1}}$ | $-0.024$ | $-0.027$ | $-0.032$ | $-0.019$ | $-0.022$ |
| | $(-0.762)$ | $(-0.838)$ | $(-0.992)$ | $(-0.595)$ | $(-0.698)$ |
| $\theta_3 \boldsymbol{W}_{\text{down}}$ Direct labor costs (growth) | $-0.109$ | $-0.145$ | $-0.114$ | $-0.158$ | $-0.144$ |
| | $(-0.971)$ | $(-1.288)$ | $(-1.016)$ | $(-1.398)$ | $(-1.283)$ |
| $\theta_4 \boldsymbol{W}_{\text{down}}$ Indirect labor costs (level) | $0.105^{**}$ | $0.120^{***}$ | $0.105^{**}$ | $0.119^{***}$ | $0.114^{**}$ |
| | (2.305) | (2.613) | (2.305) | (2.590) | (2.486) |
| $\theta_5 \boldsymbol{W}_{\text{down}}$ Indirect labor costs (growth) | 0.178 | 0.180 | 0.180 | 0.167 | 0.168 |
| | (1.314) | (1.333) | (1.331) | (1.236) | (1.240) |
| Input-output multiplier$_{\text{SR}}$ | 1.713 | 1.764 | 1.752 | 1.573 | 1.575 |
| Input-output multiplier$_{\text{LR}}$ | 4.003 | 4.312 | 4.259 | 3.351 | 3.310 |
| $\phi + \rho_1\omega_{1\max} + \rho_2\omega_{2\max} + \rho_3\omega_{3\max} + \rho_4\omega_{4\max}$ | 0.708 | 0.891 | 0.796 | 0.827 | 0.903 |
| $CD$ | 2.407 | 1.613 | 2.518 | 0.539 | 0.266 |
| Common factors | YES | YES | YES | YES | YES |
| Nobs | 28644 | 28644 | 28644 | 28644 | 28644 |

*Notes* Common factors are $\overline{exp}_t$, $\overline{exp}_{t-1}$, $\overline{past}_t$, $tfp_{it}$, $stockx_{it}$; ***significant at 0.01 level, **significant at 0.05 level, *significant at 0.1. level; assymptotic z-statstics in parenthesis; T=42.

In the final model (column (XII)) we include only the weights matrices that showed significant coefficients for the autoregressive term in the previous regressions. We set $\boldsymbol{W}_1 = \boldsymbol{W}^{\text{dom}}_{\text{up}}$, $\boldsymbol{W}_2 = \boldsymbol{W}^{\text{for, intra}}_{\text{up}}$,$\boldsymbol{W}_3 = \boldsymbol{W}^{\text{dom}}_{\text{down}}$ and $\boldsymbol{W}_4 = \boldsymbol{W}^{\text{for, intra}}_{\text{down}}$, and obtain the following rescaled estimates: $\rho^*_1 = 0.090$, $\rho^*_2 = 0.019$, $\rho^*_3 = 0.210$, $\rho^*_4 = 0.038$. Unsurprisingly, these results are almost identical to their counterparts from the previous two regressions. Testing whether the difference between domestic inter-industry and foreign intra-industry effects is significantly different from zero, confirms the greater importance of within-country dependence against the across-countries dependence.

Figure 1: Cumulative input-output multiplier over time



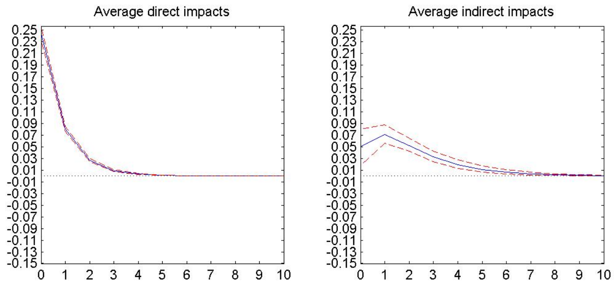

The estimates of the short-run and long-run input-output multipliers for this final model are 1.58 and 3.31. Compared to the results from the first-order models, this demonstrates that mistakenly accounting for only one of the transmission channels (up- or downstream) would make us underestimate the overall spillover effects stemming from shifts in expectations. Yet without closer investigating the diffusion process and making it more flexible, we would in turn have overestimated the generated spillovers. Figure 1 illustrates the evolution of the multiplier over time. Based on 1,000 sampled parameter estimates drawn from a multivariate normal distribution, we calculate the average multipliers as well as the corresponding 0.025 lower and 0.975 upper bound estimates (giving us the confidence interval) from the distribution of all possible multipliers. The mean multiplier is illustrated by the (blue) solid line and the confidence interval is displayed by the (red) dashed lines.

As discussed in Section 3.2, when interpreting the overall impacts of the explanatory variables on expectations, the interdependence of expectation formation needs to be taken into account.[12] Hence, we calculate the average direct impacts and average indirect impacts and again use 1,000 sampled parameter estimates to compute averages and lower and upper bounds of the distributions.[13] Figure 2 graphically demonstrates these impacts and the corresponding tables are provided in the annex (see Table A3), where the column to the right of the 0.975 upper bound estimated effects documents the accumulated impacts over time. 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.

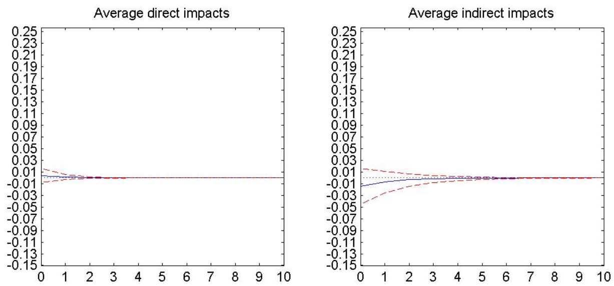
[12]We discuss the respective impact estimates only at this point because the parameter estimates of $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ from all the previously presented specifications were rather similar.

[13]Matrix $\boldsymbol{B}$ in equation (8) for spatial models of order $S$ is given by $\boldsymbol{B} = (\boldsymbol{I}_N - \sum_{s=1}^{S} \rho_s \boldsymbol{W}_s)$.

