The Network Effects of Fiscal Adjustments*

Edoardo Briganti† Carlo A. Favero‡
Madina Karamysheva§

May 11, 2021

Abstract

We study the effects of fiscal consolidations in the US and their transmission in the production network. Results are obtained using spatial econometric techniques which allow to break-down their total effect into a direct and a network effect. We find that fiscal adjustments, narratively identified as exogenous with respect to output fluctuations, based on increased taxation are more recessionary than those based on spending cuts. One-fourth of the difference in their total output effect is explained by the stronger downstream propagation of taxes, relative to the upstream propagation of government spending, which, on the contrary, is found to be rather small.

Keywords: industrial networks, fiscal adjustment plans, output growth, applied spatial econometrics.
JEL codes : E60, E62.

*This paper was presented during IAAE 2018 conference meeting, HSE and Bocconi seminars. We are grateful to participants for useful comments; in particular, we thank Roberto Perotti, Hashem Pesaran, Lung-Fei Lee and Valerie Ramey for useful comments.

†PhD student at University of California San Diego, ebrigant@ucsd.edu

‡Deutsche Bank Chair, IGIER-Bocconi, and CEPR (full address: IGIER and Dept. of Finance, Universit Commerciale Luigi Bocconi, via Roentgen 1, 20136 Milano Italy), tel: +390258363306; carlo.favero@unibocconi.it

§NRU Higher School of Economics, Moscow (full address: Faculty of Economic Sciences, National Research University Higher School of Economics, Pokrovsky Boulevard 11, office number S-639, Moscow, Russian Federation), tel: +79192370529; mkaramysheva@hse.ru

1 Introduction

In a world overwhelmed by a global pandemic, the adoption of unprecedented fiscal stimuli has deteriorated the state of public finances. Because of this, after the solution of the pandemic crisis, the implementation of some form of fiscal consolidation will be a potential device to bring sovereign debt back on a sustainable track. In April 2020, in an article entitled "After the disease, the debt", The Economist wrote: "... governments should prepare for the grim business of balancing budgets later in the decade".[1] In this context, knowledge of the effects of fiscal consolidations as well as their transmission mechanism will be very relevant to guide policymakers.
As Ramey (2019) points out, the fiscal policy literature has made great steps ahead since the Great Recession. In particular, a new fact has been consistently confirmed by a number of recent papers: fiscal consolidations implemented by raising taxes imply larger output losses compared to consolidations relying on reductions in government spending (e.g. Alesina, Favero, and Giavazzi (2015), Guajardo, Leigh, and Pescatori (2014), Ramey (2019)). Currently, we have little knowledge on the causes of such an asymmetric response. Furthermore, the fiscal consolidations literature, with the only exception of Karamysheva (2019), has focused on the comparison of the effects of austerity measures across a panel of countries, neglecting the study of their effects within a single one. Focusing on one country has two main benefits: firstly, it allows to provide estimates tailored to that specific country, resulting in more reliable guidance for policy-making than a multi-country analysis, which reports country-average effects. Secondly, the richness of industry-level data allows the researcher to keep track of the effects of fiscal consolidations at a more disaggregated level, shedding light on the transmission mechanism of fiscal policy.

Do we observe any effect of fiscal adjustments in the US? Are tax-based fiscal consolidations more recessionary than expenditure-based ones? Can the analysis of the input-output network explain their asymmetric effect? These three questions motivate our work. In particular, we study the effects of fiscal consolidations implemented in the US from 1978 to 2014 on a 62-industry breakdown of the economy.
Related to the first two questions, we find that tax-based (TB henceforth) fiscal adjustments have a recessionary output multiplier over two years of -1.4% while the effects of expenditure-based (EB henceforth) fiscal plans are not statistically different from zero. These results are in line with those obtained by

[1] The Economists, April 25th Edition - Article: "After the disease, the debt."

the current state of the literature which uses a panel of OECD countries.
We answer the last question by using cutting-edge spatial econometric techniques, as we assume that the observed units, 62 industries, are "spatially connected" via an input-output production network. The advantage of using a spatial framework is that we can decompose the aggregate total effects of fiscal consolidations into a direct and a network effect. The former represents the direct impact of the fiscal shock on each industry while the latter results from the spillovers from other industries hit by the same aggregate shock. This, in turn, enables us to test an interesting hypothesis: if TB and EB fiscal consolidations had asymmetric network effects because of different propagation mechanisms, the stronger recessionary effects of the former could be explained by its stronger network effect. To illustrate this point, suppose that taxes work mainly as a supply-side adjustment and government spending as a typical demand-side adjustment. Then, according to a simple general equilibrium framework taxes should propagate downstream - from suppliers to customers - via the price mechanism, while government spending should propagate upstream - from customers to suppliers - via changes in demand.[2]
As fiscal consolidations are multi-year plans made of a mixture of tax increases and spending cuts, differences in the propagation mechanism of taxes and government spending could explain the observed asymmetric output effect of TB and EB fiscal consolidations. The separate identification of direct and network effects delivered by the spatial econometric model allows for an explicit test of the aforementioned hypothesis, which, in turn, answers the third motivating question.
Our baseline results suggest that 27% of the total effect of TB fiscal consolidations come from downstream network spillovers, robust to different specifications; while EB plans have a more modest, and non-robust, 11% of their effect coming from the network. Overall, the stronger network effects of TB plans explain one-fourth of the differences in the total effects of TB and EB plans.

In addition to these results, we believe this paper has two other original contributions. Firstly, to the best of our knowledge, we are the first to study and detect downstream spillovers of taxes. We find that such a network transmission hinges on the role played by few key suppliers in the economy, rather than depending on the distribution of first and second-order weighed in-degrees. This result is similar to what was found by Ozdagli and Weber (2017) in the context of upstream propagation of monetary policy shocks. Sec-

[2] The model we refer to is provided in the Appendix.

ondly, as noted in Ozdagli and Weber (2017), the adoption in macroeconomics of spatial econometrics to study the effects and the transmission mechanism of aggregate shocks is novel and, to the best of our knowledge, besides Ozdagli and Weber (2017) and us, there are no other examples of papers following the same approach.

Related Literature

First of all, our paper relates to the literature of fiscal consolidations: Guajardo, Leigh, and Pescatori (2014), Alesina, Favero, and Giavazzi (2015) and Alesina, Barbiero, et al. (2017). Unlike them, we use a panel of US industries rather than countries, and, for the first time, we look at the network effects of fiscal consolidations.
Alesina, Barbiero, et al. (2017) also advance a potential theoretical explanation to the stronger effect of TB fiscal consolidations. Differently from them, we provide a network-based explanation of the asymmetric output effects of TB and EB plans.

To underpin theoretically our empirical analysis we connect to the network literature, revamped by the seminal works of Gabaix (2011) and Acemoglu, Carvalho, et al. (2012) and focused on understanding the role played by the network in amplifying the effects of localized shocks. Unlike them, our paper adopts a spatial framework to figure out how much of the total effect of a fiscal policy can be imputed to network transmission. This point has been highlighted in Ozdagli and Weber (2017), who perform a similar analysis to study the propagation of monetary policy shocks in the US stock market.
We take Acemoglu, Akcigit, and Kerr (2016)'s model as a baseline theoretical framework since it stresses the asymmetric propagation of demand and supply shocks. We adapt it to study the transmission mechanism of taxes and find that they behave as a supply shock that propagates downstream in the network, similar to a productivity shock. To the best of our knowledge, we are the first to study the propagation of taxes in an n-industries economy.

Thirdly, we relate to the literature which studies fiscal policy at an industry level: Ramey and Shapiro (1999), Perotti (2007) and Nekarda and Ramey (2011). In particular, the latter focuses on government purchases in manufacturing industries and finds evidence in support of the Neo-Classical model, as well as constructing a comprehensive measure of government's purchases capable of keeping track of downstream linkages. We borrow from them the idea that fiscal policy can be analyzed at an industry level to shed light on its transmission mechanism, however, we enrich the analysis by using all the industries in the economy and by integrating them into a production network. Cox et al. (2020) study public procurement contracts and find large sectoral bias in government spending, which corroborates the study of fiscal policy at an industry level to take into account this heterogeneity. Auerbach, Gorodnichenko, and Murphy (2019) use city-level data on local defense public procurement and find large fiscal (first-order) spillovers among industries. Their results are in stark contrast with the weak propagation of EB plans that we find. However, given the different levels of aggregation and the fact that defense public procurement is different from EB plans, make our results hard to compare.

The rest of the paper is organized as follows. We start by briefly illustrating in Section 2 the theoretical mechanism of the network diffusion of a tax shock and a government expenditure shock. Section 2 also shows the mathematics of fiscal adjustment plans and how all these elements can be fed into a spatial econometric model. Section 3 and Section 4 illustrate the database and our baseline results respectively. Section 5 provides some robustness checks and eventually Section 6 concludes.

2 From Theory to Empirics

2.1 Network Propagation Mechanism

Recall from the industrial network literature, that there are two basic types of industrial network propagation: downstream - from suppliers to customers - and upstream - from customers to suppliers. The former is driven by the elements of the rows of the input-output (downstream) matrix, which we denote by A, and it is the main transmission mechanism of supply shocks. The latter is driven by the elements of the columns of a rescaled input-output (upstream) matrix denoted by $\hat{A}$, which accounts for the principal propagation device of demand shocks (see Acemoglu, Akcigit, and Kerr (2016)).

Our initial hypothesis postulates that taxes propagate mainly downstream and government spending mainly upstream, consistently with the propagation mechanism of supply and demand shocks of Acemoglu, Akcigit, and Kerr (2016). In turn, such an asymmetric propagation mechanism is what we believe might explain the difference in the output effect of TB and EB fiscal consolidations found by the empirical literature.

We are aware of the criticism raised towards the simplicity of Acemoglu, Akcigit, and Kerr (2016)'s model, which forces each type of shock to propagate only in one direction at a time. However, simplicity makes the implication of the model easily testable. For example, we anticipate now that testing for multiple directions of propagation is not feasible. We will go back to this point in Section 2.3 and further address it in the robustness section of the paper 5.2. We now illustrate the main theoretical results which underpin our hypothesis.

Taxes and Downstream Propagation

The industrial network literature states that a shock to the economy propagates downstream if the following type of closed form structural relationship holds true:

$$\underset{n\times 1}{d\log \boldsymbol{y}} = \rho \cdot \underset{n\times n}{A} \cdot \underset{n\times 1}{d\log \boldsymbol{y}} + \beta \cdot \underset{n\times 1}{\text{Shock}} \tag{1}$$

where n represents the number of industries, $d\log \boldsymbol{y}$ is the vector of log-differences in industry output, ρ is a parameter which regulates the intensity of the industrial network connection and β is the "Direct" marginal effect of the vector "*Shock*".
From the above expression, notice that $d\log y_i$ is contemporaneously affected by a weighted average of the whole vector of percent changes, $d\log \boldsymbol{y}$, with weights given by the elements of row i of the input-output matrix A. Denoting by a_{ij} the generic element of row i and column j of matrix A, the above structural equation for industry i is: $d\log y_i = \rho \sum_{k=1}^{n} a_{ik} \cdot d\log y_k + \beta \cdot \text{Shock}_i$.
The production network literature identifies the elements of matrix A from the input-output tables. Moreover, the following also holds true: $a_{ij} = \dfrac{\text{SALES}_{j\to i}}{\text{SALES}_i}$, where $\text{SALES}_{j\to i}$ accounts for the total shipments from industry j to i, while SALES_i denotes the total industrial output of industry i. Therefore, a_{ij} can be interpreted as the "reliance of industry i on the industrial supplier j".
According to this propagation mechanism, sector i's output is directly affected by all other sectors proportionally to how much it is exposed to them in terms of input purchased, namely a_{i1}, a_{i2}, ... , a_{in}.
Furthermore, in a network also higher order connections matter, that is, suppliers of suppliers as well as customers of customers (second order connection), and so on and so forth. The above structural equation takes all of them into account. In fact, solving by $d\log \boldsymbol{y}$ we have:

$$\underset{n\times 1}{d\log \boldsymbol{y}} = \underbrace{(I_n - \rho \cdot A)^{-1}}_{\text{Downstream Propagation}} \cdot \underset{n\times 1}{\text{Shock}} \cdot \ \beta.$$

where the whole complex tangle of downstream spillovers are captured by matrix $(I_n - \rho \cdot A)^{-1}$, which is referred to as the (downstream) Leontief Inverse (see Acemoglu, Carvalho, et al. (2012) and Carvalho and Tahbaz-Salehi (2019)). Because of this, we will refer to matrix A as the "*downstream matrix*".
The sum of the elements of the rows of A represents the "*weighted in-degree*" of each node of the input-output network. Intuitively, the weighted in-degree is the sum of intermediate input over industry gross output, and is therefore a measure of reliance of each industry on its industrial suppliers.

The downstream propagation mechanism illustrated here is the one that regulates the transmission of productivity shocks in both Acemoglu, Carvalho, et al. (2012) and Acemoglu, Akcigit, and Kerr (2016). More precisely, suppose a positive productivity shock hits sector i, then the price falls because of perfect competition, and all the customers will buy more of good i. Facing lower input prices, customer industries will now produce more and sell for a lower price. Therefore, an initially localized productivity shock will trickle down to the bottom of the supply chain via changes in prices.
It is possible to show that within the framework of Acemoglu, Akcigit, and Kerr (2016), a production tax follows the same downstream propagation mechanism of a productivity shock.[3] Similarly, a corporate tax on the profits would also have the same propagation effects as our production tax. On the other hand, the downstream propagation of both a labor and a lump sum tax is annihilated by the joint effects of constant return to scale and the Cobb-Douglas production function.
Putting all this together suggests that taxes might propagate mainly via the downstream channel and, therefore, we will specify our baseline empirical model accordingly.

Government Spending and Upstream Propagation

Symmetrically to the case of taxes, "propagating upstream" means that the following type of structural relationship holds true:

$$\underset{n\times 1}{d\log \boldsymbol{y}} = \rho \cdot \underset{n\times n}{\hat{A}^T} \cdot \underset{n\times 1}{d\log \boldsymbol{y}} + \beta \cdot \underset{n\times 1}{\text{Shock}} \tag{2}$$

where the T superscript denotes the transposition of the transformed input output matrix $\hat{A}$, whose generic element is $\hat{a}_{ij} = \dfrac{\text{SALES}_{j\to i}}{\text{SALES}_j}$. Notice that $\hat{a}_{ij}$

[3] We report in the Appendix the whole derivation of the model, which is a slightly modified version of Acemoglu, Akcigit, and Kerr (2016).

represents the reliance of industry j on the industrial customer i.
Therefore, $d \log y_i$ is affected by a weighted average of the whole vector of percent changes $d \log \boldsymbol{y}$, whose weights are given by the elements of column i of the transformed input-output matrix $\hat{A}$: $d \log y_i = \rho \sum_{k=1}^{n} \hat{a}_{ki} \cdot d \log y_k + \beta \cdot \text{Shock}_i$. Sector i's output is now directly affected by each other sector proportionally to how much it is exposed to it in terms of output sold, namely $\hat{a}_{1i}, \hat{a}_{2i}, \dots, \hat{a}_{ni}$.
Intuitively, if the government starts demanding more output i, industry i will have to produce more and to do that it will purchase more intermediate inputs; in turn, suppliers of i will also expand their output and purchase more inputs, and so on and so forth.
Symmetric to the case of taxes, expression:

$$\underset{n \times 1}{d \log \boldsymbol{y}} = \underbrace{\left(I_n - \rho \cdot \hat{A}^T\right)^{-1}}_{\text{Upstream Propagation}} \cdot \underset{n \times 1}{\text{Shocks}} \cdot \beta.$$

captures the whole universe of upstream spillovers by means of the matrix $\left(I_n - \rho \cdot \hat{A}^T\right)^{-1}$. Because of this, we will refer to $\hat{A}^T$ as the "*upstream matrix*". The sum of the elements of the rows of $\hat{A}^T$ represents the "*weighted outdeegree*" of each node of the input-output network. Intuitively it represents how much each sector sells to all other sectors in the economy, relative to its overall output.

We believe that the propagation of government spending shocks follows mainly the upstream direction highlighted by Acemoglu, Akcigit, and Kerr (2016), while other propagation effects might be second or even third order of importance. For instance, an increase in the government's demand of industry output i should drive up its price, and, as a consequence, the other sectors should decrease their demand for it, thus triggering an opposite direction downstream propagation via price changes. In Acemoglu, Akcigit, and Kerr (2016)'s model, this opposite direction substitution effect is canceled out by the income effect, because of a Cobb-Douglas production function. On the contrary, this more elaborate channel is explored in Bouakez, Rachedi, Emiliano, et al. (2018) employing a DSGE model calibrated to match the US economy. The authors conclude that the upstream propagation of government spending outweighs the downstream one. Because of this and following Occam's razor principle of parsimony, we assume that government spending propagates mainly in one upstream direction in the production network.

