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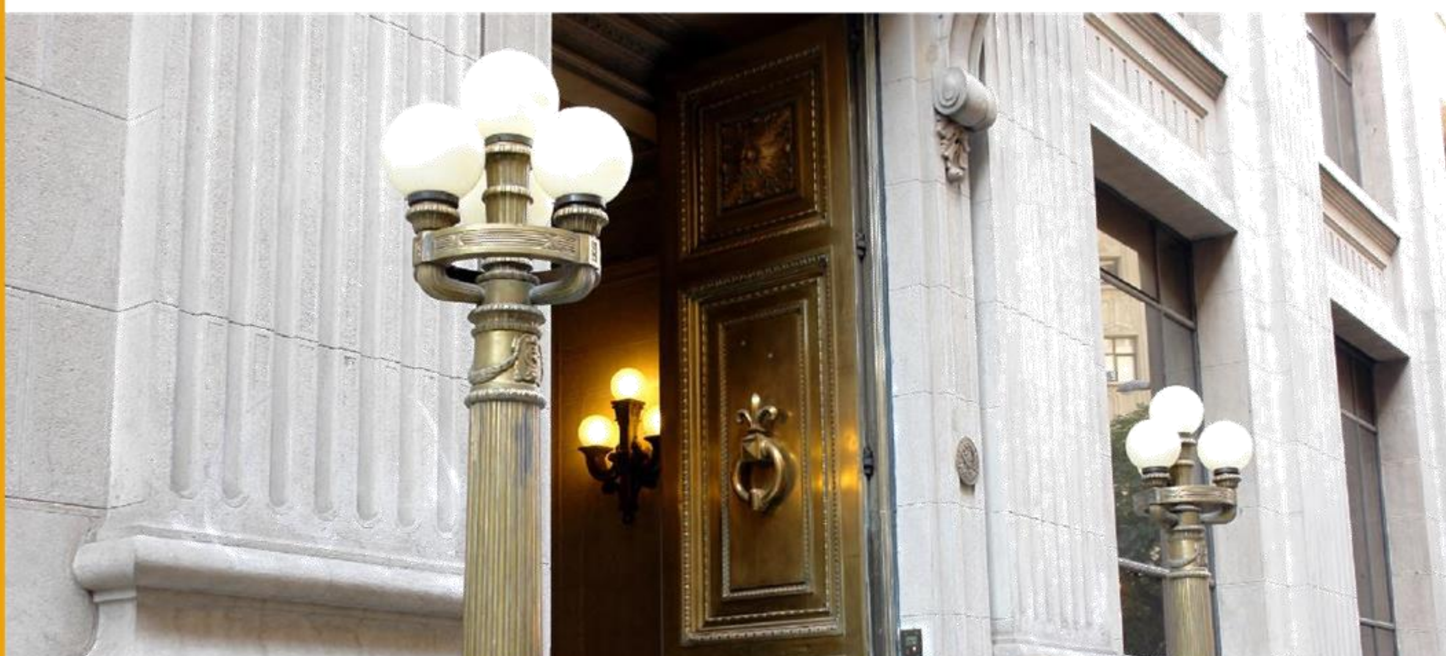

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Quantifying Aggregate Impacts in the Presence of Spillovers*

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Resumen

Una amenaza generalizada a la validez de las herramientas estándar de evaluación de políticas es la presencia de efectos indirectos (spillovers) entre los grupos tratados y no tratados. Las interacciones económicas entre unidades de análisis —debido al flujo de bienes, factores y pagos hacia y desde el gobierno, por ejemplo— generan sesgos en las estimaciones estándar de objetos de interés, como el efecto promedio del tratamiento o el efecto total de un programa. En este artículo, desarrollamos un conjunto de metodologías que permiten a los investigadores utilizar teoría y datos sobre flujos y distorsiones económicas para superar este sesgo. Aplicamos esta metodología para estimar los efectos de un gran terremoto que golpeó a Chile en 2010.

Abstract

A widespread threat to the validity of standard policy evaluation tools is the presence of spillovers between treated and untreated groups. Economic interactions across units of analysis—due to the flow of goods, factors, and payments to and from the government, for instance—result in bias in standard estimates of objects of interest such as the average treatment effect or the total effect of a program. In this paper, we develop a suite of approaches that can enable researchers to use theory and data about economic flows and distortions in order to overcome this bias. We apply this methodology to estimate the effects of a large earthquake that struck Chile in 2010.

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1 Introduction

Economic research increasingly exploits experimental and quasi-experimental variation when estimating the impact of policies and other non-policy shocks. When such "treatments" are as good as randomly assigned to units of analysis, the average effect of the treatment can be estimated credibly by simply comparing treated units to untreated ones. However, as is well understood, these methods fail whenever treating one unit affects others. For example, when regions are the units of analysis, a common concern is that economic interactions across space—via the flow of goods, factors, and payments to and from the government, for instance—will cause standard methods based on differences between treated and untreated locations to be biased in unknown directions. But non-geographical settings may be just as concerned with such spillovers. For example, training and credit programs that help targeted firms may do so partially via a shift in market share from non-targeted firms (Rotemberg, 2019; Cai and Szeidl, 2024).

In this paper, we advance the set of tools that economists can use for program evaluation in settings where economic spillovers across units are thought to be important. We develop a suite of economic models in which economic interactions across units of analysis—firms, regions, individuals, industries, etc.—give rise to treatment spillovers, but ones that can nevertheless be incorporated into standard quasi-experimental methods straightforwardly. We then illustrate this approach via an application to evaluate the total amount of Chile's real GDP that was destroyed by the catastrophic earthquake that occurred in February 2010.

Section 2 describes the broad framework that we consider: a treatment (e.g., a natural disaster or a randomized credit intervention) affects some units (e.g., firms or residential neighborhoods) in the economy by shifting the units' fundamental characteristics (e.g., their productivity levels or amenities). In line with the standard potential outcomes approach to the (quasi-) experimental study of treatments, we allow the treatment to have arbitrarily heterogeneous treatment effects on units' fundamentals. While fundamentals may be unobserved, they are nevertheless linked to observable outcomes (e.g., firms' sales or workers' commuting choices) available for the units of interest. Importantly, spillovers may occur between the fundamental characteristic of any unit j and the observed outcome of any other unit i. We refer to the matrix that summarizes these spillover effects as the *exposure matrix*.

In this environment, we consider a researcher whose goal is to estimate the effect of the entire set of treatments on an aggregate quantity of interest (e.g. real GDP or a measure of aggregate inequality such as the Gini index). This aggregate impact can be approximated, to first-order, as a weighted sum of the effects of the treatment on underlying fundamentals. The weights represent the responsiveness of the aggregate to changes in each unit's fundamental characteristic, so we refer to them as *responsiveness weights*.