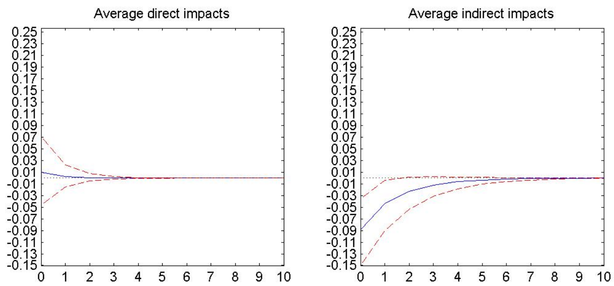
Figure 2: Impacts estimates of explanatory variables over time, model (XII)



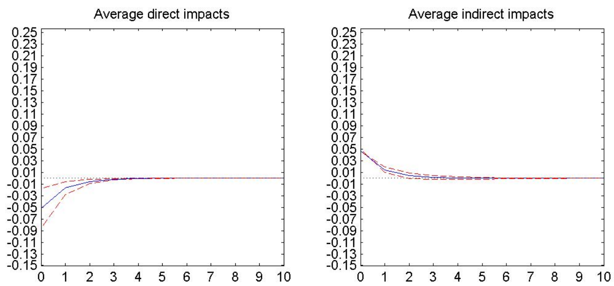

(a) Past experience



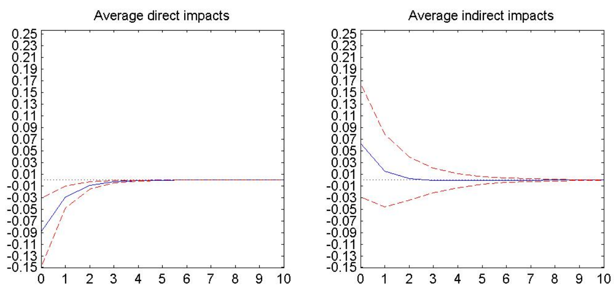

(b) Price expectations$_{t-1}$




(c) Direct labor costs (growth)




(d) Indirect labor costs (level)




(e) Indirect labor costs (growth)

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

The left top panel in Figure 2 demonstrates the strong relation between firms' assessment of previous changes in their business situation with their optimism about its future development: a one standard deviation increase in the net-balance of how firms evaluate recent changes in their business situation in period $t$ increases the net-balance of these firms' expectations by 6.41 points (0.27 standard deviations) in the same quarter. This positive direct impact gradually decreases over time and is zero after approximately a year. After this period, the cumulated impact of such a one standard deviation increase amounts to 9.01 index points. Concerning the spillovers to other industries and countries, the top right panel also shows a positive and statistically significant indirect impact of changes in previous production assessments on expectations. This is remarkable, given the negative estimate of $\theta_1$ in column (XII), but can be explained by the fact that a positive change of past experience in an industry in a particular country is associated with a sharp increase of expectations in the same industry. Even though the immediate effect of the past experience variable on other industries and countries is negative, due to the positive correlation of expectations over the network, this sharp rise of expectations in the own industry increases confidence in the other industries as well. The positive indirect impact even becomes stronger one period after the shock, because the positive mechanism over the network is still active and is also serially correlated, and thereby outweighs the negative immediate effect by an even larger margin. However, and in particular as the indirect impacts represent spillovers to all other European industries *in total*, the size of this positive indirect impact needs to be interpreted as being fairly moderate.

Concerning the other covariates included in the model, average direct impacts of the lagged price expectation variable and the growth rate of direct labor costs are statistically insignificant. Social security contributions and payroll taxes, in contrast, show negative direct impacts on expectations which are statistically significant but negligible in size. A one standard deviation increase in the growth rate of indirect labor costs reduces confidence only by 0.31 index points in the same period. Likewise, the indirect impacts arising from changes in these covariates are economically not relevant.

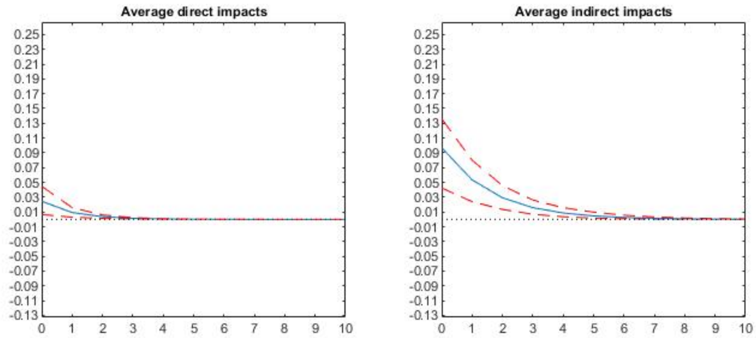
## 4.2 Robustness analysis

### 4.2.1 Controlling for actual production growth

The results from the previous analysis suggested a strong effect of how firms assess their recent business activity on how they form expectations about the near future. As a robustness check we include *actual* production or turnover growth as additional covariate in our model. This variable is not only likely to be correlated with expectation formation but also autocorrelated over the input-output network. Thus, by controlling for production changes we make sure that the identified spillovers associated with expectation formation are not simply production spillovers.

The robustness checks for Tables 3 and 4 when adding the variable on actual production growth are presented in Table A4 in the appendix and in Table 5. Concerning the transmission of expectations, the

Figure 3: Impacts estimates of production growth over time, model (XII)




autocorrelation parameters are still positive and highly significant, but reduced in particular for the downstream network, implying slightly smaller IO-multipliers (1.45 in the short-run and 2.98 in the long-run). We further find positive and statistically significant direct as well as indirect impacts of actual production growth on expectation formation, where the latter are also substantial in magnitude (see Figure 3).[14]

#### 4.2.2 A Placebo test

Our results indicate significant spillover effects in the formation of firms' expectations. 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 check 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, we consider the elements of the empirical weights matrix, but shuffle them for each row over the columns. In this way, the empirical distribution of the entries in the matrix (and for each row) stays the same, but we randomize which European industries are economically close to each other. We do this for the upstream as well as for the downstream network, set the main diagonal to zero and maximum normalize the resulting matrices. The results for first-order models with these randomized weights matrices are depicted in the first two columns of Table 6, which correspond to Specifications (V) and (VII) presented in the previous sections. When differing between domestic between-industry and foreign within-industry linkages (Specification (XII)), we employ two different ways to randomize the input-output structure. In the first approach, we use the full randomized upstream (or downstream) weights matrix, and split it according to the true country and industry structure. In other words, the randomized domestic network matrix does not set random whether two industries belong to the same country, but only to what

[14]We do not illustrate the impact estimates of the other explanatory variables on expectation formation, since the results are relatively similar to the results presented in Figure 2 for the full sample.