2.2 Fiscal Adjustments

Measuring the propagation of fiscal adjustments requires the identification of an exogenous demand and supply shock. Our identification strategy relies upon fiscal adjustment plans, which represent a recent innovation in the fiscal policy literature and consist of a combination of narrative exogenous shocks employed as a proxy to fiscal consolidation policies. They have been introduced by Alesina, Favero, and Giavazzi (2015) to take into account that fiscal adjustments are implemented through multi-year plans that involve both an intertemporal and an intratemporal dimension.

The intratemporal dimension depends on the fact that fiscal consolidations are implemented with a mix of measures on the expenditure side and the revenue side. In other words, governments (US included) tend to execute their fiscal austerity using a mix of tax increases and spending cuts. At the same time, also an intertemporal dimension is relevant because plans involve measures that are implemented both upon announcement (the unanticipated component of the plan) and measures that are announced for the future years (the anticipated component of the plan). Alesina, Favero, and Giavazzi (2015) point out that each country has its own specific "recipe" to implement fiscal consolidations and they refer to this as the country-specific "style of the plan".

Because of the intertemporal and intratemporal correlation, which we analyze in Section 3, identifying pure and isolated tax hikes and spending cuts in years of fiscal consolidation is hard and the adoption of fiscal plans is a solution to overcome this problem.

Modeling Fiscal Plans:

From a mathematical standpoint, plans are sequences of fiscal corrections, announced at time t and implemented between t and $t + K$, where K is the anticipation horizon. In year t two types of fiscal corrections are possible:

1. The *unanticipated fiscal shock*, that is, the surprise change in the primary surplus at time t, which we denote by:

$$f_t^u := tax_t^u + exp_t^u,$$

   where tax_t^u is the surprise increase in taxes announced and implemented at time t, while exp_t^u is the surprise reduction in government expenditure also announced and implemented at time t.

2. The *anticipated fiscal shock*: the change in the primary surplus at time t which had already been announced in the previous years and is either

implemented in year t or is scheduled to happen within K years. In particular, we denote as $tax^a_{t,j}$ and $exp^a_{t,j}$ the tax and expenditure changes announced by the fiscal authorities at date t with an anticipation horizon of j years (*i.e.* to be implemented in year $t+j$). Therefore, we distinguish between:

(a) The *anticipated implemented shock*: scheduled in the past and implemented in year t:

$$f^a_t := \; tax^a_{t,0} + exp^a_{t,0}$$

(b) The *anticipated future shocks*: sum of scheduled tax and government spending changes which have to be implemented within K years from their announcement:

$$f^f_t := \sum_{j=1}^{K} tax^a_{t,j} + \sum_{j=1}^{K} exp^a_{t,j}$$

In a fiscal adjustment database, as long as no policy revision takes place, the anticipated shocks are rolled over year by year. In formulae:

$$tax^a_{t,j} = \underbrace{tax^a_{t-1,j+1}}_{\textit{Old shock, rolled over}} \qquad exp^a_{t,j} = \underbrace{exp^a_{t-1,j+1}}_{\textit{Old shock, rolled over}} \; .$$

However, if from one year to another, a policy revision takes place, then, the new anticipated future shock will embed such change:[4]

$$\begin{aligned} tax^a_{t,j} &= \underbrace{tax^a_{t-1,j+1}}_{\textit{Old shock, rolled over}} + \underbrace{\left(tax^a_{t,j} - tax^a_{t-1,j+1}\right)}_{\textit{Policy Revision}}, \quad \text{with } j \geq 1 \\ exp^a_{t,j} &= \underbrace{exp^a_{t-1,j+1}}_{\textit{Old shock, rolled over}} + \underbrace{\left(exp^a_{t,j} - exp^a_{t-1,j+1}\right)}_{\textit{Policy Revision}}, \quad \text{with } j \geq 1 \end{aligned}$$

TB versus EB classification:

We have already argued that fiscal plans have the benefit of capturing the intertemporal and intratemporal correlation of the multi-year fiscal consolidation plans. The next problem to be solved is to classify plans into categories

[4] In the above expression $j \geq 1$ since any policy revision introduced upon implementation ($j = 0$) is no longer a part of an anticipated shock; in fact, it is a new unanticipated component.

that can be simulated independently. To this end, we exploit the fact that not all the plans are the same. Some fiscal plans are designed to increase taxes more than cutting expenditures and are labeled as TB (tax-based). On the contrary, those plans relying more on expenditure cuts rather than tax hikes are labeled as EB (expenditure-based).
The criterion to determine whether a fiscal consolidation is labeled as TB, is:

$$\underbrace{\left(tax_t^u + tax_{t,0}^a + \sum_{j=1}^{K} tax_{t,j}^a\right)}_{\text{overall tax hike in } t} > \underbrace{\left(exp_t^u + exp_{t,0}^a + \sum_{j=1}^{K} exp_{t,j}^a\right)}_{\text{overall expenditure cut in } t}$$

that is, if the overall tax hike in year t is larger than the overall spending cut, then we label year t as an year of TB fiscal consolidation.[5] We keep track of these years by constructing a dummy variable, TB_t, which takes on value one if year t is labeled as TB. Viceversa, we label years where the overall spending cut exceeds the tax hike, as EB, and set the dummy variable EB_t equal to one to denote the occurrence of an EB fiscal consolidation.
By construction TB and EB plans are mutually exclusive, therefore when an EB plan is activated no TB plan can simultaneously occur. Classifying plans into TB and EB is an identification strategy that allows simulating their effect on the economy taking into account the correlation between tax adjustments and expenditure adjustments.

Industry Specific Shares:

Finally, we construct $n \times 1$ vectors of weights which can "redistribute" the aggregate fiscal consolidation components among the industries. Following Acemoglu, Akcigit, and Kerr (2016), we construct the vector of industry-specific weights by exploiting information from the input-output tables, namely: $\omega_i^{EB} = \dfrac{Sales_{i \to G}}{Sales_i}$; where "G" stands for Government.[6] By doing so, we take into account the fact that the government purchases goods and services differently from each sector.[7] Lastly, the vector of weights for the EB plan, denoted by $\boldsymbol{\omega}^{EB}$, is then normalized to one.
On the contrary, we assume that aggregate TB fiscal plans impact each sector

[5] Here "overall" means "all the components": unanticipated, anticipated and future.

[6] Our definition of Government encompasses both Federal and State&Local government spending. We therefore exclude here Government Enterprises, which instead are considered as part of the industrial network.

[7] We thank Roberto Perotti for this point.

in the same fashion, therefore, we set $\omega_i^{TB} = 1/n$ for all i and the $n \times 1$ vector will be: $\boldsymbol{\omega}^{TB} = 1/n \cdot \mathbf{1}_n$.

2.3 Empirical strategy

We start from an econometric specification that builds on Alesina, Favero, and Giavazzi (2015), who regress country-level output growth on the 3 components of TB and EB country-specific fiscal plans. Unlike them, we focus on a single country, the US, by breaking down the economy into $n = 62$ industries. Furthermore, we enrich their specification with two spatial variables to take into account the input-output connections among sectors, and the spatial correlation generated by them. Therefore, representing in blue the parameters to estimate, our baseline econometric model is:

$$\Delta \log y_{i,t} = \underbrace{\alpha_i}_{Industry\ FE} + \underbrace{\rho^{down} \cdot \Delta y_{i,t}^{down} \cdot TB_t}_{TB\ Plan\ Downstream\ Propagation} + \underbrace{\rho^{up} \cdot \Delta y_{i,t}^{up} \cdot EB_t}_{EB\ Plan\ Upstream\ Propagation} +$$

$$+ \underbrace{\left(\tau_u \cdot f_t^u + \tau_a \cdot f_t^a + \tau^f \cdot f_t^f\right) \cdot \omega_i^{TB} \cdot TB_t}_{TB\ Fiscal\ Consolidations} + \underbrace{\left(\gamma_u \cdot f_t^u + \gamma_a \cdot f_t^a + \gamma^f \cdot f_t^f\right) \cdot \omega_i^{EB} \cdot EB_t}_{EB\ Fiscal\ Consolidations} + \underbrace{\nu_{i,t}}_{Noise},$$

where α_i is an industry fixed effect, $\Delta y_{i,t}^{down} = \sum_{j=i}^{n} a_{ij} \cdot \Delta \log y_{j,t}$ and $\Delta y_{i,t}^{up} = \sum_{j=i}^{n} \hat{a}_{ji} \cdot \Delta \log y_{j,t}$ are the spatial variables and $\nu_{i,t}$ is an error term.
The model can conveniently be rewritten in matrix notation:

$$\begin{aligned} \Delta \log \boldsymbol{y}_t = \boldsymbol{\alpha} + &\left(\boldsymbol{\omega}^{TB} \cdot \underbrace{\boldsymbol{\tau}^T \cdot \boldsymbol{f}_t}_{1\times1} + \rho^{down} \cdot A \cdot \Delta \log \boldsymbol{y}_t\right) \cdot TB_t + \\ &+ \left(\boldsymbol{\omega}^{EB} \cdot \underbrace{\boldsymbol{\gamma}^T \cdot \boldsymbol{f}_t}_{1\times1} + \rho^{up} \cdot \hat{A}^T \cdot \Delta \log \boldsymbol{y}_t\right) \cdot EB_t + \boldsymbol{\nu}_t. \end{aligned} \quad (3)$$

where

$$\boldsymbol{\tau}^T \cdot \boldsymbol{f}_t = \begin{bmatrix} \tau^u & \tau^a & \tau^f \end{bmatrix} \cdot \begin{bmatrix} f_t^u \\ f_t^a \\ f_t^f \end{bmatrix} \qquad \boldsymbol{\gamma}^T \cdot \boldsymbol{f}_t = \begin{bmatrix} \gamma^u & \gamma^a & \gamma^f \end{bmatrix} \cdot \begin{bmatrix} f_t^u \\ f_t^a \\ f_t^f . \end{bmatrix}$$

Notice that if $TB_t = 1$ then $EB_t = 0$ (plans are mutually exclusive) and Equation (3) resembles the structural relationship expressed by (1), where the vector "*Shock*" is now replaced by the TB fiscal plan. On the contrary, if

$EB_t = 1$ then $TB_t = 0$, and Equation (3) resembles the structural relationship expressed by (2), where the vector "*Shock*" is now replaced by the EB fiscal plan. By doing so, we are consistent with our initial theoretical hypothesis that TB plans should propagate mainly downstream and EB plans mainly upstream.
In Section 5.2 we will invert this interaction to test whether when TB and EB are forced to move in a direction opposite to the one assumed by theory, delivers statistically stronger or weaker results. Unfortunately, given the multicollinearity between $\Delta y_{i,t}^{down}$ and $\Delta y_{i,t}^{up}$, and the limited sample size, we cannot test at the same time for multiple directions of propagation by including them in the same regression interacted with both TB_t and EB_t.

Finally, it could be argued that, instead of including spatial lags in the model, a standard panel data model with several "cross-terms" representing the first-order, second-order, and higher-order degrees of connection should have been preferred, as in Hale, Kapan, and Minoiu (2019). However, when the network is persistent, and even higher-order propagation effects are relevant, the number of variables to be included would increase accordingly, thus increasing indefinitely the number of coefficients to estimate. On the contrary, a spatial variable is capable of capturing the entire feedback effect: an infinite number of orders of connection whose impact decays geometrically $(I_n - \rho \cdot A)^{-1} = I_n + \rho \cdot A + \rho^2 \cdot A^2 + ...$
The downstream and upstream networks for the US economy with 62 sectors, represented by the matrix A and $\hat{A}^T$ respectively, are both quite persistent: even the fifth order of propagation matter. Such a persistence justifies the adoption of a spatial model.[8]

2.4 Causal Estimand

We are interested in estimating the weighted average (across sectors) marginal effect of a fiscal adjustment - which we refer to as Average Total Effect, or ATE - and its decomposition in Average Direct and Average Network Effect, or ADE and ANE respectively. The distinction between direct and network effect allows us to test our initial hypothesis: TB plans are more recessionary because they have stronger network effects.
We now illustrate their construction.

[8]Section 7.2 of the Appendix illustrates a partitioning of the industrial network effects in orders of propagation.

Fiscal consolidations are made of three components (unanticipated, anticipated and future), therefore, the standard definition of impulse response as the derivative of a dependent variable with respect to a single shock, is not applicable. What we do is to construct the impulse response by taking a convex combination of the derivatives of $\Delta \log \boldsymbol{y_t}$ with respect to each of the three components. Their weights will be given by the "$\boldsymbol{s}$tyle" of the plan, defined analytically by:

$$\underbrace{\boldsymbol{s_{TB}}}_{3\times 1} := \left[s^u_{TB}\ s^a_{TB}\ s^f_{TB}\right]^T \qquad \underbrace{\boldsymbol{s_{EB}}}_{3\times 1} := \left[s^u_{EB}\ s^a_{EB}\ s^f_{EB}\right]^T$$

For instance, if we want to simulate a TB fiscal plan made of 30% of its unanticipated component, 0% of anticipated part and 70% of future parts, then we would set: $s^u_{TB} = .3$, $s^a_{TB} = 0$, $s^f_{TB} = .7$ and the vector of the "style" would be: $\boldsymbol{s}_{TB} = [.3\ 0\ .7]^T$.
Secondly, given the above definition of impulse response and Equation (3), the $n \times 1$ vector of industry specific Total Effect of a TB plan is:

$$TE_{TB} := s^u_{TB} \cdot \frac{\partial \Delta \log \boldsymbol{y}_t}{\partial f^u_t}\Big|_{TB_t=1} + s^a_{TB} \cdot \frac{\partial \Delta \log \boldsymbol{y}_t}{\partial f^a_t}\Big|_{TB_t=1} + s^f_{TB} \cdot \frac{\partial \Delta \log \boldsymbol{y}_t}{\partial f^f_t}\Big|_{TB_t=1}$$

$$= \underbrace{\left(I_n - \rho^{down} \cdot A\right)^{-1}}_{:=\boldsymbol{H}^{TB}} \cdot \boldsymbol{\omega}_{TB} \ \cdot \ \boldsymbol{\tau}^T \cdot \boldsymbol{s_{TB}} = \underbrace{\mathbf{H}^{TB} \ \cdot \ \boldsymbol{\omega}_{TB}}_{n\times 1} \ \cdot \ \underbrace{\boldsymbol{\tau}^T \cdot \boldsymbol{s_{TB}}}_{1\times 1}$$

Analogously, for an EB plan we have:

$$TE_{EB} := \underbrace{(I_n - \rho^{up} \cdot \hat{A}^T_0)^{-1}}_{:=\boldsymbol{H}^{EB}} \cdot \boldsymbol{\omega}_{EB} \ \cdot \ \boldsymbol{\gamma}^T \cdot \boldsymbol{s_{EB}} = \underbrace{\mathbf{H}^{EB} \ \cdot \ \boldsymbol{\omega}_{EB}}_{n\times 1} \ \cdot \ \underbrace{\boldsymbol{\gamma}^T \cdot \boldsymbol{s_{EB}}}_{1\times 1}.$$

Thanks to the spatial framework, the TE can be broken down into a Direct and Network Effect, as done in Acemoglu, Akcigit, and Kerr (2016) and Ozdagli and Weber (2017). The former represents the direct impact of the fiscal plan, the latter the network spillovers:

$$\begin{aligned} DE_{TB} &= \boldsymbol{\omega}_{TB} \ \cdot \ \boldsymbol{\tau}^T \cdot \boldsymbol{s_{TB}} & NE_{TB} &= (\boldsymbol{H}^{TB} - I_n) \cdot \boldsymbol{\omega}_{TB} \ \cdot \ \boldsymbol{\tau}^T \cdot \boldsymbol{s_{TB}} \\ DE_{EB} &= \boldsymbol{\omega}_{EB} \ \cdot \ \boldsymbol{\gamma}^T \cdot \boldsymbol{s_{EB}} & NE_{EB} &= (\boldsymbol{H}^{EB} - I_n) \cdot \boldsymbol{\omega}_{EB} \ \cdot \ \boldsymbol{\gamma}^T \cdot \boldsymbol{s_{EB}} \end{aligned}$$

The TE, DE and NE are $n \times 1$ vectors of industry specific effects of fiscal adjustment plans. However, we are interested in their aggregate effect. Therefore, we take a weighted average across industries with weights given by each

industry's output share.[9]
By averaging TE we obtain the Average Total Effect, ATE, which represents the aggregate contraction of fiscal consolidation. By averaging DE we obtain the Average Direct Effect, ADE. By averaging NE we obtain the Average Network Effect, ANE. Notice that, given the linearity of the weighted average operation, we still have: $ATE = ADE + ANE$.