Section 3 describes an unbiased and consistent estimator of the aggregate impact of the treatment in the case where the exposure matrix and responsiveness weights are known to the researcher. Under the standard assumption that the treatments are as good as randomly assigned (perhaps conditional on predetermined covariates), we show that the aggregate impact is simply the slope coefficient from a regression (potentially augmented to include covariates) of observed outcomes on a modified measure of treatment exposure. In particular, this novel measure of treatment exposure combines the exposure matrix and the responsiveness weights into one appropriately weighted measure of effective exposure to the underlying latent fundamentals that treatments affect. Even though the underlying effects of treatment on fundamentals are arbitrarily heterogeneous, and the latent fundamentals are unobserved, the proposed regression uses the observed outcomes to reveal the weighted average of such underlying heterogeneous effects that matters for the goal at hand.

This result can be applied in any setting where the researcher knows the exposure matrix and responsiveness weights that apply to their setting and to the aggregate impact that they aim to estimate. These knowledge requirements are strong but they are unavoidable since, by definition, the essence of the spillover problem is that pure empirical comparisons across treated and untreated units cannot answer the question of interest. In addition, these knowledge requirements are already available to the user of any model-based solution to the treatment spillovers problem such as ones that simulate the treatment in an estimated quantitative model. Our procedure is designed to push this knowledge further by relying only on what is required given the goal at hand and the outcomes that are observed (i.e. to the exposure matrix and responsiveness weights). Auxiliary assumptions—such as how the treatments affect latent fundamentals, how other outcomes respond to treatment, or what responsiveness weights would be needed for other goals—inside the researcher's model are therefore dispensed with.

Even though any researcher can apply our procedure by using the exposure matrix and responsiveness weights that are already available to them, we believe there may still be value in delineating the steps that researchers can follow to arrive at these two ingredients from more primitive beliefs and data. Section 4 aims to make this straightforward for applied practitioners. It describes a flexible model economy that nests a wide range of applied problems in fields where economic spillovers take place. In particular, we consider an economy with a set of production units referred to as firms; a set of households who own firms, consume final goods, and supply factors for production; a government sector that levies taxes on certain transactions and makes lump-sum transfers to certain households; and a set of arbitrary distortions in production and consumption.

Given data on the economic linkages between units in the economy (the flows of goods from firms to households and other firms, the flows of factors from households to firms, and the flows of government taxes/transfers from and to firms and households), as well as the extent to which firms and households can substitute between the different goods and factors they consume, the tools in Baqaee and Farhi (2020) can be used to express how any set of shocks to fundamentals would affect any other endogenous outcomes of interest as a function of baseline flow data an elasticities. We show how to map such effects into the exposure matrix and responsiveness weights that are required for our regression method to be applied. Importantly, our exposition highlights how certain data ingredients that may not be available in many contexts (such as the mapping of firms to their owners, or the mapping of firms to their clients and suppliers) can be populated by a range of assumptions that allow the researcher to probe the sensitivity of their results to missing data features.

Section 5 presents an application of our approach. We consider the case of the earthquake that hit Chile in February 2010—one of the most violent in recorded history—and seek to quantify this natural disaster's effect on aggregate Chilean real GDP. Existing approaches to questions such as this one compare the path of output (or value-added) in regions of the country that were hit by a natural disaster to those that weren't. However, such an approach is only unbiased if these regions are autarkic in terms of trade, factor flows, and government taxes and transfers—a presumption that is clearly rejected by all available data. We find that in this context the estimated effects of the earthquake on GDP are approximately 2 percent per year for at least five years after the event.

Related literature. The econometric issues raised by spillovers have been widely documented (see Cox, 1958, Rubin, 1980, and Manski, 1993 for early discussions). In particular, Rubin's Stable Unit Treatment Value Assumption (SUTVA)—that treatments affect the unit in question and do not spillover onto other units—is widely considered to be necessary for comparisons between treated and untreated units to deliver unbiased estimates of typical estimands of interest.

There are two classes of approaches to correcting for spillover bias. The first relies on the researcher's *a priori* belief that particular units of observation are "pure controls", in the sense that are always unaffected by the treatment(s) received by other units, that spillovers only exist within disjoint clusters of units (Hudgens and Halloran, 2008; Zigler and Papadogeorgou, 2020). This strategy underpins the design of stratified randomized trials that assign treatments to spatial units (such as schools in Miguel and Kremer, 2004, cities in Crépon et al., 2013, or urban neighborhoods in Franklin, Imbert, Abebe and Mejia-Mantilla, 2024) that are believed to be large enough that all spillovers take place within them. It also motivates the widely used "buffer" technique, in both experimental and quasi-experimental settings, of excluding from the analysis all units that lie within a certain distance, according to some suitable metric, of the directly treated units.[1]

This approach suffers from two widely-recognized limitations, the first of which is that economic interactions across units of analysis need not correspond to the simple distance metrics (such as physical proximity) that are used in practice, and a researcher's choice of metric may seem ad-hoc. For example, while flows of goods and people are commonly found to fit a so-called gravity equation in which they do decline with physical distance, a far more important predictor of flows is the economic size of the sending and receiving regions regardless of distance. A second limitation is that discarding observations on the basis of their suspected exposure to indirect treatment, as done by the buffer approach, systematically ignores a potentially important component of the aggregate effect of the program of interest.

The second broad approach to the treatment spillovers problem is to develop and estimate a complete empirical model of the setting of interest and all the potential economic interactions within it. Having done so, simulations performed on the model can be used to answer any counterfactual question, including that concerning the overall effect of a treatment. The benefit of this "structural" approach is that it can draw on economic theory and auxiliary data (such as data on the amount of trade between locations) in order to inform the model's stance on treatment spillovers and thereby correct for the bias. But the cost is that it relies on parametric choices made by the modeler, and may invoke stronger assumptions than are required for the question at hand.

The methodology developed in this paper aims to draw on the complementary strengths

[1] Other related approaches assume that the effect of spillovers can be captured by simple exposure metrics, such as the existence of a treated neighbor (Aronow and Samii, 2017) or the number of treated neighbors (Leung, 2020). Munro, Kuang and Wager (2025) describe a methodology to estimate treatment effects when spillovers are mediated by market prices.

of each of these two approaches. In particular, it relies on a linear approximation to a researcher's structural model of interest—and we provide a suite of modeling foundations that allow researchers to map their own beliefs about the economy's fundamentals into the exposure matrix and responsiveness weights that matter for them.[2] This allows the researcher to build measures of responsiveness and exposure that are theoretically motivated and account for the richness and heterogeneity of links between economic agents. However, in contrast to the fully structural approach described above, our methodology stops short of the full specification of every ingredient of the model. In particular, it allows for arbitrarily heterogeneous treatment effects in the direct effect(s) of the shock(s) of interest. This is possible given that the questions of interest, just as in standard potential-outcomes setups, rely only on a measure of particular weighted averages of treatment effects.