Table 5: Dynamic higher-order Spatial Durbin Model estimates, TSLS estimates, small sample

| Model | (VIII) | (IX) | (X) | (XI) | (XII) |
|---|---|---|---|---|---|
| $\phi \boldsymbol{exp}_{t-1}$ | $0.350^{***}$ | $0.346^{***}$ | $0.351^{***}$ | $0.348^{***}$ | $0.345^{***}$ |
| | (27.455) | (28.018) | (28.465) | (28.329) | (27.981) |
| $\rho_1 \boldsymbol{W}_1 \boldsymbol{exp}_t$ | $0.395^{***}$ | $0.408^{***}$ | $0.431^{***}$ | $0.514^{***}$ | $0.415^{***}$ |
| | (5.468) | (5.985) | (6.340) | (9.900) | (6.027) |
| $\rho_2 \boldsymbol{W}_2 \boldsymbol{exp}_t$ | $0.453^{***}$ | $0.590^{***}$ | $0.226^{**}$ | $0.234^{***}$ | $0.269^{***}$ |
| | (7.897) | (4.017) | (2.502) | (2.946) | (2.680) |
| $\rho_3 \boldsymbol{W}_3 \boldsymbol{exp}_t$ | | $0.517^{***}$ | 0.002 | $-0.175^{*}$ | $0.514^{***}$ |
| | | (9.864) | (0.015) | (−1.692) | (9.768) |
| $\rho_4 \boldsymbol{W}_4 \boldsymbol{exp}_t$ | | 0.032 | $0.509^{***}$ | $0.421^{***}$ | $0.208^{**}$ |
| | | (0.324) | (9.185) | (6.135) | (2.288) |
| $\beta_1$ Past experience | $0.255^{***}$ | $0.254^{***}$ | $0.253^{***}$ | $0.253^{***}$ | $0.254^{***}$ |
| | (35.199) | (35.638) | (35.440) | (35.553) | (35.589) |
| $\beta_2$ Production (growth) | $0.023^{**}$ | $0.024^{**}$ | $0.023^{**}$ | $0.023^{**}$ | $0.023^{**}$ |
| | (2.145) | (2.185) | (2.134) | (2.130) | (2.144) |
| $\beta_3$ Price expectations$_{\text{t-1}}$ | 0.000 | 0.000 | 0.000 | −0.001 | 0.000 |
| | (−0.011) | (0.018) | (−0.058) | (−0.132) | (−0.018) |
| $\beta_4$ Direct labor costs (growth) | −0.020 | −0.020 | −0.021 | −0.021 | −0.020 |
| | (−0.577) | (−0.589) | (−0.604) | (−0.605) | (−0.577) |
| $\beta_5$ Indirect labor costs (level) | $-0.039^{**}$ | $-0.040^{**}$ | $-0.039^{**}$ | $-0.037^{**}$ | $-0.038^{**}$ |
| | (−2.136) | (−2.221) | (−2.166) | (−2.019) | (−2.113) |
| $\beta_6$ Indirect labor costs (growth) | $-0.065^{*}$ | $-0.066^{*}$ | $-0.065^{*}$ | $-0.065^{*}$ | $-0.065^{*}$ |
| | (−1.862) | (−1.880) | (−1.843) | (−1.850) | (−1.847) |
| $\theta_1 \boldsymbol{W}_{\text{up}}$ Past experience | $-0.137^{**}$ | $-0.189^{***}$ | $-0.175^{***}$ | $-0.181^{***}$ | $-0.183^{***}$ |
| | (−2.469) | (−3.550) | (−3.278) | (−3.411) | (−3.462) |
| $\theta_2 \boldsymbol{W}_{\text{up}}$ Production (growth) | $0.211^{***}$ | $0.206^{***}$ | $0.210^{***}$ | $0.209^{***}$ | $0.208^{***}$ |
| | (3.052) | (2.972) | (3.027) | (3.022) | (3.015) |
| $\theta_3 \boldsymbol{W}_{\text{down}}$ Price expectations$_{\text{t-1}}$ | 0.011 | 0.006 | 0.002 | 0.004 | −0.001 |
| | (0.345) | (0.170) | (0.066) | (0.124) | (−0.021) |
| $\theta_4 \boldsymbol{W}_{\text{down}}$ Direct labor costs (growth) | 0.029 | −0.023 | 0.022 | −0.030 | −0.013 |
| | (0.240) | (−0.187) | (0.185) | (−0.249) | (−0.105) |
| $\theta_5 \boldsymbol{W}_{\text{down}}$ Indirect labor costs (level) | 0.071 | 0.074 | 0.070 | 0.065 | 0.068 |
| | (1.592) | (1.643) | (1.552) | (1.453) | (1.515) |
| $\theta_6 \boldsymbol{W}_{\text{down}}$ Indirect labor costs (growth) | 0.076 | 0.062 | 0.076 | 0.038 | 0.052 |
| | (0.502) | (0.404) | (0.498) | (0.249) | (0.342) |
| Input-output multiplier$_{\text{SR}}$ | 1.487 | 1.525 | 1.523 | 1.409 | 1.452 |
| Input-output multiplier$_{\text{LR}}$ | 3.168 | 3.320 | 3.351 | 2.823 | 2.983 |
| $\phi + \rho_1\omega_{1\max} + \rho_2\omega_{2\max} + \rho_3\omega_{3\max} + \rho_4\omega_{4\max}$ | 0.656 | 0.796 | 0.741 | 0.758 | 0.840 |
| $CD$ | 2.661 | 1.560 | 2.817 | 1.125 | 1.123 |
| Common factors | YES | YES | YES | YES | YES |
| Nobs | 21042 | 21042 | 21042 | 21042 | 21042 |

*Notes* Common factors are $\overline{exp}_t$, $\overline{exp}_{t-1}$, $\overline{past}_t$, $tfp_{it}$, $stockx_{it}$; ***significant at 0.01 level, **significant at 0.05 level, *significant at 0.1. level; assymptotic z-statstics in parenthesis; T=42.

extend they interact with each other. In the second approach (b), we shuffle the elements of the true domestic weights matrix for each row over *all* columns, and therefore randomize which European industry lies is which country. We do this for the foreign intra-industry weights matrix accordingly and make sure that it remains mutually exclusive to the domestic weights matrix by using the same random column indices when shuffling. We set the main diagonals to zero and separately maximum-normalize each matrix.