Before concluding this section we make two remarks. Firstly, given estimates of the parameters ρ^{down}, ρ^{up}, $\boldsymbol{\tau}$ and $\boldsymbol{\gamma}$, any fiscal plan with style defined by $\boldsymbol{s_{TB}}$ and $\boldsymbol{s_{EB}}$ can be simulated and its corresponding ATE decomposed in an ADE and ANE. This is done in Section 4.2.
Secondly, the ATE of an EB plan is different from the Input-Output Tables' fiscal multipliers. The latter provides accounting calculations of government spending multipliers, which do not involve any statistics at all. On the contrary, we will provide estimates of the ATE by estimating fiscal coefficients, $\boldsymbol{\tau}$ and $\boldsymbol{\gamma}$. Moreover, we study fiscal consolidations, not government spending shocks. Finally, the I-O estimates assume that the intensity of the spatial correlation is 1; unlike them, we estimate such intensity by estimating ρ^{down} and ρ^{up}.

3 Data

3.1 Industry Data

We focus on a partition of the US economy made by 62 industries, observed from 1978 to 2014 at a yearly frequency. The disaggregation level, 62, is determined by starting from the finest decomposition available on the BEA at a yearly frequency, namely 71 sectors, and then aggregating those sectors whose data are not available for older years. Moreover, we exclude the Government sector and consider only Government Enterprises as the only public, but politically independent, sector.[10]

[9] We use average output shares in years of TB fiscal consolidation for aggregating TB effects. We use average output shares in years of EB fiscal consolidation for aggregating EB effects

[10] The Government sector needs to be excluded since its outcome variable is G, government spending, which mechanically falls when a fiscal adjustment occurs.

Value Added

We use real industry value-added as the dependent variable, Δy_{it}. Value-added equals gross output minus intermediate inputs; it consists of compensation of employees, taxes on production and imports less subsidies (formerly indirect business taxes and non-tax payments), and gross operating surplus (formerly "other value added"). We prefer it over gross output, since, as pointed out in Acemoglu, Akcigit, and Kerr (2016), value-added is adjusted for energy costs, non-manufacturing input, and inventory changes which are all outside of the general equilibrium model which provides the theoretical underpinning of our empirical strategy.

Input-Output matrices

The Bureau of Economic Analysis (BEA) provides I-O tables that report the amount of commodity used (Use Table) and made (Make Table) by each industry. Horowitz, Planting, et al. (2006) outline the procedure to construct an industry-by-industry direct requirement matrix, with elements given by $SALES_{j\to i}/SALES_i$ for each sector. Therefore, following their instructions we construct directly from the Make and Use Tables an empirical counterpart of matrix A, the downstream propagation matrix introduced in Section 2, at our desired disaggregation level of 62 industries. In particular, we use data from the year 1997, which is the closest to the occurrence of fiscal plans.[11]
Finally, we construct the upstream propagation matrix $\hat{A}^T$ by transposing the transformed downstream propagation matrix: $\hat{A} = A \odot S$, where $\odot$ represents the Hadamard, or element-wise, product, and S is a scaling matrix whose $(i-j)_{th}$ element is given by $SALES_i/SALES_j$. By doing so, the generic $(i-j)_{th}$ element of $\hat{A}^T$ will be $SALES_{i\to j}/SALES_i$, consistently with what illustrated in Section 2. The scaling matrix is constructed using industry specific gross output, available from the BEA.

3.2 Database of US Exogenous Fiscal Adjustment Plans

We adopt the annual database on fiscal adjustment plans constructed by Alesina, Favero, and Giavazzi (2015) and consider only fiscal consolidations that occurred in the US from 1978 to 2014.
Alesina, Favero, and Giavazzi (2015) identify fiscal adjustments exogenous with respect to output fluctuations by adopting a narrative identification

[11] I-O matrices are fairly stable over time, as they reflect the technological mix of input required to produce a specific industrial output.

method. This approach is similar to C. D. Romer and D. H. Romer (2010), who identify exogenous tax shocks by referring to presidential speeches, congressional debates, budget documents, and congressional reports to identify the size, timing, and principal motivation for all major postwar tax policy actions. Legislated changes are then classified into two categories: 1) endogenous, if induced by short-run counter-cyclical concerns; 2) exogenous, if taken in response to the state of government debt (deficit-driven).
Concerning changes in expenditure, we emphasize that Alesina, Barbiero, et al. (2017) disentangle transfers from taxes and government spending, our sample does the same and exclude transfers.

As anticipated in Section 2, one benefit of using fiscal adjustment plans is the possibility of controlling for the correlation between and within the tax and the expenditure components, which we report in Table I:

Table I: Correlation matrix of Fiscal Adjustments

	tax_t^u	$tax_{t,0}^a$	tax_t^f	exp_t^u	$exp_{t,0}^a$	exp_t^f
tax_t^u	1	0.041	0.570	0.596	-0.126	0.105
$tax_{t,0}^a$	0.041	1	0.038	0.098	0.361	0.310
tax_t^f	0.570	0.038	1	-0.047	0.019	0.180
exp_t^u	0.596	0.098	-0.047	1	-0.050	0.014
$exp_{t,0}^a$	-0.126	0.361	0.019	-0.050	1	0.782
exp_t^f	0.105	0.310	0.180	0.014	0.782	1

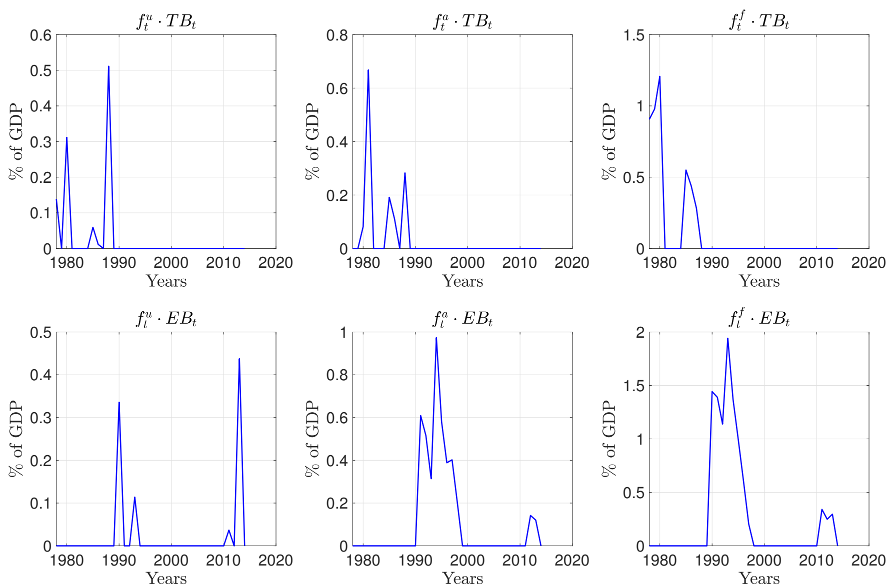
Table I: linear correlation matrix of legislated changes in taxes and expenditure identified by the narrative analysis. The definitions of tax_t^u, exp_t^u, $tax_{t,0}^a$, $exp_{t,0}^a$, tax_t^f *and* exp_t^f *are the same provided in Section 2.2.*

Notice from Table I that the (intra-temporal) correlation between unanticipated tax and unanticipated expenditure adjustments is 0.596. Similarly, the (inter-temporal) correlation between future and anticipated components of expenditure is even 0.782. As both the inter-temporal and the intra-temporal dimension matter, it is worth considering multi-year fiscal plans instead of individual measures of tax and government spending shocks.

We scale all the nominal changes in taxes and expenditure by GDP of the year before the consolidation occurs to avoid potential endogeneity issues. Then, we construct unanticipated, anticipated, and future fiscal adjustments as illustrated in Section 2.2. The future component of the fiscal adjustment

plans is constructed by setting the maximum anticipation horizon, K in Section 2.2, equal to three years, in line with the small numbers of occurrences of policy shifts, anticipated four and five years ahead, and consistently with Pescatori et al. (2011)'s database.
Figure 1 plots our fiscal adjustment database. On the top row, the three components of fiscal adjustments are interacted with the dummy TB_t to identify the components of tax-based fiscal consolidations. Analogously, the bottom row reports the components of fiscal adjustments interacted with the EB_t dummy, which identifies years of expenditure-based fiscal consolidations.

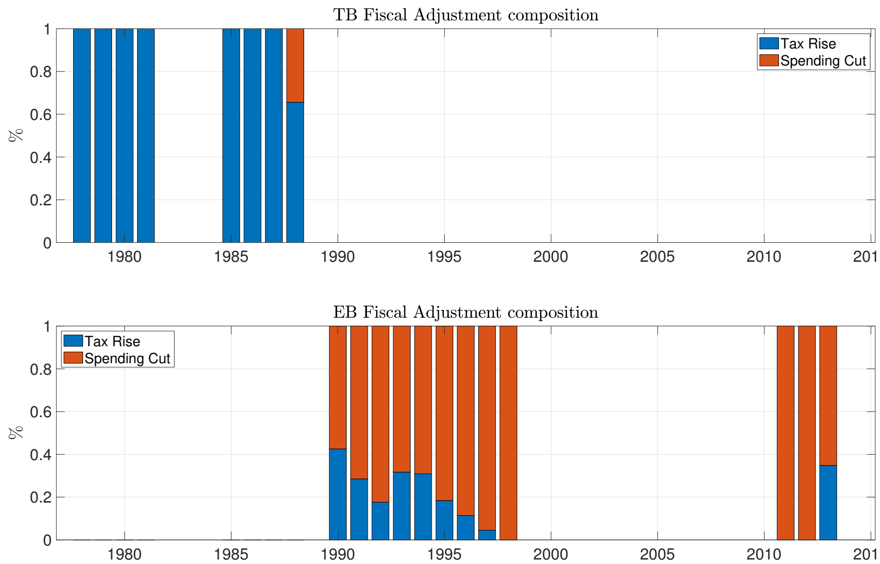
Figure 1: Fiscal Adjustments Database



Concerning when fiscal consolidations are implemented in the US, we identify: 1) two periods of tax-based fiscal adjustments, $TB_t = 1$, namely 1978-1981 and 1985-1988; 2) three periods of expenditure-based fiscal corrections, $EB_t = 1$, that is, 1990-1992, 1993-1998 and 2011-2013. The classification of a fiscal adjustment as either a TB or an EB plan is carried out by following the criterion outlined in Section 2. Figure 2 shows the composition of each total fiscal adjustment, $f_t^u + f_t^a + f_t^f$, in terms of tax increases and spending cuts.

Notice that EB plans are mainly made of spending cuts rather than tax hikes: on average, only 20% of them comes from a tax increase. On the other

Figure 2: Fiscal Adjustment Composition



hand, TB plans are all pure tax hikes except for the year 1988, which is the result of a hybrid fiscal plan where about 30% of it comes from spending cuts.

4 Estimation

Equation (3) is a static spatial autoregressive panel data model that allows for tracking the effect on industry output growth of EB and TB fiscal adjustment plans. Total adjustments are separated into their three components, and each component is allowed to have a different impact on output growth by allowing separate coefficients on the unexpected (τ^u and γ^u), announced (τ^a and γ^a) and future (τ^f and γ^f) components of the fiscal adjustments.
Equation (3) can be rewritten in this way:

$$\underset{n\times 1}{\Delta y_t} = \rho^{down} \cdot \underset{n\times n}{A_0} \cdot \underset{n\times 1}{\Delta y_t} \cdot TB_t + \rho^{up} \cdot \underset{n\times n}{\hat{A_0^T}} \cdot \underset{n\times 1}{\Delta y_t} \cdot EB_t + \underset{n\times(n+6)}{X_t} \cdot \underset{(n+6)\times 1}{\beta} + \varepsilon_t \quad (4)$$

where

$$X_t = \Big[\underbrace{I_n}_{Industry\ FE} \quad \underbrace{f_t^u \cdot TB_t \cdot \boldsymbol{\omega}_{TB} \quad f_t^a \cdot TB_t \cdot \boldsymbol{\omega}_{TB} \quad f_t^f \cdot TB_t \cdot \boldsymbol{\omega}_{TB}}_{TB\ Plans} \quad \underbrace{f_t^u \cdot EB_t \cdot \boldsymbol{\omega}_{EB} \quad f_t^a \cdot EB_t \cdot \boldsymbol{\omega}_{EB} \quad f_t^f \cdot EB_t \cdot \boldsymbol{\omega}_{EB}}_{EB\ Plans}\Big].$$

$$\beta = \begin{bmatrix}\boldsymbol{\alpha}^T & \boldsymbol{\tau}^T & \boldsymbol{\gamma}^T\end{bmatrix}^T$$

$$\nu_t \sim \mathcal{N}(\mathbf{0}_n, \Omega), \quad \Omega = diag(\sigma_1^2, ..., \sigma_n^2), \quad \varepsilon_t \perp \varepsilon_j \ \forall t \neq j.$$

We assume no serial correlation in the error term ε_t. Moreover, Δy_t is also serially uncorrelated; this assumption is motivated by the low persistence of yearly industry value-added growth rates, and it will be relaxed in section 5.1. Finally, notice that the error term is heteroskedastic to allow for different sectors' volatility, consistently with observed in the data.

Concerning the adoption of fiscal plans, we are aware of the criticism that focusing only on tax increases and spending cuts might cause upward bias in the fiscal multipliers' estimates.[12] However, our goal is not to estimate fiscal multipliers. We are looking at the effects of fiscal consolidations, a mixture of tax hikes and spending cuts implemented for deficit reduction reasons, during particular economic conjunctures. We are not censoring changes in "G" or "T", because we are looking at a different variable, namely f_t, fiscal consolidations. To be consistent with this view, we cannot claim that our estimates will be externally valid for a generic spending cut or tax increase, which is what the time series fiscal multipliers literature is interested in. However, if the US government will be willing to implement either a TB or EB deficit-driven fiscal consolidation, our estimates are valid and can be used as a guideline by policy-makers.

4.1 Bayesian MCMC and Statistical Details

The standard way to estimate the parameters of Equation (4) is via maximum likelihood; see LeSage and Pace (2009) for an introduction to spatial econometrics. The asymptotic and small sample properties of the MLE have been studied in Lee (2004) for cross-sectional data, and in Yu, DeJong, and Lee (2008), for dynamic panel data.
However, notice that we have two "prior" pieces of information on the value of the spatial parameters, ρ^{down} and ρ^{up}.
Firstly, the MLE of a spatial model is obtained by concentrating the log-likelihood with respect to the spatial parameters and then by maximizing over a set which ensures that the data have positive definite variance-covariance matrix (see Ord (1975)). In particular, we need to maximize over: $\left(\lambda_{min}^{-1}, \lambda_{max}^{-1}\right) \times \left(\hat{\lambda}_{min}^{-1}, \hat{\lambda}_{max}^{-1}\right)$ where λ_{min} is the smallest (negative) eigenvalue of A and λ_{max} is the largest (positive) eigenvalue of A. $\hat{\lambda}_{min}$ and $\hat{\lambda}_{max}$ are the same for matrix $\hat{A}^T$. Therefore the support of each spatial parameter is a narrow open interval

[12] We thank Valerie Ramey to make us aware of this risk and criticism.

on the real line. Values of ρ^{down} and ρ^{up} close to the boundaries will deliver unrealistically high values of ATE, ADE and ANE, since the determinant of matrices $(I_n - \rho^{down} \cdot A)$ and $(I_n - \rho^{down} \cdot A)$ will approach zero by definition of eigenvalue. In turn, the elements of their inverse matrices (Leontief Inverse) will tend to explode. Therefore, we should assign less weight to values of ρ^{down} and ρ^{up} close to the boundaries.
Secondly, we know that industries that are close to each other in the production network will co-move. For instance, if industry X faces increasing prices for its input, it will shrink production and increase prices; in turn, customers of X will also face the same problem and will react similarly, by reducing production and increasing prices. Therefore, the direction of the spatial correlation among industries' output is positive: $\rho^{down} > 0$ and $\rho^{up} > 0$.
We can integrate such prior information into our estimation, as well as avoid stationarity problems whose illustration goes beyond the (macroeconomic) scope of this paper, by adopting a Bayesian MCMC similar to the one introduced by LeSage and Parent (2007).
The technical details on the Bayesian MCMC are outlined in the Appendix; we report here only the priors we employ on the parameters of Equation (4):

$$
\begin{aligned}
&\pi(\beta) \propto constant \\
&\Omega = \sigma^2 \cdot V \quad \text{with } V = diag(v_1, ..., v_n) \\
&\pi(\sigma^2) \propto \frac{1}{\sigma^2} \\
&\pi(v_i) \overset{iid}{\sim} \Gamma^{-1}\left(\frac{r}{2}, \frac{r}{2}\right), \quad i = 1, ..., n \\
&\rho^{down} \sim Gen.Beta(d, d) \\
&\rho^{up} \sim Gen.Beta(d, d).
\end{aligned}
$$