Finally, we contribute to a large literature on the economic costs of natural disasters. Barrot and Sauvagnat (2016), Boehm, Flaaen and Pandalai-Nayar (2019), and Carvalho, Nirei, Saito and Tahbaz-Salehi (2021) show in the context of natural disasters in the U.S. and the 2011 Tōhoku earthquake that disruptions caused by disasters propagated through trade links, with clearly visible effects far up or down the supply chains of affected firms. Boustan, Kahn, Rhode and Yanguas (2020) show that natural disasters in the U.S. tend to be followed by outmigration, and Strobl (2011) shows that such outmigration can account for a large share of the lower growth of U.S. counties after a hurricane hits them. Deryugina (2017) finds, again in the context of hurricanes in the U.S., that these catastrophes lead to substantial government transfers that largely offset their damages. Together, these findings highlight that spillovers likely severely impact the estimation of environmental disasters' economic effects. Several approaches have been explored to estimate the economic effects of natural catastrophes despite this problem. Some studies (e.g., Cavallo et al., 2013; Hsiang and Jina, 2014) have focused on cross-country analyses that are less subject to spillovers. Others (e.g., Felbermayr, Gröschl, Sanders, Schippers and Steinwachs, 2018; Lima and Barbosa, 2019) have relied on within-country analyses paired with the buffer approach to estimate spillover effects. Finally, a large literature (summarized in Botzen, Deschenes and Sanders, 2019) has leveraged computable general equilibrium models to estimate the costs of environmental catastrophes. As described above, our approach to

[2] This component draws on the literature describing how economic shocks propagate through networks, and in particular on the important theoretical advances of Long and Plosser (1983), Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi (2012) and Baqaee and Farhi (2019a,b, 2020), as well as empirical investigations such as Di Giovanni, Levchenko and Mejean (2014), Barrot and Sauvagnat (2016), Carvalho et al. (2021), and Korovkin and Makarin (2022).

the study of economic impacts of natural disasters illustrates how one can combine the complementary strengths of these theoretical and empirical methods.

2 Aggregate effects of shocks

2.1 Setting

We consider a setting in which the goal is to evaluate the effect of a vector of treatments T on some aggregate outcome denoted by W. The treatment shifts a latent, fundamental variable A, with potentially heterogeneous treatment effects β_i:

$$\Delta \log A_i = \beta_i T_i + \varepsilon_i^a. \tag{1}$$

While A is unobserved, it affects another variable, y, that is observed. We assume that we know the exposure matrix E, where $E_{ij} \equiv \frac{\mathrm{d} \log y_i}{\mathrm{d} \log A_j}$ measures the exposure of unit i to latent variable shocks affecting unit j.

To the first order, shifts in observables are given by

$$\Delta \log y_i = \sum_{j=1}^{N} \underbrace{\frac{\mathrm{d} \log y_i}{\mathrm{d} \log A_j}}_{E_{ij}} \Delta \log A_j + \sum_{k=1}^{p} \gamma_k X_{ik} + \varepsilon_i^y, \tag{2}$$

where the X_{ik} capture p observable characteristics of firm i. Denoting by $\mathcal{T} \equiv \{i \mid T_i = 1\}$ the set treated units, by $N_T = |\mathcal{T}|$ the number of treated units, by $E_T \in \mathbb{R}^{N \times N_T}$ the submatrix of E that keeps the columns indexed by $\mathcal{T}$, and by $\beta_T \equiv (\beta_j)_{j \in \mathcal{T}} \in \mathbb{R}^{N_T}$ the vector of size N_T that collects treatment effects for treated observations, the expression above can be simplified in vector notation as

$$y = E_T \beta_T + X\gamma + \varepsilon, \tag{3}$$

where $\varepsilon = \varepsilon^y + E\varepsilon^a$.

Our goal is to measure the aggregate impact of this set of treatments on W. To first order, this impact is given by:

$$\theta \equiv \Delta \log W = \sum_{i \in \mathcal{T}} \beta_i \frac{\mathrm{d} \log W}{\mathrm{d} \log A_i} = \sum_{i \in \mathcal{T}} \beta_i \kappa_i = \kappa_T^\top \beta_T, \tag{4}$$

where $\kappa_T \equiv (\kappa_j)_{j\in\mathcal{T}} \in \mathbb{R}^{N_T}$ the vector of size N_T that collects responsiveness weights for treated observations.

2.2 Examples

Three examples from recent work illustrate the notation introduced above.

Example 1: Natural disaster.

- **Setting**: A natural disaster hits some firms and destroys a share of their capital. We want to measure the effect of the disaster on GDP. This is the setting of Carvalho et al. (2021).
- **Source of spillovers**: Input-output linkages.
- **Latent variable** A: Firm-specific capital.
- **Observed variable** y: Firm sales.
- **Responsiveness weights** κ: Firms' capital expenditure shares.

Example 2: Loan program

- **Setting**: A loan program helps some firms grow. We want to measure the effect of the treatment on consumer surplus. This is the setting of Cai and Szeidl (2024), and is related to that in Rotemberg (2019).
- **Source of spillovers**: Demand spillovers (business stealing).
- **Latent variable** A: Firm productivity.
- **Observed variable** y: Firm sales.
- **Responsiveness weights** κ: Change in prices caused by productivity shifts weighted by firms' market shares.

Example 3: Public works program

- **Setting**: A public works program locally provides labor to the residents of some neighborhoods, reducing the number of workers in the labor market. We want to measure the effect of the program on the incomes of less-educated workers. This is similar to the setting of Franklin et al. (2024).
- **Source of spillovers**: Commuting.
- **Latent variable** A: Labor supply in different neighborhoods.
- **Observed variable** y: Wages in different locations.

- **Responsiveness weights** κ: Changes in local wages caused by changes in local labor supply, weighted by the initial labor supply in different neighborhoods.

Next steps. Estimating θ is associated with two challenges. First, even if we know the weights κ and the exposure matrix E, estimating θ is complicated by the fact that treatment shifts a latent variable, and equation (1) cannot be directly estimated. Second, knowledge of κ and E is far from guaranteed. In Section 3, we describe how θ can be estimated when κ and E are known. Then, in Section 4, we show how κ and E can be computed in a broad class of models.

3 Measuring treatment effects in the presence of spillovers

Equation (3) gives us a linear mapping between shocks to latent variables and observable outcomes. If treatment is randomly assigned and under typical rank and regularity assumptions, this linear mapping allows us to recover the weighted sum of treatment effects θ without having to observe or infer the latent variable.