The estimation results reported in Table 6 suggest that the repercussion effects identified in the previous sections do not mechanically 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 expectations across European industries. For the first-order models (V) and (VII), the estimates of the cross-sectional autocorrelation coefficient $\rho$ take values which are statistically not different from zero. Hence, a shock of one unit to the error term immediately increases expectations by approximately only one unit on average, since no feedback effects are created. Concerning the higher-order model, the results for model (XII) show that when using the true country and industry structure, but randomizing the extend of intermediate trade, domestic upstream as well as downstream linkages still show positive and statistically significant autocorrelation coefficients ($\rho_1$ and $\rho_3$ in model (XII)(a)). However, they are substantially smaller in magnitude than when estimated with the true matrix, demonstrated by the rescaled coefficients being $\rho_1^* = 0.003$ and $\rho_3^* = 0.009$. Nevertheless, the result suggests some additional importance of nationality for the transmission of expectations. In contrast, when further randomizing the country and industry structure, the autocorrelation parameter for the (randomized) domestic linkages is also negligible not only in size but also in statistical significance. This is the case for the upstream and the downstream network as shown by the estimates of $\rho_1$ and $\rho_3$ in column (XII)(b). In brief, the results indicate that it is the specific structure of the input-output network which matters for the transmission of business expectations within the European economy.

## 5 Discussion and conclusions

In this paper we investigate whether expectations of firms are transmitted via the European value chain. We base our analysis on harmonized business survey data provided by the European commission and gathered by economic research institutes located in the member states. On the one hand, when aggregated and summarized to indices, these data are typically used as early indicators on the short-term economic development of countries due to their frequent availability. On the other hand, the new expectations literature exploits their variation on the micro level to study (i) the formation of expectations and (ii) the impact of firms' beliefs on economic outcomes. This paper uses firms' expectations on the industry level for the EU member states and contributes to the literature by shedding light on the cross-sectional and time dependence of these business survey data.

The cross-sectional correlations could either be explained by the force of common global factors simultaneously influencing expectations or seizable spillover effects associated to their formation. Thus, we explicitly analyze how expectations are propagated within the EU, within and across industries and national borders

Table 6: Estimation results for randomized weights matrices

| Model | (V) | (VII) | (XII)(a) | (XII)(b) |
|---|---|---|---|---|
| $\phi \boldsymbol{exp}_{t-1}$ | $0.326^{***}$ | $0.326^{***}$ | $0.348^{***}$ | $0.356^{***}$ |
| | (52.119) | (52.113) | (31.464) | (32.241) |
| $\rho_1 \boldsymbol{W}_1 \boldsymbol{exp}_t$ | −0.049 | 0.008 | $0.205^{**}$ | −0.102 |
| | (−1.332) | (0.232) | (2.304) | (−1.412) |
| $\rho_2 \boldsymbol{W}_2 \boldsymbol{exp}_t$ | | | −0.133 | $-0.147^{*}$ |
| | | | (−0.799) | (−1.844) |
| $\rho_3 \boldsymbol{W}_3 \boldsymbol{exp}_t$ | | | $0.241^{**}$ | −0.009 |
| | | | (2.232) | (−0.135) |
| $\rho_4 \boldsymbol{W}_4 \boldsymbol{exp}_t$ | | | 0.005 | $0.154^{*}$ |
| | | | (0.092) | (1.748) |
| $\beta_1$ Past experience | $0.268^{***}$ | $0.268^{***}$ | $0.258^{***}$ | $0.256^{***}$ |
| | (55.249) | (55.246) | (40.879) | (40.573) |
| $\beta_2$ Price expectations$_{\text{t-1}}$ | $0.012^{***}$ | $0.012^{***}$ | 0.007 | 0.006 |
| | (2.852) | (2.863) | (1.142) | (1.015) |
| $\beta_3$ Direct labor costs (growth) | 0.026 | 0.025 | 0.020 | 0.021 |
| | (1.382) | (1.353) | (0.872) | (0.923) |
| $\beta_4$ Indirect labor costs (level) | $-0.044^{***}$ | $-0.044^{***}$ | $-0.043^{***}$ | $-0.042^{***}$ |
| | (−3.647) | (−3.673) | (−3.469) | (−3.342) |
| $\beta_5$ Indirect labor costs (growth) | $-0.085^{***}$ | $-0.085^{***}$ | $-0.085^{***}$ | $-0.085^{***}$ |
| | (−3.388) | (−3.385) | (−3.331) | (−3.351) |
| $\theta_1 \boldsymbol{W}_{\text{up}}$ Past experience | 0.015 | −0.013 | −0.046 | 0.046 |
| | (0.429) | (−0.427) | (−1.328) | (0.952) |
| $\theta_2 \boldsymbol{W}_{\text{down}}$ Price expectations$_{\text{t-1}}$ | 0.036 | 0.035 | 0.040 | 0.039 |
| | (0.898) | (0.878) | (1.092) | (1.044) |
| $\theta_3 \boldsymbol{W}_{\text{down}}$ Direct labor costs (growth) | 0.073 | 0.071 | 0.065 | 0.072 |
| | (0.616) | (0.599) | (0.572) | (0.633) |
| $\theta_4 \boldsymbol{W}_{\text{down}}$ Indirect labor costs (level) | $0.117^{***}$ | $0.117^{***}$ | $0.117^{***}$ | $0.110^{***}$ |
| | (3.603) | (3.622) | (3.412) | (3.200) |
| $\theta_5 \boldsymbol{W}_{\text{down}}$ Indirect labor costs (growth) | 0.234 | 0.235 | 0.247 | 0.243 |
| | (1.317) | (1.324) | (1.404) | (1.382) |
| Input-output multiplier$_{\text{SR}}$ | 0.984 | 1.004 | 1.127 | 0.979 |
| Input-output multiplier$_{\text{LR}}$ | 1.449 | 1.491 | 1.857 | 1.503 |
| $\phi + \rho_1\omega_{1\max} + \rho_2\omega_{2\max} + \rho_3\omega_{3\max} + \rho_4\omega_{4\max}$ | 0.310 | 0.329 | 0.463 | 0.336 |
| $CD$ | −0.425 | −0.394 | 0.266 | 0.266 |
| Common factors | YES | YES | YES | YES |
| Nobs | 28644 | 28644 | 28644 | 28644 |

*Notes* Common factors are $\overline{exp}_t$, $\overline{exp}_{t-1}$, $\overline{past}_t$, $tfp_{it}$, $stockx_{it}$; ***significant at 0.01 level, **significant at 0.05 level, *significant at 0.1. level; assymptotic z-statstics in parenthesis; T=42.

while allowing unit-specific reactions to common factors. Regarding the methodology, we rely on a space-time econometric model, imposing trade of intermediates as transmission channel for expectation formation.