We adopt non-informative priors for σ^2 and β to reflect our lack of information around the values of these parameters. Concerning r, a lower value generates more diffusion in the distributions of v_i, thus regulating our confidence towards heteroskedasticity. Unlike LeSage and Pace (2009), who suggest a value of 4, we set r equal to 3 to reflect a strong belief towards heteroskedasticity. For instance, industries in the Agriculture (NAICS 11) as well as Mining (NAICS 21) macro sectors, exhibit much higher volatilities than the rest of the industries.
We impose a "generalized (or non-standardized) $Beta(d, d)$ prior", with support from 0 to λ_{max}^{-1} for ρ^{down} and from 0 to $\hat{\lambda}_{max}^{-1}$ for ρ^{up}. We follow LeSage and Pace (2009) and set d equal to 1.1; which has the benefit of letting the generalized Beta prior to resemble a Uniform distribution (diffuse prior), but

with low density at the boundaries, as illustrated in Figure 3. The choice of

Figure 3: Generalized Beta prior

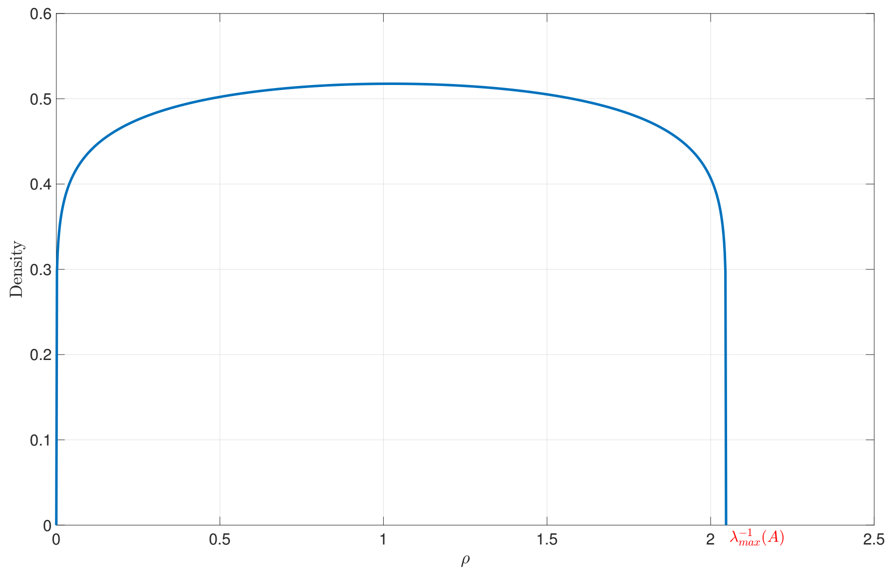


Figure 3: line-plot of a non-standardized $Beta(1.1, 1.1)$ *density function, with support from* $(0, \lambda^{-1}_{max}(A) = 2.047)$ *which we employ as a prior for the spatial parameter* ρ^{down}.

such a prior allows us to be agnostic about the specific value of the spatial parameters but at the same time it allows to embed the prior information we have into their estimates.

Before going to the estimation results, the discussion of some econometrics issues is in order.
In any standard spatial econometrics textbook or paper, researchers adopt weighting matrices for their networks which have two common features: 1) have zero entries on the main diagonal; 2) are row-stochastic.
The first assumption, a zero-entries main diagonal, reflects the lack in the data of spillovers within the same observed unit ("intra-unit feedback"). As long as observations are individuals, it does not make any sense to have non-zero entries on the main diagonal: an individual cannot trigger a spillover on itself. At the same time, row normalization is assumed because each individual has the same degree of connections within the network.
Concerning the first issue, in our estimation, we do not remove the main diagonal of A and $\hat{A}^T$, by replacing the observed entries with zeros. This is done

because our units of observations are industries, which are an aggregation of firms operating similar technologies, and that undertake intra-industry input-output relationships. This is confirmed by the observed heavily dense main diagonals in A and $\hat{A}^T$ (see Figure 5).

One concern of leaving the main diagonal is that it could create an endogenous regressor since the dependent variable now shows up also on the right-hand side of equation (4). This claim would be justified if the parameters were estimated via OLS, however, we employ spatial econometric techniques that are robust to this sort of endogeneity. Aquaro, Bailey, and Pesaran (2019) point out that a weighting matrix with zero entries on the main diagonal is simply a reparameterization of the spatial model and it does not affect the statistical properties of the estimators.[13]

Concerning the issue of row-normalization, in our estimation, we do not row-normalize A and $\hat{A}^T$. This is done because industries have different degrees of openness: the observed weighted in-degree and out-degree differ industry by industry. Some sectors rely more on industrial suppliers and customers than others. Aquaro, Bailey, and Pesaran (2019) propose a heterogenous spatial autoregressive (HSAR) model with unit-specific spatial parameters to cope with the problem that not all units are equally important or influential. Unlike them, we go for Bayesian MCMC and assume that there is only one intensity of propagation in the network, either ρ^{down} or ρ^{up}, but we do not row-normalize the weighting matrices to let each industry have its own intensity of connection.[14]

4.2 Baseline Empirical Results

We report in Table II descriptive statistics of the estimated posterior distributions of the parameters of interest of model (4), estimated via Bayesian MCMC. For completeness, we also report in the first two columns the maximum likelihood point estimates with their standard deviations constructed using the analytical Fisher Information matrix.

Firstly, looking at Table II we notice that the maximum likelihood estimates are very close to the expected value and standard deviation of the posterior distributions; a consequence of using mainly non-informative priors. Secondly, parameters $D2008$ and $D2009$ report the 2008 and 2009 year fixed effects; this is done to improve the precision of our estimates by capturing

[13] We are grateful to Hashem Pesaran for making us aware of this.

[14] We thank Lung-Fei Lee for pointing out to us that the assumptions of a row-stochastic weighting matrix as well as a zero-entries main diagonal in Yu, DeJong, and Lee (2008), are not necessary for their results, and can be easily relaxed.

Table II: Maximum Likelihood Estimates for the Baseline Model.

Parameters	MLE		Bayesian MCMC - Posterior Distributions:									
	$\hat{\theta}_i^{\text{ML}}$	MLE Std.	$\mathbb{E}(\theta_i)$	$\sqrt{\mathbb{V}(\theta_i)}$	$Pr(\theta_i < 0)$	5%	10%	16%	50%	84%	90%	95%
ρ^{down}	0.603	0.125	0.569	0.117	0.000	0.374	0.419	0.453	0.569	0.687	0.720	0.761
τ_u	0.411	1.278	0.555	1.196	0.322	-1.411	-0.971	-0.629	0.551	1.743	2.095	2.533
τ_a	-1.259	0.990	-1.294	0.930	0.917	-2.820	-2.488	-2.218	-1.295	-0.366	-0.100	0.237
τ_f	-0.192	0.432	-0.219	0.404	0.708	-0.887	-0.735	-0.621	-0.220	0.182	0.300	0.447
ρ^{up}	0.271	0.092	0.247	0.096	0.000	0.088	0.121	0.148	0.246	0.343	0.372	0.407
γ_u	-0.167	1.129	-0.132	1.046	0.551	-1.855	-1.460	-1.166	-0.130	0.907	1.207	1.582
γ_a	0.942	0.616	1.037	0.582	0.038	0.077	0.292	0.461	1.039	1.610	1.779	1.997
γ_f	-0.477	0.283	-0.482	0.261	0.968	-0.908	-0.817	-0.742	-0.481	-0.224	-0.148	-0.053
D2008	-2.941	0.671	-2.903	0.633	1.000	-3.946	-3.714	-3.532	-2.902	-2.274	-2.092	-1.861
D2009	-5.664	0.671	-5.326	0.658	1.000	-6.416	-6.173	-5.981	-5.321	-4.672	-4.488	-4.248

Table II: *θ_i denotes a generic parameter that we estimate. The columns report the following: $\hat{\theta}_i^{ML}$ is the ML point estimate; "MLE Std." is the standard deviation of the ML estimate, calculated using the analytical Fisher Information Matrix: $\sqrt{\mathcal{I}(\hat{\theta}^{ML})^{-1}_{ii}}$; $\mathbb{E}(\theta_i)$ is the expected value of the posterior distribution; $\sqrt{\mathbb{V}(\theta_i)}$ is the standard deviation of the posterior distribution; $Pr(\theta < 0)$ is the probability that a parameter is negative, calculated by integrating the posterior distribution; p% is the p-th percentile of the posterior distribution. For brevity we don't report here the Industry Fixed Effects and the Industry specific variances.*

the industry-wide dip caused by the Great Recession. Thirdly, notice that during years of TB consolidations the downstream spatial correlation is much stronger than the upstream one activated during EB fiscal consolidations, in fact, ρ^{down} is larger and more statistically significant (relatively smaller standard deviations) than ρ^{up}.

The ATE of fiscal adjustments and its decomposition into an ADE and ANE are constructed as specified in Section 2. Their posterior distributions are constructed via Monte-Carlo, by drawing parameters from their posterior distributions. The style of the plans, $\boldsymbol{s}_{TB}$ and $\boldsymbol{s}_{EB}$, which determines the composition of a fiscal plan in terms of unanticipated, anticipated, and future components, are randomly drawn at each iteration from a distribution which mimics the in-sample ones and that satisfies three conditions: 1) the overall size of a plan is 1%; 2) the anticipated component is zero; 3) it has a horizon of two years.[15] By doing so, our results are robust to different styles of fiscal plans and, therefore, are not driven by a specific redistribution of the 1% fiscal shock into this or that component of the plan.
Table III provides descriptive statistics of the posterior distributions of 2 years ATE, ADE and ANE.

First of all, notice that consistently with the new fact in the literature, we find that TB fiscal adjustments imply larger output losses, compared to EB consolidations: the expected value of ATE_{TB} is -1.397 against 0.370 of ATE_{EB}.

[15]See Appendix, section 7.5, for further information on the empirical distribution of the style of US fiscal plans.

Table III: The Average Output Effects of Fiscal Adjustment Plans

	$\mathbb{E}(\theta)$	%	$\sqrt{\mathbb{V}(\theta)}$	$Pr(\theta<0)$	5%	10%	16%	50%	84%	90%	95%
ATE_{TB}	-1.397	1	1.109	0.904	-3.297	-2.835	-2.487	-1.346	-0.308	-0.027	0.328
ADE_{TB}	-1.017	0.728	0.789	0.904	-2.327	-2.031	-1.798	-1.006	-0.238	-0.021	0.258
ANE_{TB}	-0.380	0.272	0.337	0.904	-1.014	-0.825	-0.694	-0.328	-0.066	-0.006	0.065
ATE_{EB}	0.370	1	0.371	0.152	-0.265	-0.103	0.014	0.386	0.727	0.825	0.950
ADE_{EB}	0.326	0.883	0.327	0.152	-0.225	-0.088	0.012	0.336	0.643	0.732	0.845
ANE_{EB}	0.043	0.117	0.052	0.152	-0.038	-0.014	0.001	0.041	0.090	0.106	0.130

Table III: *descriptive statistics of posterior distributions of Average Effects of a 1% fiscal plan. The style of the plan is simulated from a distribution which mimics the observed one; see Appendix for technical details. Columns:* $\mathbb{E}(\theta)$ *is the expected value of the posterior distribution; % is the share of ATE represented by ADE and ANE.* $\sqrt{\mathbb{V}(\theta)}$ *is the standard deviations of the posterior distribution;* $Pr(\theta < 0)$ *is the probability of negative values, calculated by integrating the posterior distribution; "p%" is the p-th percentile of the posterior distribution.*

This implies that a 2 years TB fiscal consolidation of 1% causes a cumulative average contraction of 1.397% over two years.
Secondly, 27.2% of ATE_{TB} comes from network spillovers, confirming the relevance of the industrial network in the transmission of the TB fiscal adjustments. On the other hand, the network propagation of an EB fiscal plan is much smaller, accounting for only 11.7% of ATE_{EB}. This finding partially answers the research question which motivated this paper: verify whether the larger output losses associated with TB consolidations could be imputed to different network effects. In addition to this, we also calculate how much differences in the network effects account for differences in the total effects of TB and EB consolidations, on average:

$$\frac{|\mathbb{E}(ANE_{TB}) - \mathbb{E}(ANE_{EB})|}{|\mathbb{E}(ATE_{TB}) - \mathbb{E}(ATE_{EB})|} = \frac{|-0.380 - 0.043|}{|-1.397 - 0.370|} \approx 25\% \tag{5}$$

Thirdly, the effect of an EB fiscal consolidation is recessionary only in the first year of implementation, while in the second year, when the announced part is implemented, the consolidation is on average expansionary, thus making the cumulative percentage change positive, even if not statistically different from zero. In fact, notice from Table II that only 3.8% of the values of the posterior distribution of γ_a takes on negative values. This result is in line with the overall consensus around the milder effects of EB consolidations, as documented also in Alesina, Favero, and Giavazzi (2020).

To summarize our first set of results: 1) we find stronger effects of TB fiscal consolidations, with an average two years contraction of -1.397%; 2) we find evidence of network effects of TB consolidations which, being mainly made of tax hikes (recall top panel of Figure 2), allows us to claim that we find evidence of downstream propagation of tax shocks, capable of explaining 27% of the overall contraction; 3) EB fiscal consolidations are not statistically different from zero, or else, they point at mild expansionary effects after two years; 4) 25% of the differences in the ATE of TB and EB plans can be attributed to differences in the network propagation.

5 Robustness

5.1 Dynamics

The baseline model specified by Equation (4) did not include any time lag. We adopted a fully static specification for at least two valid reasons: 1) our database is observed at yearly frequency; 2) industry value-added growth rates are not very persistent, in particular at the fine disaggregation level of 62 sectors. Nevertheless, few sectors still show a non-negligible degree of autocorrelation, therefore, we decided to check whether our results were robust to the inclusion of a lagged variable.

Adding a spatial lag to equation (4) yields:

$$\underset{n\times 1}{\Delta y_t} = \underbrace{\underset{n\times n}{\mathbf{\Phi}} \cdot \underset{n\times 1}{\Delta y_{t-1}}}_{\text{Time Linkage}} + \underbrace{\rho^{down} \cdot \underset{n\times n}{A} \cdot \underset{n\times 1}{\Delta y_t} \cdot TB_t + \rho^{up} \cdot \underset{n\times n}{\hat{A}^T} \cdot \underset{n\times 1}{\Delta y_t} \cdot EB_t}_{\text{Spatial Linkage}} + \underset{n\times(n+6)}{X_t} \cdot \underset{(n+6)\times 1}{\beta} + \nu_t \tag{6}$$

where $\mathbf{\Phi} = diag(\phi_1, \phi_2, ..., \phi_n)$, represents a diagonal autoregressive matrix. As done before, we also include year dummies for 2008 and 2009 to model the generalized large fall due to the Great Recession and gain precision.

The results are summarized by cumulative dynamic ATE, ADE and ANE, which now take the form of impulse response functions. The "shock" is constructed by simulating a two years fiscal adjustment plan of 1% of GDP, exactly as done earlier to derive our static baseline results, that is, by drawing different styles from a distribution which mimics the one observed in our sample.