Assumption 1 (Exogeneity). $\mathbb{E}[\varepsilon \mid X, T] = 0$.

Assumption 2 (Rank). *The matrix $[X\ E_T]$ has full column rank. This implies that:*

- *$X^\top X$ is invertible (as $X^\top X$ and X have the same kernel), allowing to define the usual OLS residual-maker $M_X \equiv I - X(X^\top X)^{-1}X^\top$.*
- *The Gram matrix of residualized treated exposures $G \equiv E_T^\top M_X E_T \in \mathbb{R}^{N_T \times N_T}$ is positive definite (as M_X is symmetric and idempotent).*

Assumption 3 (Regularity). *Write $\Sigma_a \equiv \mathrm{Var}(\varepsilon^a \mid X, E)$ and $\Sigma_y \equiv \mathrm{Var}(\varepsilon^y \mid X, E)$. We assume:*

(i) Information growth: $\kappa_T^\top G^{-1} \kappa_T \to_p 0$.

(ii) Well-behaved errors and exposure matrix: $\|\Sigma_a\|_{\mathrm{op}} \leq C_a < \infty$, $\|\Sigma_y\|_{\mathrm{op}} \leq C_y < \infty$, $\|E\|_{\mathrm{op}} \leq C_E < \infty$, and $\varepsilon^a \perp \varepsilon^y$ conditional on (X, E).

Here, limits are taken as $N \to \infty$ while the number of observable covariates p stays constant.

Proposition 1 (Estimation of weighted sums of treatment effects with spillovers). *Under Assumptions 1 and 2, define weights w and weighted exposure to treatment z as*

$$w \equiv \frac{G^{-1}\kappa_T}{\kappa_T^\top G^{-1}\kappa_T}, \qquad z \equiv E_T w. \tag{5}$$

Consider the OLS regression

$$y = \theta z + X\gamma + \varepsilon, \tag{6}$$

and let $\widehat{\theta}$ be the OLS coefficient on z. $\widehat{\theta}$ is a finite-sample unbiased estimator of $\theta = \sum_{i \in \mathcal{T}} \beta_i \kappa_i$. Under Assumption 3, this estimator is consistent.

This proposition is proved in Appendix A. The appendix further shows that the estimator of equation (6) is BLUE under homoskedasticity, and shows how Proposition 1 can be extended to GLS.

Special case of homogeneous treatment effects. If treatment effects are homogeneous ($\beta_i = \beta$ for all $i \in \mathcal{T}$), then the target reduces to $\theta = \kappa_T^\top \beta_T = \left(\sum_{i \in \mathcal{T}} \kappa_i\right) \beta$. In this case, there is no need to compute w or invert G. To estimate θ, it suffices to compute the exposure $\tilde{T} = ET$ of each node to treatment, and regress changes in Domar weights on exposure to treatment and controls:

$$y = \tilde{T}\beta + X\gamma + \varepsilon.$$

The target can then be recovered as $\hat{\theta} = \left(\sum_{i \in \mathcal{T}} \kappa_i\right) \hat{\beta}$.

Recovering average treatment effects on the treated. Proposition 1 is valid for any vector of κ weights as long as Assumptions 1–3 hold. When using as κ weights the measures for $\frac{\mathrm{d} \log W}{\mathrm{d} \log A_i}$, $\hat{\theta}$ will yield an estimate of the aggregate effect of the shock on welfare. To recover instead an estimate of the average treatment effect on the treated, one can apply Proposition 1 using as κ weights the uniform vector $\frac{1}{N_T} \mathbf{1}_{N_T}$.

4 Computing exposure measures

Implementing the estimation strategy of Proposition 1 requires knowledge of the exposures $E_{ij} = \frac{\mathrm{d} \log y_i}{\mathrm{d} \log A_j}$ of each node to shocks to treated nodes, as well as the weights $\kappa_i = \frac{\mathrm{d} \log W}{\mathrm{d} \log A_j}$. These quantities typically cannot be directly observed or estimated, but they can be recovered given assumptions on the channels through which spillovers propagate (e.g., input-output linkages, income shocks, etc.) In this section, we build on the results of Baqaee and Farhi (2019b) to show how to compute exposure measures in a broad range of settings.

4.1 Setup

We consider a flexible model of the economy using the notation of Baqaee and Farhi (2019b). It features F factors indexed by f, C consumers indexed by c, and N firms indexed by i. Goods in the economy are produced by firms through an aggregation of factors and goods, while factors are supplied ex nihilo.

Consumers. Each consumer c supplies a quantity L_{cf} of each factor f (at a price w_f) and consumes a composite consumption good $Y_c = \mathcal{D}_c(c_{c1}, \ldots, c_{cF})$, where c_{ci} is c's consumption of good i (exchanged at a price p_i) and $\mathcal{D}_c$ is homothetic. Consumers solve

$$\begin{aligned} \max \quad & U_c(\mathcal{D}_c(c_{c1}, \ldots, c_{cF}), L_{c1}, \ldots, L_{cF}) \\ \text{s.t.} \quad & \sum_{i=1}^{N} p_i c_{ci} = \sum_{f=1}^{F} w_f L_{cf} + \Pi_c, \end{aligned}$$

where Π_c denotes the income that c derives from government transfers or the profits of the firms they own. The total supply of factor f is given by $L_f = \sum_{c=1}^{C} L_{cf}$.

Firms. The production function of firm i is given by $Y_i = A_i F_i(L_{i1}, \ldots, L_{iF}, x_{i1}, \ldots, x_{iN})$, where A_i is a Hicks-neutral productivity shifter, L_{ij} is firm i's usage of factor j, and x_{ij} is its consumption of intermediate input j. Firms sell the good they produce at a markup μ_i over their production cost.

The economy's production and consumption network can be summarized by a (revenue-based) input-output matrix Ω of size $(C + N + F) \times (C + N + F)$, where the first C rows and columns correspond to consumers, the following N rows and columns to firms, and the final F rows and columns to factors.[3] The entry Ω_{ij} of the matrix corresponds to node i's spending on inputs from j as a share of i's sales, $\Omega_{ij} = \frac{p_j x_{ij}}{p_i y_i}$. Its Leontief inverse is then defined by $\Psi = (I - \Omega)^{-1} = I + \Omega + \Omega^2 + \Omega^3 + \cdots$. While Ω measures the direct reliance of each node on every other node for production, Ψ measures both the direct and indirect reliance of any node on every other node.