Our empirical investigation provides evidence for substantial spillover effects of firms' expectations stemming from EU-wide value chains. As a consequence, after expectations about future production or turnover are enhanced by one index point in an industry, expectations in all industries are estimated to contemporaneously increase by 1.58 in total. Due to persistence in the expectation data, the change in expectations also creates direct effects and spillovers in the subsequent quarters, such that the multiplier amounts to 3.19 after one year. This indicates that part of the interdependence between countries and industries can neither be traced back to aggregate changes, nor to country-level technology shifts and news about them, nor to spillovers stemming from the covariates including output, charged prices and labor costs. Instead, it implies that what is (also) transmitted are shocks to the unexplained component of expectations, which could originate from the inherently unobservable information gathering process within industries (in countries) but also from some form of attitude, generating waves of optimism and pessimism across European industries. The result is robust to (i) adding an alternative output variable to the model and to (ii) a placebo test to examine whether some mechanical process in our econometric model drives the spillover effects.

Theory and former empirical evidence suggest that demand shocks are mainly propagated downstream while supply shocks are mainly propagated upstream the production network (see e.g., Acemoglu et al., 2016). According to our empirical findings, the result for changes in expectations is not so clear: They are transmitted both upstream and downstream the value chain, but the downstream channel is more important. This result very much resembles the findings by Carvalho et al. (2016), who compare sales responses of upstream and downstream firms after a natural disaster shock. Moreover, we find that the multiplier effects are mainly transmitted through domestic linkages and partly through foreign within-industry linkages, but that foreign linkages across industries are negligible.

Regarding the effects of the covariates, firms' own assessment about previous changes in their production (turnover) shows strong positive direct effects on how they expect their future production (turnover) to change. This result for the industry-level in European countries is very much in line with firm-level findings of Massenot and Pettinicchi (2018). Also the variable for actual production growth has a positive and statically significant effect on expectations, however, this effect is rather small in magnitude. Economic insignificance also applies to the effects of the other covariates and the spillovers originating from them. This demonstrates the difficulty of modeling business expectations by "hard" factors, but also highlights the importance of spillover effects in the formation of firm expectations via an industry's trade network.

## References


Acemoglu, D., Akcigit, U., and Kerr, W. (2016). Networks and the macroeconomy: An empirical exploration. *NBER Macroeconomics Annual*, *30*(1), 273 – 335.

Acemoglu, D., Carvalho, V., Ozdaglar, A., and Tahbaz-Salehi, A. (2012). The network origins of aggregate fluctuations. *Econometrica*, *80*(5), 1977–2016.

Acemoglu, D., Ozdaglar, A., and Tahbaz-Salehi, A. (2017). Microeconomic origins of macroeconomic tail risks. *American Economic Review*, *107*(1), 54–108.

Angeletos, G.-M. and La'O, J. (2013). Sentiments. *Econometrica*, *81*(2), 739–779.

Bachmann, R. (2019). Comments on "Monetary policy announcements and expectations: Evidence from german firms". *Journal of Monetary Economics*, *108*, 64–68. "Central Bank Communications: From Mystery to Transparency" May 23-24, 2019 Annual Research Conference ofthe National Bank of Ukraine organized in cooperation with Narodowy Bank Polski.

Badinger, H. and Egger, P. (2011). Estimation of higher-order spatial autoregressive cross-section models with heteroscedastic disturbances. *Papers in Regional Science*, *90*(1), 213–235.

Badinger, H. and Egger, P. (2016). Productivity spillovers across countries and industries: New evidence from OECD countries. *Oxford Bulletin of Economics and Statistics*, *78*(4), 501–521.

Baqaee, D. and Farhi, E. (2019). The macroeconomic impact of microeconomic shocks: Beyond hulten's theorem. *Econometrica*, *87*(4), 1155–1203.

Beaudry, P. and Portier, F. (2006). Stock prices, news, and economic fluctuations. *The American Economic Review*, *96*(4), 1293–1307.

Böck, M. and Zörner, T. O. (2019). The impact of credit market sentiment shocks - a TVAR approach. Department of economics working papers, Vienna University of Economics and Business, Department of Economics.

Boneva, L., Cloyne, J., Weale, M., and Wieladek, T. (2019). Firms' price, cost and activity expectations: Evidence from micro data. Discussion Papers 1905, Centre for Macroeconomics (CFM).

Buchheim, L. and Link, S. (2017). The effect of disaggregate information on the expectation formation of firms. CESifo Working Paper Series 6768, CESifo Group Munich.

Carvalho, V. (2010). Aggregate fluctuations and the network structure of intersectoral trade. Economics working papers, Department of Economics and Business, Universitat Pompeu Fabra.

Carvalho, V., Nirei, M., Saito, Y., and Tahbaz-Salehi, A. (2016). Supply chain disruptions: Evidence from the great east japan earthquake. Cambridge working papers in economics, Faculty of Economics, University of Cambridge.

Cohen, J. and Morrison Paul, C. (2005). Agglomeration economies and industry location decisions: the impacts of spatial and industrial spillovers. *Regional Science and Urban Economics*, *35*(3), 215–237.

Coibion, O., Gorodnichenko, Y., and Kumar, S. (2018). How do firms form their expectations? New survey evidence. *American Economic Review*, *108*(9), 2671–2713.

De Grauwe, P. and Ji, Y. (2017). The international synchronisation of business cycles: the role of animal spirits. *Open Economies Review*, *28*(3), 383–412.

Debarsy, N., Ertur, C., and LeSage, J. P. (2012). Interpreting dynamic space-time panel data models. *Statistical Methodology*, *9*(1), 158–171.

di Giovanni, J., Levchenko, A., and Mejean, I. (2014). Firms, destinations, and aggregate fluctuations. *Econometrica*, *82*(4), 1303–1340.

di Giovanni, J., Levchenko, A. A., and Mejean, I. (2018). The micro origins of international business-cycle comovement. *American Economic Review*, *108*(1), 82–108.