The median of the posterior distribution of the cumulative impulse response functions are reported in Table IV:

Table IV: Cumulative Impulse Response Function

	1 year	%	*2 years*	%	⋯	*Long Run*	%
ATE_{TB}	-0.695	100%	-1.865	100%	⋯	-2.351	100%
ADE_{TB}	-0.526	76.7%	-1.403	75.2%	⋯	-1.683	71.6%
ANE_{TB}	-0.162	23.3%	-0.445	24.8%	⋯	-0.644	28.4%
ATE_{EB}	-0.523	100%	0.486	100%	⋯	0.628	100%
ADE_{EB}	-0.472	90.2%	0.433	89.1%	⋯	0.573	91.2%
ANE_{EB}	-0.049	9.8%	0.041	10.9%	⋯	0.063	8.8%

Similarly, Figure 4 plots the median cumulative impulse response functions with confidence bands represented by the 5^{th} and 95^{th} percentile of their posterior distributions:

Figure 4: Cumulative Impulse Response Functions

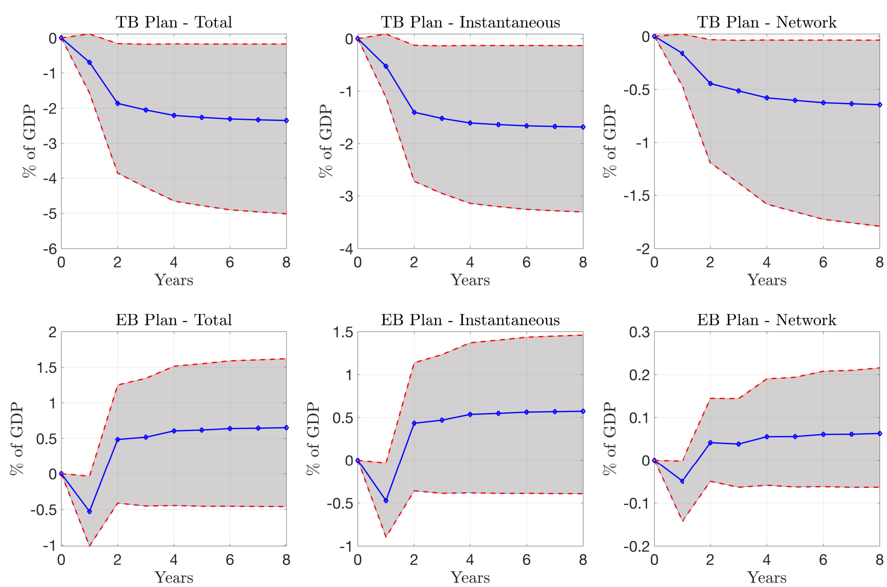


Figure 4: Confidence intervals (red dotted lines) are constructed taking the 5^{th} and 95^{th} percentiles of the posterior distributions.

Notice that after year 2, the end of the fiscal consolidation, the dynamic response is minimal, corroborating our static analysis. In general, the effects are slightly larger in year 2 compared to the ones estimated in the static model and reported in Table III. Except for this, the results are comparable: 1) TB fiscal consolidations are recessionary and statistically different from zero; 2) the network effect is around one-fourth of the total effect of a TB plan; 3) EB fiscal consolidations have a minor network effect in the order of 10% of the total effect; 4) EB fiscal consolidations seem to be expansionary, but nothing can be concluded since they are not statistically different from zero.

We conclude this section by highlighting one fact: from Table IV we notice that the relevance of ANE_{TB} increases over time, from 23.3% to 28.4% in the long-run. This could be indicative of *delayed network effects*. Suppose a price shock takes longer than a year to travel from one sector to another, then the relevance of the network effect will increase over time since the spillover takes time to kick-in. For instance, Smets, Tielens, and Van Hove (2019) show that the autocorrelation between inflation in crude oil's price and synthetic rubber's price spikes after three months, then the autocorrelation between inflation in synthetic rubber's price and tires' price also spikes after three months but, the autocorrelation between inflation in tires' price and transport costs, spikes after 16 months. Therefore downstream propagation of price changes does seem to have delayed effects which might explain why we observe an increasing relevance over time of the network effect of TB fiscal adjustments. However, more research on the timing of the network effects is needed to draw any conclusion.

5.2 Inverted propagation channels

As anticipated in Section 2, our baseline model (4) interacts the TB fiscal plans with the downstream spatial variable: $A \cdot \Delta y_t \cdot TB_t$. Such interaction is consistent with what was theoretically predicted by our model, which is a slight modification of the one in Acemoglu, Akcigit, and Kerr (2016). In particular, we interpret a TB fiscal consolidation as a supply shock that propagates downstream via the price mechanism, behaving as the productivity shock of their model.

Similarly, we interpreted an EB plan as a pure demand shock, which, according to the aforementioned theoretical model, should propagate upstream in the network, from customers to suppliers, via the demand-change mechanism. Because of this, in our baseline analysis we interacted the EB fiscal plans with the upstream spatial variable: $\hat{A}^T \cdot \Delta y_t \cdot EB_t$.

However, there are good reasons to believe that fiscal plans might also propagate the other way around. Firstly, even if TB plans are almost purely made by tax hikes (recall Figure 2), tax shocks might behave also as demand shocks thus propagating upstream in the network. Secondly, EB fiscal consolidations

are mainly made of spending cuts, however, one-fifth of them come from tax increases on average (recall again Figure 2), therefore, they could still inherit part of the downstream transmission from their tax components.
In order to detect network effects which move in a less theoretically intuitive fashion, we repropose here the same estimates of Section 4.2 by "switching the order of the dummies": we now interact the upstream spatial variable with TB fiscal consolidations, $\hat{A}^T \cdot \Delta y_t \cdot TB_t$, and the downstream spatial variable with EB fiscal consolidations $A \cdot \Delta y_t \cdot EB_t$.
Notice that this is also a robustness check: if we obtained results completely flipped relative to the baseline - stronger effects and network propagation of EB plans - this would indicate that results are driven entirely by the theoretical interaction we impose. On the other hand, if we found similar but less statistically significant results, this would be indicative of two things: 1) our baseline results are robust to different specification of network interaction and are not driven by the specific theoretical direction we assume; 2) there is evidence in support of a mainly downstream propagation of TB plans and a mainly upstream propagation of EB plans, in accordance with the theory.
Table V reports the estimation outcome for the inverted model:

Table V: Maximum Likelihood Estimates for the Inverted Model

Parameters	MLE		Bayesian MCMC - Posterior Distributions:									
	$\hat{\theta}_i^{\mathrm{ML}}$	MLE Std.	$\mathbb{E}(\theta_i)$	$\sqrt{\mathbb{V}(\theta_i)}$	$Pr(\theta_i < 0)$	5%	10%	16%	50%	84%	90%	95%
ρ^{up}	0.554	0.103	0.528	0.097	0.000	0.368	0.405	0.432	0.528	0.625	0.653	0.687
τ_u	0.684	1.283	0.815	1.193	0.247	-1.143	-0.712	-0.372	0.814	2.002	2.351	2.778
τ_a	-1.298	0.986	-1.290	0.919	0.920	-2.794	-2.463	-2.202	-1.293	-0.382	-0.112	0.225
τ_f	-0.080	0.426	-0.084	0.391	0.585	-0.726	-0.585	-0.474	-0.082	0.301	0.415	0.562
ρ^{down}	0.096	0.114	0.125	0.083	0.000	0.014	0.026	0.040	0.112	0.211	0.241	0.281
γ_u	0.073	1.126	0.050	1.034	0.480	-1.650	-1.272	-0.973	0.051	1.073	1.370	1.760
γ_a	1.286	0.617	1.296	0.567	0.011	0.361	0.572	0.732	1.295	1.861	2.023	2.226
γ_f	-0.502	0.282	-0.499	0.259	0.973	-0.923	-0.831	-0.757	-0.499	-0.241	-0.169	-0.075
D2008	-2.984	0.674	-2.934	0.633	1.000	-3.973	-3.744	-3.562	-2.936	-2.307	-2.120	-1.891
D2009	-5.710	0.674	-5.371	0.661	1.000	-6.469	-6.216	-6.025	-5.368	-4.717	-4.529	-4.290

Table V: *θ_i denotes a generic parameter that we estimate. The columns report the following: $\hat{\theta}_i^{ML}$ is the ML point estimate; "MLE Std." is the standard deviation of the ML estimate, calculated using the analytical Fisher Information Matrix: $\sqrt{\mathcal{I}(\hat{\theta}^{ML})^{-1}_{ii}}$; $\mathbb{E}(\theta_i)$ is the expected value of the posterior distribution; $\sqrt{\mathbb{V}(\theta_i)}$ is the standard deviation of the posterior distribution; $Pr(\theta < 0)$ is the probability that a parameter is negative, calculated by integrating the posterior distribution; p% is the p-th percentile of the posterior distribution. For brevity we don't report here the Industry Fixed Effects and the Industry specific variances.*

From Table V we notice immediately that the estimates are quite similar to the ones of the baseline model reported in Table II. However, notice that the spatial coefficients estimates are now smaller and less precise.
We then calculate the ATE, ADE and ANE for both types of fiscal consolidations and report the descriptive statistics of their posterior distributions in Table VI. Firstly, notice from Table VI that the ATE_{TB} is now quantitatively

Table VI: The Average Output Effects of Fiscal Adjustment Plans - Inverted Model

	$\mathbb{E}(\theta)$	%	$\sqrt{\mathbb{V}(\theta)}$	$Pr(\theta < 0)$	*5%*	*10%*	*16%*	*50%*	*84%*	*90%*	*95%*
ATE_{TB}	-1.148	1	1.034	0.872	-2.909	-2.481	-2.162	-1.107	-0.131	0.140	0.480
ADE_{TB}	-0.848	0.738	0.756	0.872	-2.106	-1.819	-1.593	-0.835	-0.101	0.107	0.375
ANE_{TB}	-0.300	0.262	0.290	0.872	-0.828	-0.682	-0.572	-0.263	-0.029	0.030	0.102
ATE_{EB}	0.522	1	0.337	0.064	-0.048	0.096	0.203	0.536	0.847	0.936	1.046
ADE_{EB}	0.491	0.940	0.318	0.064	-0.044	0.089	0.188	0.501	0.799	0.886	0.990
ANE_{EB}	0.031	0.060	0.032	0.064	-0.002	0.002	0.005	0.024	0.059	0.073	0.091

Table VI: *descriptive statistics of posterior distributions of Average Effects of a 1% fiscal plan. The style of the plan is simulated from a distribution which mimics the observed one; see Appendix for technical details. Columns:* $\mathbb{E}(\theta)$ *is the expected value of the posterior distribution; % is the share of ATE represented by ADE and ANE.* $\sqrt{\mathbb{V}(\theta)}$ *is the standard deviations of the posterior distribution;* $Pr(\theta < 0)$ *is the probability of negative values, calculated by integrating the posterior distribution; "p%" is the p-th percentile of the posterior distribution.*

smaller and less statistically significant. The ANE_{TB} is also slightly smaller, but still quite close to the one observed in the baseline case. Overall, this result is indicative of a mildly worse fit of the inverted transmission relative to the baseline.

Interestingly, ATE_{EB} becomes larger and statistically significant, however, all the increase in the effect comes from ADE_{EB}, since ANE_{EB} effect is now halved on average, suggesting a weaker transmission of EB plans when forced to propagate downstream, against what would be more theoretically appropriate. A potential theoretical explanation to this stronger effect might come from the results of Bouakez, Rachedi, Emiliano, et al. (2018): spending cuts might reduce the price of goods, thus generating a positive downstream spillover which might boost demand for other goods, and therefore increase ATE_{EB}. In Bouakez, Rachedi, Emiliano, et al. (2018)'s model, this opposite direction downstream propagation effect is small and fully outweighed, as anticipated earlier, by the other upstream spillover (the effect of the negative demand shock); this is in line with a smaller value of ANE_{EB}.

5.3 Placebo Experiments

The main result of this paper is to record for the first time the downstream propagation of taxes, by observing significant ANE of TB fiscal consolidations. It is therefore worth exploring in more detail this result.

First of all, we plot in Figure 5 the downstream network A associated with the downstream propagation of TB fiscal consolidations. Recall from Section 2 that the generic element a_{ij} is given by the reliance of sector i (row) on industrial input j (column): $SALES_{j\to i}/SALES_i$.

Figure 5: Small, medium and large elements of Downstream Network A

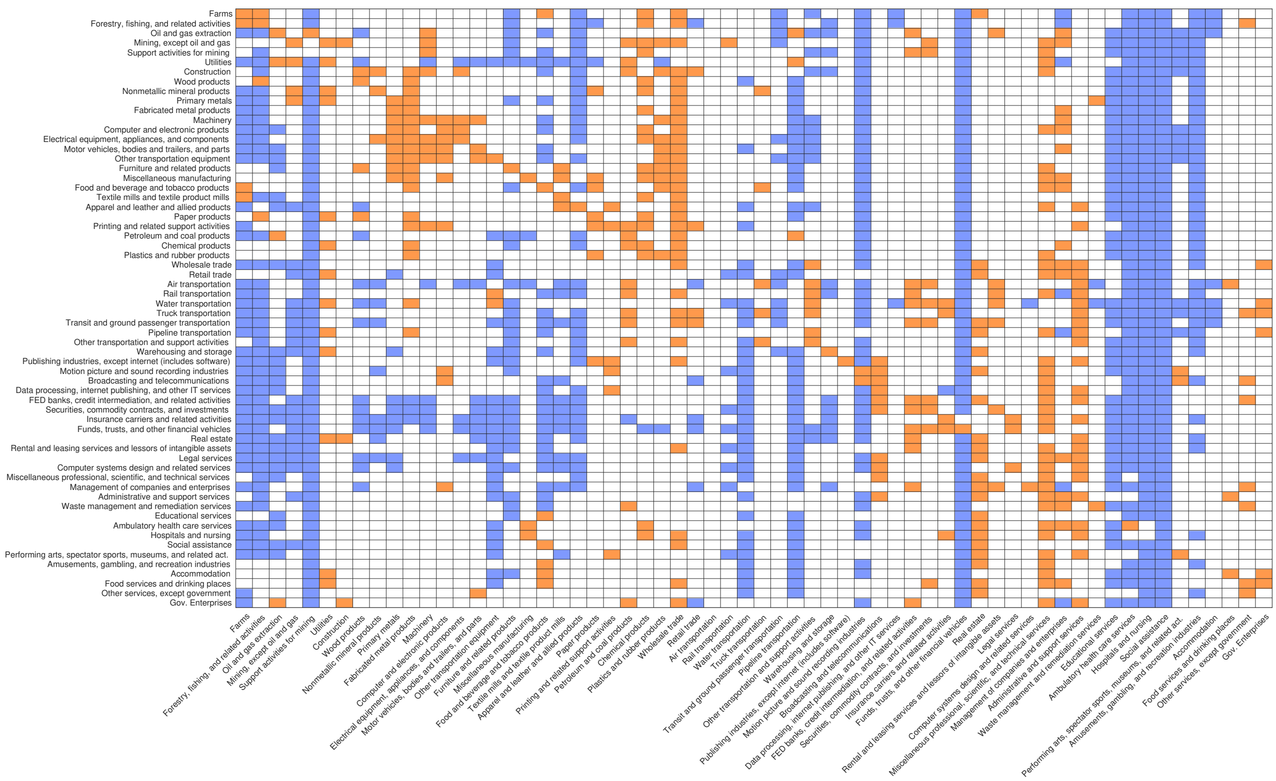


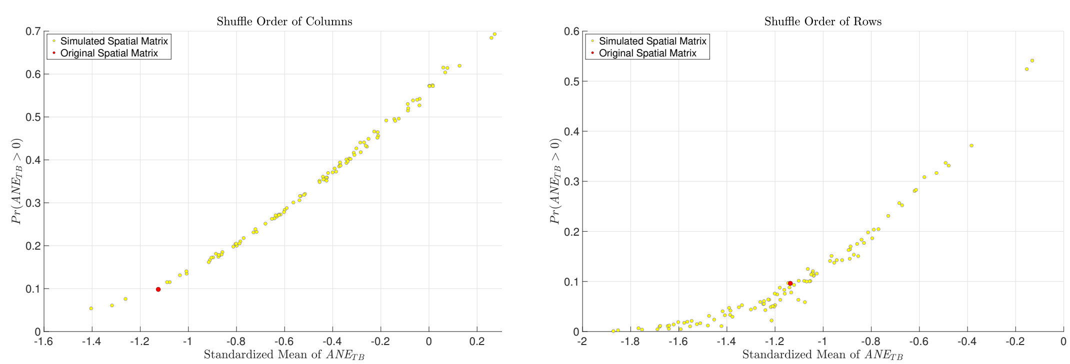
Figure 5 is a "threshold heat-map" which reports a blue cell if $a_{ij} < 0.0001$, an orange cell if $a_{ij} > 0.03$ and a white cell otherwise.[16] Two facts are salient from this "X-ray" of the downstream network. Firstly, the columns of A tend to contain either only very small or only very large values. Secondly, the rows of A do not exhibit such a pattern. In other words, some sectors, such as "Social Assistance" or "Motion Picture and Sound Recording Industries", produce an output that is either not employed at all as an intermediate by other sectors, or it is employed only in minor quantity. Unlike them, some other sectors, such as "Wholesale Trade" and "Miscellaneous Professional, Scientific and Technical Services", produce an output which is a key input of production for many sectors. The bottom line is that the US downstream network is characterized by the presence of key suppliers and the lack of key customers. This asymmetric nature of the I-O connections is a well-known feature in the

[16]The choice of 0.0001 is motivated by the presence of several values of A which are close to zero but not exactly zero. The choice of 0.03 is motivated by the presence of only a few values above this threshold. In general, tweaking these numbers still allows observing such a visual pattern of matrix A.

production network literature (see Acemoglu, Carvalho, et al. (2012)).