GDP and Domar weights. Nominal GDP corresponds to the value of final consumption: $\text{GDP} = \sum_{i=1}^{N} \sum_{c=1}^{C} p_i c_{ci}$. The importance of a node in the economy is captured by its

[3] The input-output matrix groups collects flows of consumption goods, intermediates, and factors. It is therefore convenient to use the slight abuse of notation of Baqaee and Farhi (2019b) and use interchangeably w_f and p_{N+f} for factor prices; L_{if} and $x_{i,N+f}$ for factor usage; L_f and y_f for factor supply; and c_{ci} and x_{ci} for final consumption.

revenue-based Domar weight λ_i, equal to its sales as a fraction of GDP: $\lambda_i = (p_i Y_i)/\text{GDP}$. Because only a fraction of production is typically used in final consumption, the sum of the λ_i is usually larger than one. For convenience, we denote by Λ_f the Domar weight of factors.

The importance of a final good in total consumption is captured by the vector b of final demand expenditures as a share of GDP, $b_i = \left(\sum_{c=1}^{C} p_i c_{ci}\right)/\text{GDP}$. Final demand is linked to producers' Domar weights by the Leontief inverse: $\lambda^\top = b^\top \Psi = b^\top (I + \Omega + \Omega^2 + \Omega^3 + \cdots)$. Indeed, Domar weights equal final demand shares propagated through the whole input–output network. This measure of final demand also allows us to measure variations in real GDP (denoted by Y): $\mathrm{d}\log Y = \sum_{i=1}^{N} b_i \,\mathrm{d}\log c_i$.

On top of the revenue-based input-output matrix, we can define a cost-based input-output matrix $\tilde{\Omega}$, whose entry $\tilde{\Omega}_{ij}$ corresponds to the cost share of input j in the production of good i: $\tilde{\Omega}_{ij} = \frac{p_j x_{ij}}{\sum_k p_k x_{ik}}$ This allows to define, by analogy, the cost-based Leontief inverse $\tilde{\Psi} = (I - \tilde{\Omega})^{-1}$, the cost-based Domar weights $\tilde{\lambda}_i = b^\top \tilde{\Psi}$. For factors, we use the notation $\tilde{\Lambda}_f$. In the absence of distortions, cost-based and revenue-based objects are equal.

4.2 Computing κ weights

A central case of interest is that where W corresponds to real GDP.

In this case, Baqaee and Farhi (2020) have shown that the elasticity of total real GDP to productivity shocks is given by

$$\kappa_i = \frac{\mathrm{d}\log Y}{\mathrm{d}\log A_i} = \tilde{\lambda}_i - \sum_{f=1}^{F} \tilde{\Lambda}_f \frac{\mathrm{d}\log \Lambda_f}{\mathrm{d}\log A_i}. \tag{7}$$

The first term of the expression is a technology effect. In the case of an efficient economy, it is the only channel at work, and equation (7) simplifies to $\kappa_i = \lambda_i$, which is Hulten's theorem. The second term captures an allocative efficiency effect: it captures the change in aggregate output arising from the reallocation of factors across producers. When this reallocation move resources toward more distorted sectors, allocative efficiency worsens; when they move toward less distorted ones, efficiency improves.

When the economy is efficient, κ_i can typically be observed in the data. When the economy is inefficient, computing κ_i requires measures of the exposure of factors to productivity shocks, $\frac{\mathrm{d}\log \Lambda_f}{\mathrm{d}\log A_i}$. We will describe in Section 4.3 how to compute such exposures.

4.3 Computing exposure measures

4.3.1 Representative agent and single factor

We start with the simple case of an economy with a representative agent supplying inelastically a single factor (e.g., labor) to an fixed number of firms, which can be linked by arbitrary input-output linkages. We further assume that there are no distortions in the economy, and that all production and consumption nodes are CES, i.e., that

$$\frac{y_i}{\bar{y}_i} = \frac{A_i}{\bar{A}_i} \left(\sum_{j \in N,F} \omega_{ij} \left(\frac{x_{ij}}{\bar{x}_{ij}} \right)^{\frac{\theta_i - 1}{\theta_i}} \right)^{\frac{\theta_i}{\theta_i - 1}},$$

with variables with a bar representing pre-shock values. In this scenario, the elements of the exposure matrix are given by

$$E_{ij} = \frac{\mathrm{d} \log \lambda_i}{\mathrm{d} \log A_j} = \sum_{k \in C,N} \frac{\lambda_k}{\lambda_i} (\theta_k - 1) \operatorname{Cov}_{\Omega^{(k)}} \left(\Psi_{(i)}, \Psi_{(j)} \right), \tag{8}$$

where θ_k is the elasticity of substitution between the inputs of node k, and $\operatorname{Cov}_{\Omega^{(k)}} \left(\Psi_{(i)}, \Psi_{(j)} \right)$ is the input-output covariance operator, defined by:

$$\operatorname{Cov}_{\Omega^{(k)}} \left(\Psi_{(i)}, \Psi_{(j)} \right) = \sum_{l \in N,F} \Omega_{kl} \Psi_{li} \Psi_{lj} - \left(\sum_{l \in N,F} \Omega_{kl} \Psi_{li} \right) \left(\sum_{l \in N,F} \Omega_{kl} \Psi_{lj} \right).$$

Hence, it corresponds to the covariance between the ith and jth columns of Ψ, using the kth row of Ω as weights.

4.3.2 Multiple consumers and factors

Importantly, exposure matrices can be computed when there are an arbitrary number of final consumers and factors of production. Define the network-adjusted consumption share of good i for agent c as

$$\lambda_i^c = \sum_{j \in N} \Omega_{cj} \Psi_{ji},$$

reflecting the direct and indirect consumption of good i by consumer c. We can similarly compute Λ_f^c as the reliance of consumer c on factor f. Furthermore, let $\Phi_{cf} = \frac{w_f L_{cf}}{w_f L_f}$ denote the share of factor f's income accruing to consumer c. With these additional objects in hand, Baqaee and Farhi (2019b) show that in efficient economies, we can express the elements of the exposure matrix as follows:

$$\frac{\mathrm{d}\log\lambda_i}{\mathrm{d}\log A_j} = \sum_{k\in C,N} \frac{\lambda_k}{\lambda_i}(\theta_k - 1)\,\mathrm{Cov}_{\Omega^{(k)}}\left(\Psi_{(i)}, \Psi_{(j)}\right) - \sum_{f\in F}\sum_{k\in C,N} \frac{\lambda_k}{\lambda_i}(\theta_k - 1)\,\mathrm{Cov}_{\Omega^{(k)}}\left(\Psi_{(i)}, \Psi_{(f)}\right)\frac{\mathrm{d}\log\Lambda_f}{\mathrm{d}\log A_j} + \frac{1}{\lambda_i}\sum_{f\in F}\sum_{c\in C}(\lambda_i^c - \lambda_i)\,\Phi_{cf}\Lambda_f\frac{\mathrm{d}\log\Lambda_f}{\mathrm{d}\log A_j}. \quad (9)$$

The first term of this equation is the same as in equation (8) and reflects how productivity shocks propagate through the input-output network, keeping fixed relative factor prices. The second term adjusts exposure for changes in relative factor prices caused by the shock. Finally, the third term provides a further adjustment to account for the changes in consumers' relative incomes.