Elhorst, J. P. (2014). *Spatial econometrics: From cross-sectional data to spatial panels*. Springer.

Elhorst, J. P., Zandberg, E., and de Haan, J. (2013). The impact of interaction effects among neighbouring countries on financial liberalization and reform: A dynamic spatial panel data approach. *Spatial Economic Analysis*, *8*(3), 293–313.

Enders, Z., Hünnekes, F., and Müller, G. (2019). Firm expectations and economic activity. CESifo Working Paper Series 7623, CESifo Group Munich.

Enders, Z., Hünnekes, F., and Müller, G. J. (2019). Monetary policy announcements and expectations: Evidence from german firms. *Journal of Monetary Economics*, *108*, 45–63. "Central Bank Communications: From Mystery to Transparency" May 23-24, 2019 Annual Research Conference ofthe National Bank of Ukraine organized in cooperation with Narodowy Bank Polski.

European Commission (2016). The joint harmonised EU programme of business and consumer surveys. User guide, Directorate-General for Economic and Financial Affairs.

Eurostat (2017). Structural Business Statstics. `http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=sbs_na_sca_r2&lang=en`. Accessed: 2016-16-12.

Eurostat (2019). Labour Cost Index. `http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=lc_lci_r2_q&lang=en`. Accessed: 2019-20-03.

Gabaix, X. (2011). The granular origins of aggregate fluctuations. *Econometrica*, *79*(3), 733–772.

Gennaioli, N., Ma, Y., and Shleifer, A. (2016). Expectations and investment. BIS Working Papers 562, Bank for International Settlements.

Halleck Vega, S. and Elhorst, J. (2016). A regional unemployment model simultaneously accounting for serial dynamics, spatial dependence and common factors. *Regional Science and Urban Economics*, *60*(C), 85–95.

Huo, Z., Levchenko, A. A., and Pandalai-Nayar, N. (2020). International comovement in the global production network. Unpublished manuscript.

Kelejian, H. H. and Prucha, I. (2010). Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances. *Journal of Econometrics*, *157*(1), 53–67.

Lee, L.-F. and Yu, J. (2010). A spatial dynamic panel data model with both time and individual fixed effects. *Econometric Theory*, *26*(02), 564–597.

Lee, L.-F. and Yu, J. (2014). Efficient gmm estimation of spatial dynamic panel data models with fixed effects. *Journal of Econometrics*, *180*(2), 174–197.

LeSage, J. P. and Pace, R. K. (2009). *Introduction to Spatial Econometrics*. Statistics: A Series of Textbooks and Monographs. CRC Press.

Levchenko, A. A. and Pandalai-Nayar, N. (2020). Tfp, News, and "Sentiments": the International Transmission of Business Cycles. *Journal of the European Economic Association*, *18*(1).

Long, J. B. and Plosser, C. (1983). Real business cycles. *Journal of Political Economy*, *91*(1), 39–69.

Lucas, R. (1977). Understanding business cycles. *Carnegie-Rochester Conference Series on Public Policy*, *5*(1), 7–29.

Massenot, B. and Pettinicchi, Y. (2018). Can firms see into the future? Survey evidence from germany. *Journal of Economic Behavior & Organization*, *145*, 66–79.

Nowzohour, L. and Stracca, L. (2017). More than a feeling: confidence, uncertainty and macroeconomic fluctuations. Working Paper Series 2100, European Central Bank.

Ozdagli, A. and Weber, M. (2017). Monetary policy through production networks: Evidence from the stock market. Unpublished manuscript, University of Chicago.

Pesaran, M. (2004). General diagnostic tests for cross section dependence in panels. Cambridge working papers in economics, Faculty of Economics, University of Cambridge.

Pesaran, M. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica*, *74*(4), 967–1012.

Pesaran, M. (2015). Testing weak cross-sectional dependence in large panels. *Econometric Reviews*, *34*(6-10), 1089–1117.

Timmer, M., Dietzenbacher, E., Los, B., Stehrer, R., and de Vries, G. (2015). An illustrated user guide to the World Input-Output Database: The case of global automotive production. *Review of International Economics*, *23*(3), 575–605.

Wanzenböck, I. and Piribauer, P. (2016). R&D networks and regional knowledge production in Europe: Evidence from a space-time model. *Papers in Regional Science*, *97*, S1–S24.

# Appendix: Additional tables and figures

Table A1: Number of industries per country

| Country | Number of industries in sample |
|---|---|
| Austria | 28 |
| Belgium | 32 |
| Bulgaria | 36 |
| Czech Republic | 33 |
| Germany | 25 |
| Denmark | 19 |
| Spain | 20 |
| Finland | 19 |
| France | 31 |
| Great Britain | 33 |
| Greece | 35 |
| Hungary | 25 |
| Italy | 33 |
| Lithuania | 33 |
| Luxembourg | 13 |
| Lativa | 32 |
| Malta | 14 |
| Netherlands | 22 |
| Poland | 41 |
| Portugal | 32 |
| Romania | 33 |
| Slovakia | 35 |
| Slovenia | 30 |
| Sweden | 28 |
| Total | 682 |