An interesting robustness exercise is to see what happens to our estimates if we employ simulated network matrices that break this pattern. We run several baseline simulations via Bayesian MCMC by employing simulated downstream matrices ("placebo") and compare their results with the original one.
In the first "placebo experiment", we randomly shuffle the order of the columns of A and create 100 simulated downstream matrices. This random permutation of the columns allows us to break that natural equilibrium in which some sectors behave as key suppliers and others are marginalized. In fact, in this first simulation, some real-world key supplier might be forced to behave as a peripheral sector and vice-versa. Therefore we expect less statistically significant results.
Notice that in a Bayesian framework it is not fully correct to talk about statistical significance, however, with a little abuse of terminology we state that the ANE_{TB} is more statistically significant if the values of $\mathbb{E}(ATE_{TB})/\sqrt{\mathbb{V}(ATE_{TB})}$ and $Pr(ATE_{TB} > 0)$ are both smaller. The first measure represents how many standard deviations we need to obtain the average ANE_{TB}: the smaller it is, the more likely is to obtain sizable negative spillovers. The second measure is simply the probability of obtaining a nonnegative network effect: the smaller it is, the higher the chances of getting recessionary spillovers.
Figure 6 plots on the horizontal axis the first measure and on the vertical axis the second one. The red dot represents the values obtained by employing the original matrix, which can be found in Table III. In particular, the left panel reports the results of the experiment of shuffling the order of the columns: the red-dot is located in the South-West region of the graph, indicative of more significant spillover effects.

Figure 6: Placebo Experiment on ANE_{TB}



In addition to shuffling the columns, we also carry out a second placebo experiment by shuffling the order of the rows of A. Unlike the first experiment, reshuffling the elements within a column (shuffle the order of the rows) does not break the aforementioned characterizing pattern of the US downstream network. Sectors that originally were key suppliers will still behave in the same way. The same is true for peripheral sectors. We are reshuffling elements with similar magnitude along a column of A. Therefore, we expect to record both stronger and weaker results in terms of statistical significance. This is confirmed by the right panel of Figure 6, where the red-dot is located almost in the middle of the cloud of simulations' results. Slightly more dots are located more South-West than the original simulation; this is not surprising if we think that we are moving the large elements of the main diagonal (see heat-map 5) outside of it, thus mechanically inflating the indirect spillover of the sector receiving the main diagonal entry.

We highlight that these three steps procedure (simulation of network matrices, re-estimation, and comparison with the original values) is analogous to Ozdagli and Weber (2017). Unlike them, our "placebo" matrices are simulated in a simpler way by simply reshuffling the orders of the columns and rows.
Our procedure has the benefit of preserving the original elements of the network matrices, thus matching one to one both the distribution of the original elements a_{ij}, as well as its sparsity (number of zero entries). Unlike the original network A, the placebo matrices do not have large entries on the main diagonal in either simulation ("dense main diagonal").
Concerning the first order weighted in-degrees ($A \cdot \mathbf{1}_n$) we have that the placebo matrices will exactly match it in the first simulation (shuffling the columns) while in the second one (shuffling the rows), the values are the same but they are assigned to different industries.
The second-order weighted in-degrees ($A^2 \cdot \mathbf{1}_n$) are not matched in either simulation, but the shape of their distribution is similar to the original one. Table VII summarizes the results.

Ozdagli and Weber (2017) conclude that matching the first and second order out-degree is not sufficient to justify the strong upstream propagation of monetary policy shocks. In fact, they say, matching the properties of the network industry by industry is necessary to obtain a strong network effect. We achieve the same conclusion in the context of downstream propagation of TB fiscal consolidations, measured by ANE_{TB}, by means of an easier experiment, namely shuffling the order of rows and columns.

Table VII: Placebo Experiment Results

Network Features:	*Shuffling the Columns*	*Shuffling the Rows*
Sparsity	*same*	*same*
Distribution of a_{ij}	*same*	*same*
Dense Main Diagonal	*no*	*no*
1^{st} *Weighted In-degree*	*same values*	*same distribution*
2^{nd} *Weighted In-degree*	*similar distribution*	*similar distribution*
Key Suppliers	*same*	*different*
Peripheral Suppliers	*same*	*different*
Is original ANE_{TB} *stronger?*	*yes*	*no*

6 Conclusions

This paper has investigated the effects of fiscal consolidations in the US from 1978 onward and their transmission via the industrial network.

We have found stronger effects of tax-based fiscal adjustments, with an average contraction over two years of about -1.4% of value-added, following an adjustment of one percent of GDP. 27% of this effect can be imputed to downstream spillovers from a supplying industry to a customer one. In addition, as TB plans are made almost entirely by tax increases, we claim to be the first to have detected significant statistical evidence for downstream propagation of tax shocks.

On the contrary, we find no evidence for a statistically significant recessionary impact of fiscal consolidations achieved by means of spending cuts. Our evidence points to mild expansionary effects. Furthermore, only 11% of it comes from an upstream network transmission which is non-robust to an inverted direction of propagation: no network spillovers are detected when EB plans are let travel downstream in the network.

We find that almost one-fourth of the different average total effects of TB and EB fiscal consolidations can be explained by stronger network spillovers of the former, thus confirming only partially our initial hypothesis. Moreover, placebo experiments find that such a network effect of TB fiscal plans are originated from the presence of key suppliers in the economy and does not hinge on the particular shape of the distribution of first and second-order in-degrees of the network. When those key suppliers are forced to behave as peripheral suppliers the downstream propagation of TB plans vanishes or becomes significantly weaker.

The analysis of the propagation of an aggregate macroeconomic shock within an economy is a novel approach, and, to the best of our knowledge, can be found only in Ozdagli and Weber (2017). The spatial framework is used to control for the spatial correlation among the units, industries in our case, originating from an underlying structural network, and allows the breakdown of the total aggregate effect into a direct and a network effect.
Overall, our research fits into that recent trend which aims at bridging micro and macro by breaking down an aggregate economy into its sectoral levels, thus increasing our comprehension of how aggregate shocks propagate and affect the economy. In terms of policy implications, we provide further evidence, that a fiscal consolidation based on spending cuts should be preferred over one based on tax hikes, partly because smaller negative spillovers reduce the overall output cost.
We plan further research on the timing of the propagation, as well as on the heterogeneous effects of fiscal policy and their implications for optimal policymaking. Particular attention should be paid towards the role played by those key suppliers of the economy in propagating tax shocks.

References

[1] Daron Acemoglu, Ufuk Akcigit, and William Kerr. "Networks and the macroeconomy: An empirical exploration." In: *NBER Macroeconomics Annual* 30.1 (2016), pp. 273–335. DOI: 10.1086/685961.

[2] Daron Acemoglu, Vasco Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. "The network origins of aggregate fluctuations." In: *Econometrica* 80.5 (2012), pp. 1977–2016. DOI: 10.3982/ECTA9623.

[3] Alberto Alesina, Omar Barbiero, Carlo Favero, Francesco Giavazzi, and Matteo Paradisi. "The effects of fiscal consolidations: Theory and evidence." In: (2017). DOI: 10.3386/w23385.

[4] Alberto Alesina, Carlo Favero, and Francesco Giavazzi. *Austerity: When it Works and when it Doesn't*. Princeton University Press, 2020.

[5] Alberto Alesina, Carlo Favero, and Francesco Giavazzi. "The output effect of fiscal consolidation plans." In: *Journal of International Economics* 96 (2015), S19–S42. DOI: 10.1016/j.jinteco.2014.11.003.

[6] Michele Aquaro, Natalia Bailey, and M Hashem Pesaran. "Estimation and inference for spatial models with heterogeneous coefficients: an application to US house prices." In: *USC-INET Research Paper* 19-07 (2019).

[7] Alan J Auerbach, Yuriy Gorodnichenko, and Daniel Murphy. *Local Fiscal Multipliers and Fiscal Spillovers in the United States*. Tech. rep. National Bureau of Economic Research, 2019. DOI: 10.3386/w25457.

[8] Hafedh Bouakez, Omar Rachedi, Santoro Emiliano, et al. "Sectoral heterogeneity, production networks, and the effects of government spending." In: *Cahiers de recherche. Centre interuniversitaire de recherche en economie quantitative, CIREQ* (2018).

[9] Vasco Carvalho. "Aggregate fluctuations and the network structure of intersectoral trade." In: (2007).

[10] Vasco Carvalho. "From micro to macro via production networks." In: *Journal of Economic Perspectives* 28.4 (2014), pp. 23–48. DOI: 10.1257/jep.28.4.23.

[11] Vasco Carvalho and Alireza Tahbaz-Salehi. "Production networks: A primer." In: *Annual Review of Economics* 11 (2019), pp. 635–663.

[12] Lydia Cox, Gernot Muller, Ernesto Pasten, Raphael Schoenle, and Michael Weber. *Big g*. Tech. rep. National Bureau of Economic Research, 2020.

[13] Xavier Gabaix. "The granular origins of aggregate fluctuations." In: *Econometrica* 79.3 (2011), pp. 733–772. DOI: 10.3982/ECTA8769.

[14] Jaime Guajardo, Daniel Leigh, and Andrea Pescatori. "Expansionary austerity? International evidence." In: *Journal of the European Economic Association* 12.4 (2014), pp. 949–968. DOI: 10.1111/jeea.12083.

[15] Galina Hale, Tumer Kapan, and Camelia Minoiu. "Shock transmission through cross-border bank lending: Credit and real effects." In: (2019). DOI: 10.17016/FEDS.2019.052.

[16] Karen J Horowitz, Mark A Planting, et al. *Concepts and Methods of the us input-Output Accounts*. Tech. rep. Bureau of Economic Analysis, 2006.

[17] Madina Karamysheva. "How Do Fiscal Adjustments Work? An Empirical Investigation." In: (2019). DOI: 10.2139/ssrn.3512027.

[18] LungFei Lee. "Asymptotic distributions of quasi-maximum likelihood estimators for spatial autoregressive models." In: *Econometrica* 72.6 (2004), pp. 1899–1925.

[19] James LeSage. "Bayesian estimation of spatial autoregressive models." In: *International Regional Science Review* 20.1-2 (1997), pp. 113–129. DOI: 10.1177/016001769702000107.

[20] James LeSage and Robert Pace. "Introduction to spatial econometrics." In: (2009). DOI: 10.1111/j.1538-4632.2010.00797.x.

[21] James LeSage and Olivier Parent. "Bayesian model averaging for spatial econometric models." In: *Geographical Analysis* 39.3 (2007), pp. 241–267. DOI: 10.1111/j.1538-4632.2007.00703.x.

[22] Christopher J Nekarda and Valerie A Ramey. "Industry evidence on the effects of government spending." In: *American Economic Journal: Macroeconomics* 3.1 (2011), pp. 36–59.

[23] Keith Ord. "Estimation methods for models of spatial interaction." In: *Journal of the American Statistical Association* 70.349 (1975), pp. 120–126. DOI: 10.1080/01621459.1975.10480272.

[24] Ali Ozdagli and Michael Weber. "Monetary policy through production networks: Evidence from the stock market." In: (2017). DOI: 10.3386/w23424.

[25] Roberto Perotti. "In search of the transmission mechanism of fiscal policy." In: *NBER Macroeconomics Annual, Chicago University Press* 22.1 (2007), pp. 169–226.

[26] Andrea Pescatori, Mr Daniel Leigh, Jaime Guajardo, and Mr Pete Devries. "A new action-based dataset of fiscal consolidation." In: 11-128 (2011). DOI: 10.5089/9781462346561.001.A001.

[27] Valerie A Ramey. "Ten years after the financial crisis: What have we learned from the renaissance in fiscal research?" In: *Journal of Economic Perspectives* 33.2 (2019), pp. 89–114.

[28] Valerie A Ramey and Matthew D Shapiro. *Costly capital reallocation and the effects of government spending*. Tech. rep. National Bureau of Economic Research, 1999.

[29] Christina D Romer and David H Romer. "The macroeconomic effects of tax changes: estimates based on a new measure of fiscal shocks." In: *American Economic Review* 100.3 (2010), pp. 763–801. DOI: 10.1257/aer.100.3.763.

[30] Frank Smets, Joris Tielens, and Jan Van Hove. "Pipeline pressures and sectoral inflation dynamics." In: (2019). DOI: 10.2139/ssrn.3346371.

[31] Jihai Yu, Robert DeJong, and LungFei Lee. "Quasi-maximum likelihood estimators for spatial dynamic panel data with fixed effects when both n and T are large." In: *Journal of Econometrics* 146.1 (2008), pp. 118–134.

7 Appendix

7.1 Theoretical Framework

We show here the theoretical framework which we have in mind when we refer to the theoretical transmission of demand and supply shocks. The model is a slight modification of Acemoglu, Akcigit, and Kerr (2016), which we adapted to allow for the propagation of a production tax.

The model considers a perfectly competitive economy with n sectors, where the market clearing condition for the generic industry i is:

$$y_i = c_i + \sum_{j=1}^{n} x_{ji} + G_i \tag{7}$$

where c_i is household's consumption of good produced by industry i; x_{ij}[17] is the quantity of goods produced in industry j used as inputs by industry i; G_i are government purchases, funded by imposing either a lump sum or a sales-type tax:[18]

$$\sum_{i=1}^{n} p_i G_i = T + \tau \sum_{i=1}^{n} p_i y_i \tag{8}$$

Each sector solves the following profit maximization problem:

$$\max_{l_i, \{x_{ij}\}_{j=1}^{n}} (1-\tau) \cdot p_i \cdot y_i - w l_i - \sum_{j=1}^{n} p_j x_{ij}$$

with a production function similar to the one in Acemoglu, Carvalho, et al. (2012) and Carvalho (2014):[19]

$$y_i = l_i^{\alpha_i^l} \cdot \big(\prod_{j=1}^{n} x_{ij}^{\alpha_{ij}}\big)^{\rho}$$

[17]In Equation (7) we actually have x_{ji}, that is, the amount of good i used as input by industry j; we then sum over the j-s to obtain the total demand of good i from all the industries.

[18]For example, an excise is a special type of sales tax, which is sector-specific. Excise tax might be of two types: ad valorem (percentage of values of a good) and specific (tax paid per unit). The excise tax may be paid by the producer, retailer, and consumer. Moreover, it might be taken on federal, state, and local levels.

[19]We omit the productivity component because we are not interested in studying productivity shocks.

All alpha's are non negative, and we assume constant return to scale: $\alpha_i^l + \rho \cdot \sum_{j=1}^n a_{ij} = 1$. Notice here, that thanks to the Cobb-Douglas specification, ρ can be interpreted as the share of intermediates in production.

The economy is populated by a representative agent, who maximizes utility subject to a budget constraint:

$$\max_{l,\{c_i\}_{i=1}^n} (1-l)^\lambda \cdot \prod_{i=1}^n c_i^{\beta_i}$$
$$\text{s.t.} \sum_{i=1}^n p_i c_i \leq wl - T$$

with $\sum_{i=1}^n \beta_i = 1$.
Firms and households take all prices as given, and the market-clearing conditions are satisfied in the goods market and the labor market. Government actions are taken as given and the wage is chosen as a numeraire $(w = 1)$.

Network effect of a tax shock

By log-differentiating the equations which characterize the equilibrium the following closed-form expression of a tax shock effect is obtained:[20]

$$d\log y_i = d\log(1-\tau) + \alpha_i^l \cdot d\log(1-T) + \rho \underbrace{\cdot \sum_{j=1}^n a_{ij} \cdot d\log y_j}_{\text{downstream spatial variable}} \tag{9}$$

Now, we introduce the input-output matrix A which collects all the coefficients of the Cobb-Douglas production function, in this way we can rewrite equation (9) in matrix form:

$$\underset{n\times 1}{d\log \mathbf{y}} = \mathbf{1}_n \cdot d\log(1-\tau) + \underset{n\times 1}{\boldsymbol{\alpha}^l} \cdot d\log(1-T) + \rho \cdot \underset{n\times n}{A} \cdot \underset{n\times 1}{d\log \mathbf{y}}, \tag{10}$$

where $\mathbf{1}_n$ denotes a column vector of ones of length n.
The above expression can be simplified by collecting the dependent variable $d\log \boldsymbol{y}$ on the left hand side of the expression. By doing this, we obtain the following closed form expression[21]:

$$d\log \boldsymbol{y} = -\underbrace{(I_n - \rho \cdot A)^{-1} \cdot \mathbf{1}_n}_{\text{downstream propagation}} \cdot \frac{\tau}{1-\tau} \cdot d\log \tau - \mathbf{1}_n \frac{T}{1-T} \cdot d\log T \tag{11}$$

[20] Along this section we assume both $G_i = 0$ and $dG = 0$: no change in government spending and taxes are financed with a negative lump sum transfer T which behaves as a tax deduction.