To compute the exposure matrix using equation (9), we need to know how factor prices react to productivity shocks, as summarized by the $\frac{\mathrm{d}\log\boldsymbol{\Lambda}}{\mathrm{d}\log\boldsymbol{A}}$ matrix. This matrix can be obtained by solving the following system of equations for each value of j:

$$\frac{\mathrm{d}\log\Lambda_n}{\mathrm{d}\log A_j} = \sum_{k\in C,N} \frac{\lambda_k}{\Lambda_n}(\theta_k - 1)\,\mathrm{Cov}_{\Omega^{(k)}}\left(\Psi_{(n)}, \Psi_{(j)}\right) - \sum_{f\in F}\sum_{k\in C,N} \frac{\lambda_k}{\Lambda_n}(\theta_k - 1)\,\mathrm{Cov}_{\Omega^{(k)}}\left(\Psi_{(n)}, \Psi_{(f)}\right)\frac{\mathrm{d}\log\Lambda_f}{\mathrm{d}\log A_j} + \frac{1}{\Lambda_n}\sum_{f\in F}\sum_{c\in C}(\Lambda_n^c - \Lambda_n)\,\Phi_{cf}\Lambda_f\frac{\mathrm{d}\log\Lambda_f}{\mathrm{d}\log A_j} \quad (10)$$

4.3.3 Extensions

In Appendix B, we describe how to build the matrices $\frac{\mathrm{d}\log\boldsymbol{\lambda}}{\mathrm{d}\log\boldsymbol{A}}$ and $\frac{\mathrm{d}\log\boldsymbol{\Lambda}}{\mathrm{d}\log\boldsymbol{A}}$, describing changes in Domar weights following productivity shocks (to the first order) in a wide range of settings, including inefficient economies in which there are arbitrary wedges μ between the costs of production of each good and the price at which it is sold. We also describe how to build exposure matrices when the production and consumption nodes are not CES.

Finally, while we focused until now on the effects of productivity shocks on Domar weights, the framework of Baqaee and Farhi (2019b) allows to compute how Domar weights shift in response to changes in factor supplies, to the factor ownership matrix, or to wedges. In Appendix B, we provide expressions for $\frac{\mathrm{d}\log \boldsymbol{\lambda}}{\mathrm{d}\log \boldsymbol{L}}$, $\frac{\mathrm{d}\log \boldsymbol{\lambda}}{\mathrm{d}\log \boldsymbol{\Phi}}$, and $\frac{\mathrm{d}\log \boldsymbol{\lambda}}{\mathrm{d}\log \boldsymbol{\mu}}$.

5 Application: the 2010 Chile earthquake

The results described above suggest a simple procedure to estimate the effect on GDP of a treatment shifting the productivity of some segments of the economy.

Summary of the estimation procedure

- **Step 1**: **Compute exposures of nodes to shocks** using the results of Section 4.
- **Step 2**: **Compute the κ weights** using equation (7).
- **Step 3**: **Compute the weighted exposure to treatment** z as described in equation (5).
- **Step 4**: **Regress the changes in Domar weights on z and controls**. The coefficient on z is an estimate of the target of interest.

We now apply this methodology to evaluate the economic consequences of a major natural disaster: the earthquake that struck Chile on February 27, 2010.

5.1 Context and data

With a magnitude of 8.8, the 2010 Chilean earthquake was the 7th strongest earthquake ever recorded. For comparison, it was 500 times more powerful than the earthquake that struck Haiti in January 2010. The Chilean earthquake was associated with a tsunami and landslides and caused 525 deaths. 370,000 homes were severely damaged or destroyed, and the total cost of the catastrophe to the Chilean economy has been estimated to be between 15 and 30 billion dollars. For reference, the GDP of Chile in 2010 was 217 billion dollars. Following the earthquake, the Chilean government decided to spend 8.4 billion dollars from 2010 to 2014 to assist the areas where the disaster had struck.

In this section, we apply the methodology described above to estimate the effect of this earthquake on the Chilean economy. We do so using administrative data covering the universe of formal firms in Chile. Through tax forms, we can track their yearly sales and workforce.[4] VAT data allows us to map firm-to-firm transactions. This data enables us to build an input-output matrix for the Chilean economy, which we represent in Appendix Figure S.1. In the spirit of the "disaggregated national accounts" described in Andersen, Huber, Johannesen, Straub and Vestergaard (2022), we build our input-output matrices such as to be consistent with the figures of the national accounts tables published by the Chilean government, but more detailed.

We further gathered data on the allocation of government spending from the Ministry of Finance. Finally, we gathered from government decrees data on projects funded through the National Reconstruction Fund, established in the aftermath of the disaster through law 20.444 to facilitate reconstruction efforts. This data gives us information on the spatial distribution of the government transfers allocated following the shock. Appendix Figure S.2 shows the share of government spending that was allocated to the regions hit by the earthquake during our period of study.

Consistent with the model of the Chilean economy we develop below, we aggregate data on firms' economic activity at the region $\times$ sector level. There were 15 administrative regions in Chile at the time of the earthquake, and we grouped firms in 14 sectors (e.g., mining; transportation and storage; financial and insurance activities). Following the earthquake, three regions were declared in a state of catastrophic emergency: O'Higgins, Maule, and Biobío (see Appendix Figure S.3). We consider these regions to be those "treated" by the earthquake.

5.2 Reduced-form evidence

To study the effect of the earthquake on economic activity, we start by estimating the following event study equation:

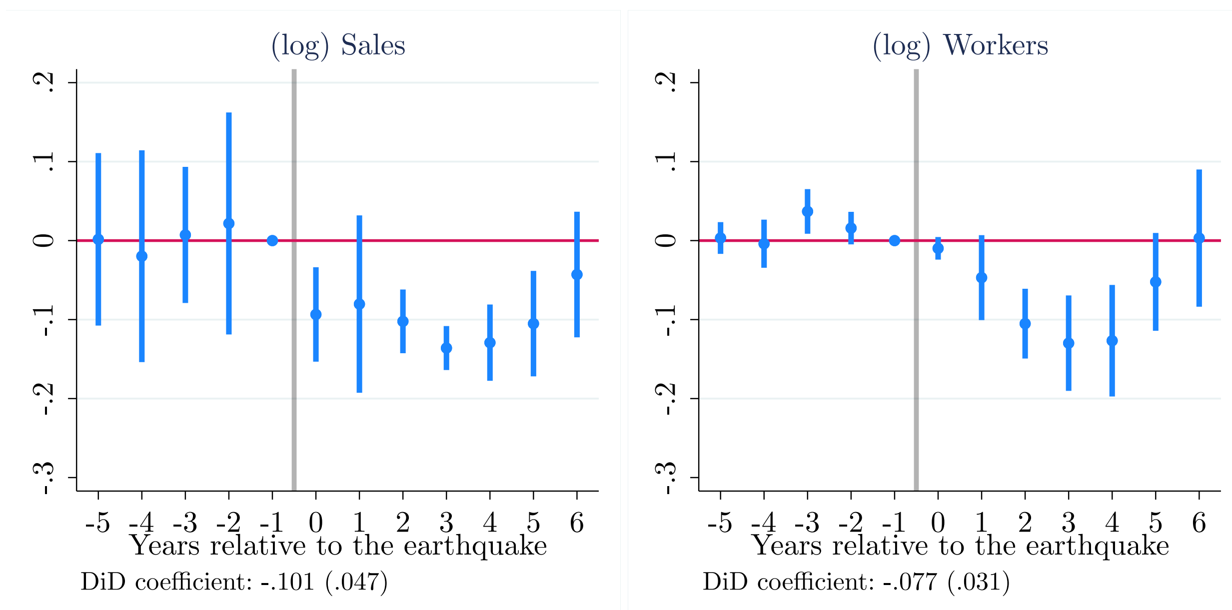
$$Y_{rst} = \sum_{\substack{\tau \in [-5,6] \\ \tau \neq -1}} \beta_\tau T_r \mathbb{1}_{t=\tau} + \gamma_{rs} + \delta_{st} + \varepsilon_{rst}, \tag{11}$$

[4]To secure the privacy of workers and firms, the Central Bank of Chile mandates that the development, extraction and publication of the results should not allow the identification, directly or indirectly, of natural or legal persons. Officials of the Central Bank of Chile processed the disaggregated data. All the analysis was implemented by the authors and did not involve nor compromise the Servicios de Impuestos Internos de Chile. The information contained in the databases of the Chilean IRS is of a tax nature originating in self-declarations of taxpayers presented to the Service; therefore, the veracity of the data is not the responsibility of the Service.

where Y_{rst} measures an outcome for sector s in region r at time t (measured relative to the year of the earthquake, 2010), γ_{rs} is a region $\times$ sector fixed effect, and δ_{st} is a sector $\times$ year fixed effect. Standard errors are two-way clustered at the region and sector level, and observations are weighted proportionally to region $\times$ sector sales in the pre-period.

The results, shown in Figure 1, show that following the earthquake, sales in the affected segments of the economy immediately dropped by about 10pp relative to trend, and continued to decline until 2013. Then, sales progressively returned to their pre-shock trend. The earthquake also appears to have caused a decline in employment in the affected firms, the estimated effect reaching -14pp three years after the shock. This effect on employment, however, took longer to materialize, and there is no discernible effect on the year of the disaster. As for sales, employment levels eventually return to trend.

Figure 1: Economic effects of the earthquake, event study



Notes: This figure shows event study estimates of the effect of the earthquake on (log) sales and workers. We include one observation per region, sector, and year relative to the earthquake, control for region $\times$ sector and sector $\times$ year fixed effects, and cluster standard errors at the region and sector level. Observations are weighted proportionally to region $\times$ sector sales in the pre-period.

5.3 A model of the Chilean economy

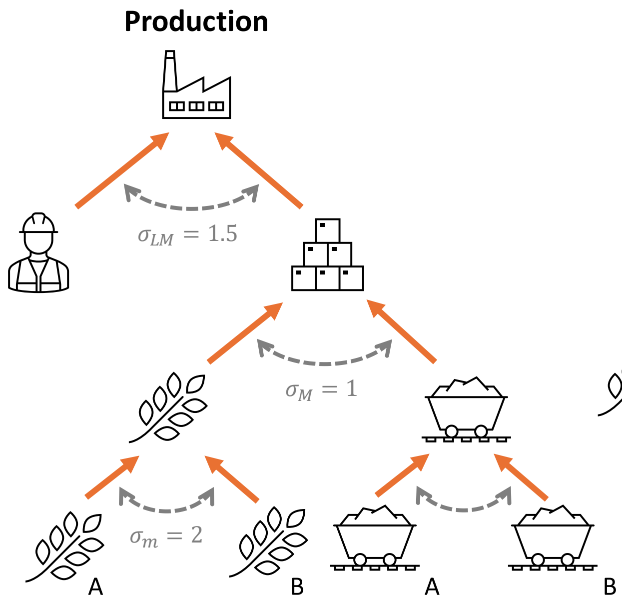
To measure the effect of the 2010 earthquake on the Chilean economy, we explicitly model the input-output links between each of its parts, which we operationalize as 210 nodes corresponding to each region $\times$ sector pair. In our model of the Chilean economy, we consider 15 representative households, each located in one of the country's regions and supplying their labor there. This labor supply corresponds to 15 separate factors in the economy. The government imposes a uniform tax of $\tau = 17\%$ on labor income. Because labor supply is inelastic, this tax is nondistortionary. The revenue raised through the tax is redistributed to households, with a share t_c of government revenue accruing to consumers in region c. We allow t_c to change over time; in particular, it will increase for the areas affected by the earthquake in the immediate aftermath of the disaster (and decrease for the unaffected regions). We do not consider any further tax or markup in the economy.

Government redistribution can be modeled in the framework of Baqaee and Farhi (2019b) by adding a wedge symbolizing the labor income tax as well as a fictitious factor to which tax income accrues, and then distributing the income from this fictitious factor across households. However, a convenient way to represent these government transfers is to directly incorporate them in the factor ownership matrix without adding wedges or a fictitious factor. In the absence of redistribution, the factor ownership matrix is simply the identity matrix: households in one region receive in full the income generated by their labor supply, and it is the only income they receive. Redistribution is equivalent to reassigning a share τ of the ownership of factors to households throughout the country, proportionally to t. In the context of our model, we can write $\Phi_{cf} = (1-\tau)\mathbb{1}_{c=f} + \tau t_c$.

Each of the production nodes in our model of the Chilean economy uses up to 211 different inputs: any of the goods produced by production nodes, and labor supplied in the region in which it is located. Firms' production is characterized by a nested aggregation of inputs, represented in Figure 2. At the highest level, firms combine labor and a composite bundle of intermediate inputs with an elasticity of substitution $\sigma_{LM} = 1.5$. The intermediate inputs bundle is, in turn, a Cobb-Douglas aggregate of composite inputs from different sectors. Finally, sector-specific inputs are CES aggregates of products from different regions, with an elasticity of substitution of $\sigma_m = 2$.