Table A2: Dynamic Spatial Durbin Model estimates, TSLS estimates

| Model | (IV) | (V) | (VI) | (VII) |
|---|---|---|---|---|
| $\phi \boldsymbol{exp}_{t-1}$ | $0.348^{***}$ | $0.346^{***}$ | $0.334^{***}$ | $0.332^{***}$ |
| | (30.383) | (30.357) | (28.805) | (28.878) |
| $\rho \boldsymbol{W} \boldsymbol{exp}_t$ | $0.696^{***}$ | $0.613^{***}$ | $0.776^{***}$ | $0.692^{***}$ |
| | (8.062) | (8.033) | (9.685) | (12.220) |
| $\eta \boldsymbol{W} \boldsymbol{exp}_{t-1}$ | $-0.161^{**}$ | | $-0.112$ | |
| | $(-2.063)$ | | $(-1.480)$ | |
| $\beta_1$ Past experience | $0.248^{***}$ | $0.248^{***}$ | $0.243^{***}$ | $0.243^{***}$ |
| | (39.169) | (39.330) | (38.514) | (38.605) |
| $\beta_2$ Price expectations$_{\text{t-1}}$ | 0.000 | 0.000 | 0.003 | 0.004 |
| | (0.012) | (0.039) | (0.547) | (0.598) |
| $\beta_3$ Direct labor costs (growth) | 0.004 | 0.001 | 0.019 | 0.019 |
| | (0.117) | (0.038) | (0.613) | (0.619) |
| $\beta_4$ Indirect labor costs (level) | $-0.041^{**}$ | $-0.041^{**}$ | $-0.053^{***}$ | $-0.052^{***}$ |
| | $(-2.274)$ | $(-2.278)$ | $(-2.953)$ | $(-2.922)$ |
| $\beta_5$ Indirect labor costs (growth) | $-0.089^{***}$ | $-0.088^{***}$ | $-0.091^{***}$ | $-0.091^{***}$ |
| | $(-2.910)$ | $(-2.864)$ | $(-2.980)$ | $(-2.962)$ |
| $\theta_1 \boldsymbol{W}_{\text{up}}$ Past experience | $-0.067$ | $-0.115^{**}$ | $0.078^{**}$ | $0.072^{**}$ |
| | $(-1.150)$ | $(-2.126)$ | (2.427) | (2.258) |
| $\theta_2 \boldsymbol{W}_{\text{down}}$ Price expectations$_{\text{t-1}}$ | $0.063^{**}$ | $0.054^{*}$ | $-0.002$ | $-0.019$ |
| | (1.997) | (1.733) | $(-0.051)$ | $(-0.590)$ |
| $\theta_3 \boldsymbol{W}_{\text{down}}$ Direct labor costs (growth) | $-0.058$ | $-0.076$ | $-0.081$ | $-0.088$ |
| | $(-0.514)$ | $(-0.678)$ | $(-0.716)$ | $(-0.781)$ |
| $\theta_4 \boldsymbol{W}_{\text{down}}$ Indirect labor costs (level) | $0.083^{*}$ | $0.076^{*}$ | $0.123^{***}$ | $0.114^{**}$ |
| | (1.810) | (1.666) | (2.674) | (2.506) |
| $\theta_5 \boldsymbol{W}_{\text{down}}$ Indirect labor costs (growth) | 0.134 | 0.131 | 0.177 | 0.171 |
| | (0.984) | (0.963) | (1.306) | (1.262) |
| Input-output multiplier$_{\text{SR}}$ | 1.280 | 1.240 | 1.508 | 1.430 |
| Input-output multiplier$_{\text{LR}}$ | 2.065 | 2.157 | 2.641 | 2.709 |
| $\phi + (\rho + \eta)\omega_{\max}$ | 0.501 | 0.520 | 0.610 | 0.619 |
| $CD$ | 0.413 | 0.323 | 0.744 | 0.985 |
| Common factors | YES | YES | YES | YES |
| Nobs | 28644 | 28644 | 28644 | 28644 |

*Notes* Common factors are $\overline{exp}_t$, $\overline{exp}_{t-1}$, $\overline{past}_t$, $tfp_{it}$, $stockx_{it}$; ***significant at 0.01 level, **significant at 0.05 level, *significant at 0.1. level; assymptotic z-statstics in parenthesis; T=42.

Table A3: Direct and indirect impact estimates, model (XII)

| Period | Average direct impacts | | | | Average indirect impacts | | | |
|---|---|---|---|---|---|---|---|---|
| | Lower 0.025 | Mean | Upper 0.975 | Cumulative | Lower 0.025 | Mean | Upper 0.975 | Cumulative |
| **Past experience** | | | | | | | | |
| 0 | 0.233 | 0.245 | 0.257 | 0.245 | 0.018 | 0.050 | 0.081 | 0.050 |
| 1 | 0.077 | 0.081 | 0.085 | 0.326 | 0.056 | 0.071 | 0.088 | 0.121 |
| 2 | 0.024 | 0.027 | 0.030 | 0.353 | 0.042 | 0.052 | 0.065 | 0.174 |
| 3 | 0.008 | 0.009 | 0.011 | 0.362 | 0.025 | 0.033 | 0.043 | 0.207 |
| 4 | 0.003 | 0.003 | 0.004 | 0.365 | 0.013 | 0.019 | 0.027 | 0.226 |
| 10 | 0.000 | 0.000 | 0.000 | 0.367 | 0.000 | 0.001 | 0.001 | 0.250 |
| **Price expectations$_{\mathbf{t-1}}$** | | | | | | | | |
| 0 | −0.009 | 0.004 | 0.016 | 0.004 | −0.045 | −0.014 | 0.016 | −0.014 |
| 1 | −0.003 | 0.001 | 0.005 | 0.005 | −0.026 | −0.007 | 0.011 | −0.021 |
| 2 | −0.001 | 0.000 | 0.002 | 0.005 | −0.015 | −0.003 | 0.007 | −0.025 |
| 3 | 0.000 | 0.000 | 0.001 | 0.005 | −0.008 | −0.002 | 0.004 | −0.026 |
| 4 | 0.000 | 0.000 | 0.000 | 0.005 | −0.005 | −0.001 | 0.002 | −0.027 |
| 10 | 0.000 | 0.000 | 0.000 | 0.005 | 0.000 | 0.000 | 0.000 | −0.029 |
| **Direct labor costs (growth)** | | | | | | | | |
| 0 | −0.047 | 0.010 | 0.071 | 0.010 | −0.150 | −0.089 | −0.036 | −0.089 |
| 1 | −0.015 | 0.003 | 0.023 | 0.013 | −0.090 | −0.044 | −0.004 | −0.134 |
| 2 | −0.005 | 0.001 | 0.007 | 0.013 | −0.053 | −0.023 | 0.002 | −0.156 |
| 3 | −0.002 | 0.000 | 0.002 | 0.014 | −0.031 | −0.012 | 0.003 | −0.168 |
| 4 | −0.001 | 0.000 | 0.001 | 0.014 | −0.018 | −0.006 | 0.002 | −0.175 |
| 10 | 0.000 | 0.000 | 0.000 | 0.014 | −0.001 | 0.000 | 0.000 | −0.183 |
| **Indirect labor costs (level)** | | | | | | | | |
| 0 | −0.086 | −0.052 | −0.018 | −0.052 | 0.051 | 0.047 | 0.045 | 0.047 |
| 1 | −0.028 | −0.017 | −0.006 | −0.069 | 0.010 | 0.014 | 0.020 | 0.062 |
| 2 | −0.009 | −0.006 | −0.002 | −0.075 | 0.000 | 0.004 | 0.009 | 0.066 |
| 3 | −0.003 | −0.002 | −0.001 | −0.076 | −0.002 | 0.001 | 0.004 | 0.067 |
| 4 | −0.001 | −0.001 | 0.000 | −0.077 | −0.002 | 0.000 | 0.002 | 0.067 |
| 10 | 0.000 | 0.000 | 0.000 | −0.077 | 0.000 | 0.000 | 0.000 | 0.067 |
| **Indirect labor costs (level)** | | | | | | | | |
| 0 | −0.150 | −0.089 | −0.032 | −0.089 | −0.029 | 0.063 | 0.166 | 0.063 |
| 1 | −0.048 | −0.029 | −0.010 | −0.118 | −0.046 | 0.016 | 0.078 | 0.079 |
| 2 | −0.016 | −0.010 | −0.003 | −0.128 | −0.035 | 0.002 | 0.039 | 0.081 |
| 3 | −0.005 | −0.003 | −0.001 | −0.131 | −0.022 | −0.001 | 0.020 | 0.081 |
| 4 | −0.002 | −0.001 | 0.000 | −0.132 | −0.013 | −0.001 | 0.011 | 0.080 |
| 10 | 0.000 | 0.000 | 0.000 | −0.132 | 0.000 | 0.000 | 0.000 | 0.078 |