[21] Thanks to Cobb-Douglas functional form assumption, $(I_n - \rho \cdot A)^{-1} \cdot \boldsymbol{\alpha}^l = \mathbf{1}_n$

The sectoral propagation of a tax adjustment is driven by the elements in the rows of the matrix $H := (I_n - \rho \cdot A)^{-1}$, which represents the Leontief inverse matrix. Notice that $H \cdot \mathbf{1}_n = \mathbf{1}_n + \rho \cdot A \cdot \mathbf{1}_n + \rho^2 \cdot A^2 \cdot \mathbf{1}_n + ...$, therefore, the downstream propagation depends on the rows of A, and describe how much intermediates sector i purchases from all other sectors. We can see this from the FOC of firm i with respect to x_{ij}:

$$a_{ij} \propto \frac{p_j \cdot x_{ij}}{p_i \cdot y_i} \approx \frac{\text{SALES}_{j \to i}}{\text{SALES}_i} \tag{12}$$

Therefore, the network propagation mechanism of a sales-type tax shock propagates downstream: at first each sector is hit by a tax shock; then firms re-optimize and increase their own price; by consequence, customer-industries face higher prices of their inputs and therefore need to also increase their own price, thus triggering a cascade effect which moves downstream from the top of the production network. This mechanism is also illustrated in our theoretical setting by the expression:

$$d \log \boldsymbol{p} = \frac{\tau}{1 - \tau} \cdot H \cdot \mathbf{1}_n \cdot d \log \tau, \tag{13}$$

where $d \log \boldsymbol{p}$ represents the vector of price changes. Notice that, prices change only in response to a tax shock. Basically, in our setting, a tax shock is the analogue of a productivity shock in Acemoglu, Akcigit, and Kerr (2016) and Carvalho (2014): it is a supply side shock which generates spillovers that trickle down to the bottom of the supply chain via production network through the price mechanism.

Network effect of a spending shock

Now let's move to government spending shocks and assume that both $\tau = 0$ and $d\tau = 0$. Except for the inclusion of parameter ρ and a slightly different notation, the following derivations are one to one found in Acemoglu, Akcigit, and Kerr (2016); we repeat them for the sake of clarity of the exposition. After log-differentiating the equations that characterize the equilibrium of the model described above, we obtain the following expression:

$$d \log y_i = -\frac{\beta_i}{1 + \lambda} \cdot \sum_{j=1}^{n} \cdot \frac{p_j \cdot y_j}{p_i \cdot y_i} \cdot d\tilde{G}_j + \underbrace{\rho \cdot \sum_{j=1}^{n} \hat{a}_{ji} \cdot d \log y_j}_{\text{upstream spatial variable}} + d\tilde{G}_i, \tag{14}$$

where $\tilde{G}_i := \frac{G_i}{y_i}$ and $\hat{a}_{ji} := \frac{x_{ji}}{y_i} = a_{ji}\frac{p_j y_j}{p_i y_i}$.
We can rewrite equation (15) in a compact matrix form:

$$\underset{n\times1}{d\log\mathbf{y}} = \rho\cdot\underset{n\times n}{\hat{A}^T}\cdot\underset{n\times1}{d\log\mathbf{y}} + (I_n + \underset{n\times n}{\tilde{\mathbf{\Lambda}}})\cdot\underset{n\times1}{d\tilde{\mathbf{G}}}, \tag{15}$$

where:

$$\tilde{\mathbf{\Lambda}} = \begin{bmatrix} -\frac{\beta_1}{1+\lambda} & -\frac{\beta_1}{1+\lambda}\cdot\frac{p_2\cdot y_2}{p_1\cdot y_1} & \cdots & -\frac{\beta_1}{1+\lambda}\cdot\frac{p_n\cdot y_n}{p_1\cdot y_1} \\ -\frac{\beta_2}{1+\lambda}\cdot\frac{p_1\cdot y_1}{p_2\cdot y_2} & -\frac{\beta_2}{1+\lambda} & \cdots & -\frac{\beta_2}{1+\lambda}\cdot\frac{p_n\cdot y_n}{p_2\cdot y_2} \\ \vdots & \vdots & \ddots & \vdots \\ -\frac{\beta_n}{1+\lambda}\cdot\frac{p_1\cdot y_1}{p_n\cdot y_n} & -\frac{\beta_n}{1+\lambda}\cdot\frac{p_2\cdot y_2}{p_n\cdot y_n} & \cdots & -\frac{\beta_n}{1+\lambda} \end{bmatrix}$$

and:

$$\hat{A} = \begin{bmatrix} a_{11} & a_{12}\cdot\frac{p_1\cdot y_1}{p_2\cdot y_2} & \cdots & a_{1n}\cdot\frac{p_1\cdot y_1}{p_n\cdot y_n} \\ a_{21}\cdot\frac{p_2\cdot y_2}{p_1\cdot y_1} & a_{22} & \cdots & a_{2n}\cdot\frac{p_2\cdot y_2}{p_n\cdot y_n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1}\cdot\frac{p_n\cdot y_n}{p_1\cdot y_1} & a_{n2}\cdot\frac{p_n\cdot y_n}{p_2\cdot y_2} & \cdots & a_{nn} \end{bmatrix} = A\odot\underbrace{\begin{bmatrix} 1 & \frac{p_1\cdot y_1}{p_2\cdot y_2} & \cdots & \frac{p_1\cdot y_1}{p_n\cdot y_n} \\ \frac{p_2\cdot y_2}{p_1\cdot y_1} & 1 & \cdots & \frac{p_2\cdot y_2}{p_n\cdot y_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{p_n\cdot y_n}{p_1\cdot y_1} & \frac{p_n\cdot y_n}{p_2\cdot y_2} & \cdots & 1 \end{bmatrix}}_{S} = A\odot S$$

where the last identity is meant to underscore the connection between $\hat{A}$ and A, the standard input-output matrix, and S represents a scaling matrix.[22]
As done for the case of taxes, we can rewrite equation (15) in its closed form expression:

$$\underset{n\times1}{d\log\mathbf{y}} = \underbrace{(I_n - \rho\cdot\hat{A}^T)^{-1}}_{\text{upstream propagation}}\cdot(I_n + \tilde{\mathbf{\Lambda}})\cdot\underset{n\times1}{d\tilde{\mathbf{G}}} \tag{16}$$

where $\tilde{\mathbf{\Lambda}}$ represents second order GE effects which come from the fact that the government budget constraint holds. The latter term is neglected in our

[22]where $*$ denotes the Hadamard product, or element wise product.

specification since a fiscal consolidation meant to reduce the deficit will not translate into a contemporaneous tax/subsidy (i.e. T) reduction.
Equation (16), tells us that the sectoral propagation of a spending shock is driven by the elements in the columns of $\hat{A}$, which describe a sector's sales to other industries. For instance, when G_i decreases, sector i faces a negative demand shock, and reacts by contracting its output and by purchasing less input: those sectors which are suppliers of input to sector i, are negatively affected and also shrink their output and purchase less input, and so on and so forth. This type of spillovers represents the aforementioned upstream propagation of demand side shocks.

7.2 Partitioning

We want to assess if the industrial network with $n = 62$ sectors generates relevant high-order spillovers. This is done in order to gauge whether the adoption of a spatial lag, which takes into account all the orders of transmission, is appropriate.
We perform the partitioning of the effect similar to what suggested by LeSage and Pace (2009). For instance, for the downstream network we have:

$$\underbrace{(I_n - A)^{-1} \cdot \mathbf{1}_n}_{\textit{Total Effect}} = \underbrace{\mathbf{1}_n}_{\textit{Direct}} + \underbrace{A \cdot \mathbf{1}_n}_{\textit{1st order In-degree}} + \underbrace{A^2 \cdot \mathbf{1}_n}_{\textit{2nd order In-degree}} + \;...$$

while for the upstream network, we have:

$$\underbrace{(I_n - \hat{A}^T)^{-1} \cdot \mathbf{1}_n}_{\textit{Total Effect}} = \underbrace{\mathbf{1}_n}_{\textit{Direct}} + \underbrace{\hat{A}^T \cdot \mathbf{1}_n}_{\textit{1st order Out-degree}} + \underbrace{(\hat{A}^T)^2 \cdot \mathbf{1}_n}_{\textit{2nd order Out-degree}} + \;...$$

By taking an average across the 62 industries of the total effects as well as of their partitioning, we can calculate how much of the average total effect can be imputed to this or that order of propagation. The results are reported in Table VIII

Table VIII: Partitioning of the network

Order	*Downstream Network - In-degree*		*Upstream Network - Out-degree*	
	%	*Cumulative*	*%*	*Cumulative*
0	53.36%	53.36%	54.53%	54.53%
1	24.53%	77.89%	23.34%	77.86%
2	11.49%	89.39%	11.33%	89.20%
3	5.48%	94.87%	5.52%	94.72%
4	2.64%	97.51%	2.70%	97.42%
5	1.28%	98.79%	1.32%	98.74%

Notice that, consistently with Acemoglu, Carvalho, et al. (2012) and Carvalho (2007), the first two orders of the in-degrees and out-degrees are enough to capture most of the spillovers, roughly 89% of the overall effects. However, to capture the whole scope of network effects we should add terms up to the 5th order, which account for almost 99% of the total effect. Since we have 6 "core regressors" (TB and EB unanticipated, announced, future components), the adoption of cross terms which capture the order of propagations, would require to include 6 times 5 orders plus one (the Direct effect) for a total of 36 core regressors. Because of this unfeasible econometric specification we opt for using a much more parsimonious spatial lag.

7.3 Log-likelihood

We provide here the derivation of the log-likelihood of model (4), necessary for the calculation of both the MLE and the conditional posterior distributions of the Bayesian MCMC:

$$\begin{aligned}
&H_t^{-1} \cdot \underset{n\times 1}{\Delta y_t} = \underset{n\times k}{X_t} \cdot \beta + \varepsilon_t \\
&H_t = \Big(I_n - \beta^{down} \cdot A \cdot TB_t - \beta^{up} \cdot \hat{A}^T \cdot EB_t\Big)^{-1} \\
&\varepsilon_t \sim \mathcal{N}(0, \Omega), \forall t \in \{1, ..., T\} \\
&\Omega = diag(\sigma_1^2, ..., \sigma_n^2) \\
&\varepsilon_t \perp \varepsilon_{t+i}, \quad \forall t \in \{1, ..., T\}, \forall i \in \mathcal{Z}
\end{aligned}$$

where k is the number of regressors, which, in our baseline is n fixed effects plust 6 fiscal adjustment components (unexpected, announced and future for both TB and EB plans) plus 2 year dummies for 2008 and 2009.

To ease notation we now use $'$ as a symbol for transposition. Given the above parametric model, we have::

$$Z_t := H_t^{-1} \cdot \Delta y_t \sim \mathcal{N}(X_t\beta, \Omega) \implies \Delta y_t \sim \mathcal{N}(H_t X_t \beta, H_t \Omega H_t')$$

The density function of the random vector Δy_t is:

$$f(\underset{n\times 1}{\Delta y_t}|X_t, \rho, \beta, \Omega) = \frac{1}{\sqrt{(2\pi)^n \cdot |H_t \Omega H_t'|}} \exp\left\{-\frac{1}{2}\cdot(\Delta y_t - H_t X_t \beta)' \cdot (H_t \Omega H_t')^{-1} \cdot (\Delta y_t - H_t X_t \beta)\right\},$$

with $\rho = \left[\beta^{down}, \beta^{up})\right]$.
In order to ease notation even more, we now set $\rho_1 = \beta^{down}$, $\rho_2 = \beta^{up}$, $A = W_1$ and $\hat{A}' = W_2$. Given that $(H_t \Omega H_t')^{-1} = (H_t')^{-1} \cdot \Omega^{-1} \cdot H_t^{-1}$ and $|H_t \Omega H_t'| = |H_t|^2 \cdot |\Omega|$, we have:

$$\begin{aligned}
f(\Delta y_t|\cdot) &= (2\pi)^{-n/2} \cdot |H_t|^{-1} \cdot |\Omega|^{-1/2} \cdot \exp\Big\{ -\frac{1}{2}(Z_t - X_t\beta)' \cdot H_t' \cdot (H_t')^{-1} \cdot \Omega^{-1} \cdot H_t^{-1} \cdot H_t \cdot (Z_t - X_t\beta
\\
&= (2\pi)^{-n/2} \cdot |(I_n - \rho_1 W1TB_t - \rho_2 W_2 EB_t)^{-1}|^{-1} \cdot |\Omega|^{-1/2} \exp\Big\{ -\frac{1}{2}\varepsilon_t'\Omega^{-1}\varepsilon_t\Big\} \\
&= (2\pi)^{-n/2} \cdot |I_n - \rho_1 \cdot W_1 \cdot TB_t - \rho_2 \cdot W_2 \cdot EB_t| \cdot |\Omega|^{-1/2} \exp\Big\{ -\frac{1}{2}\varepsilon_t'\Omega^{-1}\varepsilon_t\Big\},
\end{aligned}$$

At this point we need to find the likelihood of the random vector $\boldsymbol{\Delta y} = \begin{bmatrix}\Delta y_1' & \dots & \Delta y_T'\end{bmatrix}$. Since the model is static and we have assumed $cov(\varepsilon_t, \varepsilon_{t-k}) = \underset{n\times n}{\mathbf{0}}$, then Δy_t is *iid* over time. By consequence, the following holds:

$$\begin{aligned}
f(\underset{nT\times 1}{\boldsymbol{\Delta y}}|X_1, \dots, X_T, \rho, \beta, \Omega) &= \prod_{t=1}^{T} f(\underset{n\times 1}{\Delta y_t}|X_t, \rho, \beta, \Omega) = \big((2\pi)^n|\Omega|\big)^{-T/2} \cdot \\
&\cdot \prod_{t=1}^{T} |I_n - \rho_1 \cdot W_1 \cdot TB_t - \rho_2 \cdot W_2 \cdot EB_t| \exp\big\{ -\frac{1}{2} \cdot \sum_{t=1}^{T} \varepsilon_t'\Omega^{-1}\varepsilon_t\big\}.
\end{aligned}$$

Now we divide the time series of length T in three different sub-periods. In doing so, consider the following new parameters:

- t_1: set of years when a tax based fiscal adjustment occurs.
  Formally $t_1 := \{1, ..., t, ..., T_1|\ t \text{ such that } TB_t = 1\}$. We set: $H_t|\ t \in t_1 = (I_n - \rho_1 \cdot W_1)^{-1} = H_\tau$.

- t_2: set of years when an expenditure tax based fiscal adjustment occurs.
  Formally: $t_2 := \{1, ..., t, ..., T_2|\ t \text{ such that } EB_t = 1\}$. We set $H_t|\ t \in t_2 = (I_n - \rho_2 \cdot W_2)^{-1} = H_\gamma$.

- t_3: set of years when neither a tax based fiscal adjustment nor an expenditure based fiscal adjustment occurs.
  Formally $t_3 := \{1, ..., t, ..., T_3 | \ t \text{ such that } TB_t = 0 \wedge EB_t = 0\}$. We set $H_t| \ t \in t_3 = (I_n)^{-1} = I_n$.

Therefore, we have that t_1, t_2 and t_3 account for a partition of the whole time series and $T = T_1 + T_2 + T_3$. By consequence we have:

$$\begin{aligned}
\prod_{t=1}^{T} |I_n - \rho_1 W_1 TB_t - \rho_2 W_2 EB_t| &= \prod_{t=1}^{T} |H_t^{-1}| \\
&= \prod_{t=1}^{T} \frac{1}{|H_t|} \\
&= \prod_{t \in t_1}^{T_1} \frac{1}{|H_t|} \cdot \prod_{t \in t_2}^{T_2} \frac{1}{|H_t|} \cdot \prod_{t \in t_3}^{T_3} \frac{1}{|H_t|} \\
&= |H_\tau|^{-T_1} \cdot |H_\gamma|^{-T_2} \cdot |I_n|^{-T_3} \\
&= |I_n - \rho_1 \cdot W_1|^{T_1} \cdot |I_n - \rho_2 W_2|^{T_2}
\end{aligned}$$

At this point, we rewrite the probability density function of our dependent variable as:

$$\begin{aligned}
f(\boldsymbol{\Delta y_t} | X_1, \ldots, X_T, \rho, \beta, \Omega) = (2\pi)^{-nT/2} \cdot |\Omega|^{-T/2} \cdot \\
\cdot |I_n - \rho_1 \cdot W_1|^{T_1} \cdot |I_n - \rho_2 W_2|^{T_2} \cdot \exp\left\{ -\frac{1}{2} \cdot \sum_{t=1}^{T} \varepsilon_t' \cdot \Omega^{-1} \cdot \varepsilon_t \right\}.
\end{aligned}$$

Finally, the log-likelihood of our dataset is:

$$\begin{aligned}
\log \mathcal{L}(\rho, \beta, \Omega | \Delta y_1, \ldots, \Delta y_T, X_1, \ldots, X_T) = -\frac{nT}{2} \ln(2\pi) - \frac{T}{2} \cdot \ln(|\Omega|) + \\
+ T_1 \cdot \ln(|I_n - \rho_1 \cdot W_1|) + T_2 \cdot \ln(|I_n - \rho_2 W_2|) - \frac{1}{2} \cdot \sum_{t=1}^{T} \varepsilon_t' \cdot \Omega^{-1} \cdot \varepsilon_t.
\end{aligned}$$

with:

$$\varepsilon_t = Z_t - X_t \cdot \beta = H_t^{-1} \cdot \Delta y_t - X_t \beta = (I_n - \rho_1 W_1 TB_t - \rho_2 W_2 EB_t) \cdot \Delta y_t - X_t \cdot \beta.$$

Furthermore, we impose the condition $\lambda_{\min}^{-1} < \hat{\rho}_1 < \lambda_{\max}^{-1}$ and $\mu_{\min}^{-1} < \hat{\rho}_2 < \mu_{\max}^{-1}$, where λ and μ are the eigenvalues of the spatial matrices W_1 and W_2 respectively.

7.4 Bayesian MCMC

We show here in more details the Bayesian MCMC we employ, a slightly modifed version of the one introduced by LeSage (1997):

$$
\begin{aligned}
&H_t \cdot \underset{n\times 1}{\Delta y_t} = \underset{n\times(n+6)}{X_t} \cdot \beta + \varepsilon_t \\
&H_t = I_n - \rho^{down} \cdot A_0 \cdot TB_t + \rho^{up} \cdot \hat{A}_0' \cdot EB_t \\
&\varepsilon_t \sim \mathcal{N}(0, \Omega), \forall t \in \{1, ..., T\} \\
&\Omega = \sigma^2 \cdot V \quad \text{with } V = diag(v_1, ..., v_n) \\
&\varepsilon_t \perp \varepsilon_{t+i}, \quad \forall t \in \{1, ..., T\}, \quad \forall i \in \mathcal{Z} \\
&\pi(\beta) \propto constant \\
&\pi(\sigma^2) \propto \frac{1}{\sigma^2} \\
&\pi(\frac{r}{v_i}) \overset{iid}{\sim} \chi^2_{(r)}, \quad \forall i \in \{1, ..., n\} \\
&\rho^{down} \sim Gen.Beta(d, d) \\
&\rho^{up} \sim Gen.Beta(d, d).
\end{aligned}
$$

Furthermore, we assume that all the prior distributions are independent from each other. We use the standard "Metropolis within Gibbs" algorithm, and we obtain an approximation of the posterior densities for each parameter of the model. Once obtained the posterior distributions for each parameter, we draw from them, in order to approximate via MonteCarlo the posterior distributions of the ATE, ADE and ANE.
We now outline the precise steps of the procedure:

1. **Initialization:** Set up initial values for the parameters: $\beta_{(0)}, \sigma^2_{(0)}, V_{(0)}, \rho^{down}_{(0)}, \rho^{up}_{(0)}$, where $V_{(0)} = diag\left(v^2_{1,(0)}, ..., v^2_{n,(0)}\right)$.

2. **Gibbs Sampling:**

   a) Draw $\beta_{(1)}$ from the conditional posterior distribution, which is obtained by mixing the likelihood with a normal prior with mean c (a vector of zeros in our simulation) and covariance matrix L. In order to not add any information, we simply set L to be equal to a diagonal matrix whose entries are infinite (1e12 in our simulation):

$$P(\beta_{(0)}|\mathcal{D},\sigma^2_{(0)},V_{(0)},\rho^{down}_{(0)},\rho^{up}_{(0)}) = \mathcal{N}(c^*,L^*) \propto \mathcal{L}(\theta|\mathcal{D})\cdot\mathcal{N}(c,L)$$

$$c^* = \frac{1}{T}\cdot(\sum_{t=1}^{T} X'_t\cdot V^{-1}_{(0)}\cdot X_t + \frac{\sigma^2_{(0)}}{T}\cdot L^{-1})^{-1}\cdot(\frac{1}{T}\cdot\sum_{t=1}^{T} X'_t\cdot V^{-1}_{(0)}\cdot H_t\cdot\Delta y_t + \frac{\sigma^2_{(0)}}{T}\cdot L^{-1}\cdot c)$$

$$L^* = \frac{\sigma^2_{(0)}}{T}\cdot(\sum_{t=1}^{T} X'_t\cdot V^{-1}_{(0)}\cdot X_t + \frac{\sigma^2_{(0)}}{T}\cdot L^{-1})^{-1}$$

b) Draw $\sigma^2_{(1)}$ from the conditional posterior distribution, which is proportional to likelihood times an inverse gamma distribution as a prior:

$$P(\sigma^2_{(1)}|\mathcal{D},\beta_{(1)},V_{(0)},\rho^{down}_{(0)},\rho^{up}_{(0)}) = \Gamma^{-1}(\frac{\theta_1}{2},\frac{\theta_2}{2}) \propto \mathcal{L}(\theta|\mathcal{D})\cdot\Gamma^{-1}(a,b)$$

$$\theta_1 = nT+2a \quad \theta_2 = \sum_{t=1}^{T}\varepsilon'_t\cdot V^{-1}_{(0)}\cdot\varepsilon_t + 2b$$

In practice we draw $\sigma^2_{(1)}$ from θ_2/χ_{θ_1}.
Notice that, setting a and b (the prior's parameters) equal to 0, is like putting a Jefferey's prior on σ^2. This is exactly what we do.

c) Draw $v_{i,(1)}$ from the following conditional posterior distribution, proportional to an inverse gamma prior:

$$P(v_{i,(1)}|\mathcal{D},\sigma^2_{(1)},\rho^{down}_{(0)},\rho^{up}_{(0)}) = \Gamma^{-1}(\frac{q_1}{2},\frac{q_2}{2}) \propto \mathcal{L}(\theta|\mathcal{D})\cdot\Gamma^{-1}(\frac{r}{2},\frac{r}{2})$$

$$q_1 = r+T \quad q_2 = \frac{1}{\sigma^2_{(1)}}\cdot\sum_{t=1}^{T}\varepsilon^2_{i,t} + r$$

In practice we draw $v_{i,(1)}$ from q_2/χ_{q_1}.
As anticipated above in the paper, since we are confident on the heteroskedastic behavior of industry value added, we set our prior hyperparameter r to be equal to 3 rather than 4, as done in LeSage and Pace (2009).
Replicating this procedure n times, we get a first simulation of matrix $V_{(1)}$.

3. **Metropolis-Hastings**: We now need to draw the spatial coefficients. However we cannot apply a simple Gibbs Sampling, since the conditional posterior distribution is not defined for them. LeSage and Pace (2009)

suggest the adoption of the Metropolis-Hastings algorithm to overcome this problem. To ease notation we set $\rho_1 := \rho^{down}$ and $\rho_2 := \rho^{up}$. The algorithm is the following:

(a) Draw ρ_1^c (where the c superscript stands for "candidate") from the (random walk) proposal distribution:

$$\rho_1^c = \rho_{1,(0)} + c_1 \cdot \mathcal{N}(0,1)$$

(b) Run a bernoulli experiment to determine the updated value of ρ_1:

$$\rho_{1,(1)} = \begin{cases} \rho_1^c & \pi \quad \text{(accept)} \\ \rho_{1,(0)} & 1-\pi \quad \text{(reject)} \end{cases}$$

Where π is equal to $\pi = \min\{1, \psi_{MH_1}\}$ and, setting: $A_\tau(\rho_1) = I_n - \rho_1 \cdot W_1$, we have:

$$\begin{aligned} \psi_{MH_1} = & \frac{|A_\tau(\rho_1^c)|}{|A_\tau(\rho_{1,(0)})|} \cdot \exp\Big\{ - \frac{1}{2\sigma^2_{(1)}} \cdot \sum_{t \in t_1}^{T_1} \Big[\Delta y_t' \cdot \big(A_\tau(\rho_1^c)' \cdot V_{(1)}^{-1} \cdot A_\tau(\rho_1^c) - \\ & - A_\tau(\rho_{1,(0)})' \cdot V_{(1)}^{-1} \cdot A_\tau(\rho_{1,(0)})\big) \cdot \Delta y_t - \\ & - 2\beta' \cdot X_t' \cdot V_{(1)}^{-1}\big(A_\tau(\rho_1^c) - A_\tau(\rho_{1,(0)})\big) \cdot \Delta y_t \Big] \Big\} \cdot \\ & \cdot \left[\frac{(\rho_1^c - 0) \cdot (\lambda_{max}^{-1} - \rho_1^c)}{(\rho_{1,(0)} - 0) \cdot (\lambda_{max}^{-1} - \rho_{1,(0)})} \right]^{d-1} \cdot \mathbf{1}\big(0 \le \rho_1^c \le \lambda_{max}^{-1}\big) \end{aligned}$$

Basically, we compute the probability to accept the candidate value from the proposal distribution, and then we update the value of ρ_1 by running the bernoulli experiment with such a probability of success. Notice that if we draw a value of ρ_1 outside the support of the beta prior, $\psi_{MH_1} = 0$ and then $\pi = 0$ and we clearly reject the candidate value.
We set d equal to 1.1, on both ρ_1 and ρ_2; this is done to resemble a Uniform (0,1) but with less density on its boundary values.

(c) Once updated ρ_1, we replicate the procedure for ρ_2. Setting $A_\gamma(\rho_2) =$

$I_n - \rho_2 \cdot W_2$ we have:

$$\psi_{MH_2} = \frac{|A_\gamma(\rho_2^c)|}{|A_\gamma(\rho_{2,(0)})|} \cdot \exp\Big\{ -\frac{1}{2\sigma^2_{(1)}} \cdot \sum_{t\in t_2}^{T_2} \Big[\Delta y_t' \cdot \big(A_\gamma(\rho_2^c)' \cdot V_{(1)}^{-1} \cdot A_\gamma(\rho_2^c) -$$

$$- A_\gamma(\rho_{2,(0)})' \cdot V_{(1)}^{-1} \cdot A_\gamma(\rho_{2,(0)})\big) \cdot \Delta y_t -$$

$$- 2\beta' \cdot X_t' \cdot V_{(1)}^{-1}\big(A_\gamma(\rho_2^c) - A_\gamma(\rho_{2,(0)})\big) \cdot \Delta y_t\Big]\Big\} \cdot$$

$$\cdot \left[\frac{(\rho_2^c - 0) \cdot (\hat{\lambda}_{max}^{-1} - \rho_2^c)}{(\rho_{2,(0)} - 0) \cdot (\hat{\lambda}_{max}^{-1} - \rho_{2,(0)})}\right]^{d-1} \cdot \mathbf{1}\big(0 \leq \rho_2^c \leq \hat{\lambda}_{max}^{-1}\big)$$

(d) At this point we need to update the variance of the proposal distributions: if the acceptance rate (number of acceptances over number of iterations of the Markov Chain) of the first parameter ρ_1 falls below 40% we need to reduce the value of c_1, the so called tuning parameter, which regulates the variance of the proposal distribution. The variance is reduced by rescaling it: $c_1' = \frac{c_1}{1.1}$. In this way, we are able to draw values closer to the current state of ρ_1, and therefore, we expect to increase the acceptance rate.
On the contrary, if the acceptance rate rises above 60%, we need to increase the tuning parameter, in order to draw values far from the current state, in this way we increase the chance to explore more the low-density parts of the distribution. We increase the variance of the candidate distribution by scaling upward its standar deviation: $c_1' = 1.1 \cdot c_1$.
Clearly we replicate this procedure also for ρ_2.

4. **Repeat**: Once updated all the values, we replicate steps 2 and 3, 45,000 times to make sure the acceptance rate has converged.

5. **Burn-in**: we drop the first 35,000 iterations of the Markov Chain, thus obtaining a vector of 10,000 observations for each of the parameters, which account for the simulated posterior distributions.

7.5 ATE, ADE and ANE simulation

We construct via Monte Carlo the distribution of the ATE, ADE and ANE. In particular we follow these steps:

1. **(Parameters)** Draw ρ^{down}, ρ^{up}, $\boldsymbol{\tau}$ and $\boldsymbol{\gamma}$ from their posterior distributions. To take into account the potential correlation among them, draw from the same iteration of the Bayesian MCMC.

2. **(Style of the plan)** Construct both a TB and an EB simulated fiscal plan, by drawing the style from a distribution which mimics the empirical one.

3. **(Average effects)** Construct ATE, ADE and ANE using the parameters drawn in step 1 and the style drawn in step 2.

4. Repeat 100,000 times steps from 1 though 3, to make sure all the possible combination of styles and parameters are simulated.

Step 2 allows us to claim that the baseline results reported in the paper are robust to different styles of fiscal plans.

Empirical distribution of style of fiscal plans

We are interested in simulating a 2 years fiscal consolidation made of an unexpected part, no announced part and a single year future part to be implemented in the second year of the simulation.
First of all, we want to simulate the unexpected part of the fiscal plan, therefore, we need to look at those years when an unanticipated shock occurs. Define the two sub-samples: $TB^u := \{t : 1, ..., T \mid tax_t^u > 0\}$ and $EB^u := \{t : 1, ..., T \mid exp_t^u > 0\}$. Then calculate the mean and the standard deviation of the unexpected component conditional on the occurrence of an unexpected shock:

$$\mu_\tau := \mathbb{E}(tax_t^u \mid t \in TB^u) \qquad \sigma_\tau := \sqrt{\mathbb{V}(tax_t^u \mid t \in TB^u)}$$
$$\mu_\gamma := \mathbb{E}(exp_t^u \mid t \in EB^u) \qquad \sigma_\gamma := \sqrt{\mathbb{V}(exp_t^u \mid t \in EB^u)}$$

In order to simulate a plausible unexpected component of the plan, we draw them from the following distributions:

$$\tilde{tax}^u \sim \mathcal{U}(\mu_\tau - \sigma_\tau, \mu_\tau + \sigma_\tau)$$
$$\tilde{exp}^u \sim \mathcal{U}(\mu_\gamma - \sigma_\gamma, \mu_\gamma + \sigma_\gamma)$$

where the ˜ denotes a simulated component.
Concerning the future component, we need to predict what is the value of a one year ahead policy change, conditional on the occurrence of an unexpected policy change. Therefore, we run the following regressions:

$$tax_{t,1}^f = a_\tau + b_\tau \cdot tax_t^u \qquad \textit{with: } t \in TB^u$$
$$exp_{t,1}^f = a_\gamma + b_\gamma \cdot exp_t^u \qquad \textit{with: } t \in EB^u$$

The estimates of a_τ, b_τ, a_γ, b_γ will be stored and used to predict values of $tax^f_{t,1}$ and $exp^f_{t,1}$, conditional on the occurrence of an unexpected component. At this point we have all the ingredients to outline the steps we do in the construction of a simulated style of the plan:

1. Draw unexpected components from their candidate distributions: $\tilde{tax}^u \sim \mathcal{U}(\mu_\tau - \sigma_\tau, \mu_\tau + \sigma_\tau)$ and $\tilde{exp}^u \sim \mathcal{U}(\mu_\gamma - \sigma_\gamma, \mu_\gamma + \sigma_\gamma)$.

2. Predict the future component using the estimates of a_τ, b_τ, a_γ, b_γ. We have: $\tilde{tax}^f = \hat{a}_\tau + \hat{b}_\tau \cdot \tilde{tax}^u$ and $\tilde{exp}^f = \hat{a}_\gamma + \hat{b}_\gamma \cdot \tilde{exp}^u$.

3. Normalize the value to one: $\tilde{tax}^u + \tilde{tax}^f = 1$ and $\tilde{exp}^u + \tilde{exp}^f = 1$.

For each iteration of the MC simulation used to approximate the posterior distributions of the ATE, ADE and ANE, we repeat steps 1 through 3 to simulate the style of the plan.
In the first year of the simulation we calculate the effects of TB and EB plans with style given by: $\boldsymbol{s}_{TB} = [\tilde{tax}^u \; 0 \; \tilde{tax}^f]$ and $\boldsymbol{s}_{EB} = [\tilde{exp}^u \; 0 \; \tilde{exp}^f]$ respectively. In the second year of the simulation, the future component of the shock is rolled over and becomes an announced and implemented shock. Therefore we calculate the effects of TB and EB plans with style given by: $\boldsymbol{s}_{TB} = [0 \; \tilde{tax}^f \; 0]$ and $\boldsymbol{s}_{EB} = [0 \; \tilde{exp}^f \; 0]$ respectively.