*Notes:* Impacts computed according equation (7) and based on 1,000 sampled parameter estimates.

Table A4: Dynamic Spatial Durbin Model estimates, small sample

| Model | (IV) | (V) | (VI) | (VII) |
|---|---|---|---|---|
| $\phi \boldsymbol{exp}_{t-1}$ | $0.333^{***}$ | $0.334^{***}$ | $0.327^{***}$ | $0.328^{***}$ |
| | (46.184) | (46.474) | (45.062) | (45.676) |
| $\rho \boldsymbol{W} \boldsymbol{exp}_t$ | $0.505^{***}$ | $0.512^{***}$ | $0.435^{***}$ | $0.453^{***}$ |
| | (11.943) | (12.796) | (11.876) | (14.424) |
| $\eta \boldsymbol{W} \boldsymbol{exp}_{t-1}$ | 0.013 | | $0.047^{*}$ | |
| | (0.685) | | (1.655) | |
| $\beta_1$ Past experience | $0.271^{***}$ | $0.271^{***}$ | $0.264^{***}$ | $0.265^{***}$ |
| | (47.558) | (47.550) | (46.269) | (46.411) |
| $\beta_2$ Production (growth) | $0.026^{**}$ | $0.026^{**}$ | $0.023^{**}$ | $0.023^{**}$ |
| | (2.443) | (2.448) | (2.098) | (2.121) |
| $\beta_3$ Price expectations$_{\text{t-1}}$ | 0.003 | 0.003 | 0.005 | 0.005 |
| | (1.089) | (1.088) | (1.376) | (1.333) |
| $\beta_4$ Direct labor costs (growth) | $-0.024$ | $-0.024$ | $-0.004$ | $-0.004$ |
| | $(-0.629)$ | $(-0.591)$ | $(-0.026)$ | $(-0.013)$ |
| $\beta_5$ Indirect labor costs (level) | $-0.034^{*}$ | $-0.034^{*}$ | $-0.038^{**}$ | $-0.038^{**}$ |
| | $(-1.946)$ | $(-1.947)$ | $(-2.140)$ | $(-2.152)$ |
| $\beta_6$ Indirect labor costs (growth) | $-0.067^{*}$ | $-0.068^{*}$ | $-0.066^{*}$ | $-0.067^{*}$ |
| | $(-1.931)$ | $(-1.946)$ | $(-1.910)$ | $(-1.929)$ |
| $\theta_1 \boldsymbol{W}_{\text{up}}$ Past experience | $-0.081^{*}$ | $-0.079^{*}$ | $0.117^{***}$ | $0.124^{***}$ |
| | $(-1.740)$ | $(-1.737)$ | (3.813) | (4.202) |
| $\theta_2 \boldsymbol{W}_{\text{up}}$ Production (growth) | $0.230^{***}$ | $0.227^{***}$ | $0.222^{***}$ | $0.219^{***}$ |
| | (3.362) | (3.289) | (3.236) | (3.185) |
| $\theta_3 \boldsymbol{W}_{\text{down}}$ Price expectations$_{\text{t-1}}$ | $0.057^{*}$ | $0.058^{*}$ | 0.012 | 0.023 |
| | (1.785) | (1.844) | (0.253) | (0.716) |
| $\theta_4 \boldsymbol{W}_{\text{down}}$ Direct labor costs (growth) | 0.106 | 0.107 | 0.048 | 0.050 |
| | (0.945) | (0.953) | (0.441) | (0.475) |
| $\theta_5 \boldsymbol{W}_{\text{down}}$ Indirect labor costs (level) | $0.077^{*}$ | $0.078^{*}$ | $0.076^{*}$ | $0.081^{*}$ |
| | (1.851) | (1.886) | (1.790) | (1.953) |
| $\theta_6 \boldsymbol{W}_{\text{down}}$ Indirect labor costs (growth) | 0.056 | 0.057 | 0.067 | 0.070 |
| | (0.382) | (0.389) | (0.458) | (0.478) |
| Input-output multiplier$_{\text{SR}}$ | 1.168 | 1.171 | 1.244 | 1.258 |
| Input-output multiplier$_{\text{LR}}$ | 1.920 | 1.916 | 2.200 | 2.144 |
| $\phi + (\rho + \eta)\omega_{\max}$ | 0.466 | 0.465 | 0.545 | 0.533 |
| $CD$ | 1.031 | 1.030 | 2.133 | 1.910 |
| Common factors | YES | YES | YES | YES |
| Loglik | -81810 | -81810 | -81785 | -81787 |
| Nobs | 21042 | 21042 | 21042 | 21042 |

*Notes* Common factors are $\overline{exp}_t$, $\overline{exp}_{t-1}$, $\overline{past}_t$, $tfp_{it}$, $stockx_{it}$; ***significant at 0.01 level, **significant at 0.05 level, *significant at 0.1. level; assymptotic z-statstics in parenthesis; T=42.