Similarly, we assume that the representative household in each region consumes a bundle of all of the 210 goods produced in the economy, aggregated in a nests: the final consumption bundle is a Cobb-Douglas aggregate of composite goods from different sectors, and each sector-specific composite is a CES aggregate of goods from different regions, with elasticity of substitution $\mu_f = 2$.

Figure 2: Substitution patterns in our model of the Chilean economy



5.4 Results

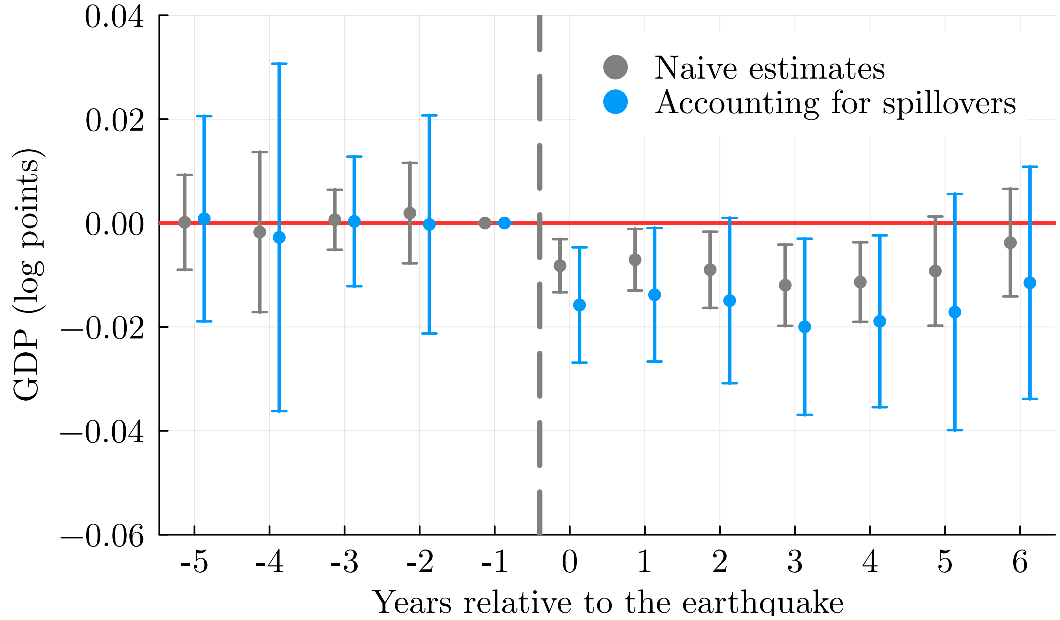
In Sections 2–4, we focused on changes between two periods. To estimate the effect of the earthquake in its immediate aftermath, we can compare the year in which it took place (2010) with the last year before the shock (2009). To show its effects in the longer run, we can compare 2011, 2012, etc., with 2009. Furthermore, comparing 2009 with other years before the earthquake provides a set of placebo tests.

We benchmark our methodology against a more naive estimation that ignores spillover effects. In this specification, we regress changes in the (log) value added of a node on treatment and sector fixed effects, and multiply the estimated coefficient by the share of the affected regions in GDP. The results of these benchmark regressions and the estimation procedure we develop are shown in Figure 3. We find that accounting for spillover effects substantially increases the estimated magnitude of GDP losses caused by the disaster.

Reassuringly, all of the placebo coefficients that we estimate are close to zero and statistically insignificant, suggesting that the nodes hit by the earthquake and those that were not were on similar trends before the shock.

We can estimate the losses in GDP caused by productivity drops in the six years following the earthquake by multiplying the estimated percentage point loss associated with each year by yearly GDP. This back-of-the-envelope calculation yields an estimate of 23 billions of dollars in losses, a figure comparable to the estimates of 15 to 30 billion dollars

Figure 3: Estimated effect of the 2010 earthquake on Chilean GDP



Notes: This figure reports estimated effects of the 2010 Chile earthquake on its GDP. The naive estimation corresponds to coefficients of a regression of (log) value added on treatment and fixed effects, multiplied by the share of the treated regions in GDP. The alternative estimation strategy (accounting for spillovers) corresponds to the methodology described in this paper.

issued by the Chilean government and insurance companies.

Taking spillovers into account in the setting studied here magnifies estimated economic effects relative to a more naive estimation strategy. There is no theoretical guarantee that this will be the case in general. Indeed, depending on the context, adjusting estimates for spillovers may either magnify or shrink them. In some cases, regressions that do not account for spillover effects may even fail to recover the correct sign of the treatment effect.

5.5 Extensions

To provide a more credible estimation of the economic effects of the 2010 earthquake, we plan to enrich our model of the Chilean economy. In particular:

- While we assumed elasticities of substitution in the Chilean economy to be known, a full estimation of the effects of the shock would involve estimating these elasticities. This can be achieved with data on prices. Indeed, within a CES nest with an elasticity of substitution θ, we have $\mathrm{d}\log(s_i/s_j) = -(\theta-1)\,\mathrm{d}\log(p_i/p_j)$, where s_i is the share of spending in the nest going to good i. Estimating θ requires exogenous variation in relative prices. In our study, exposure to the earthquake may provide such variation that is strong enough to be a reliable instrument.

- Until now, we considered the economy of Chile to be closed, while its imports/exports represented about a third of its GDP at the beginning of the 2010s. Expanding our model to incorporate international trade would increase its accuracy. This can be done by adding the rest of the world as an outside location that trades with producers and consumers in Chile.

- We have modeled the Chilean economy as efficient. If we can gather precise measures of distortions (taxes and markups) in the economy, they could be directly included in the model to evaluate how these wedges interacted with the shock.

- Finally, in our evaluation of the effects of the earthquake, we focused on the effects of the shock on GDP stemming from productivity losses. However, the earthquake may have further affected GDP through migration or the reallocation of government resources. Slight adjustments of our methodology can account for these additional consequences of the disaster.

6 Conclusion

In the past decades, applied researchers have developed a range of tools that allow them to exploit quasi-experimental variation to credibly estimate the economic effects of a "treatment". These methods compare treated units with appropriate controls and usually rely on the assumption that the treatment of one unit has no spillover effects on other units — an assumption often formalized as the Stable Unit Treatment Values Assumption, or SUTVA. While this assumption may be innocuous in some studies, spillovers are a natural feature of most economic settings because of the numerous trade, financial, and labor flows that connect different segments of the economy.

This paper develops a methodology that is a middle ground between typical adjustments to reduced-form approaches (such as "buffer" methods) and full-fledged structural exercises. It retains the transparency and ease of use of standard policy evaluation tools while leveraging increasingly accessible data on economic linkages to measure the extent of spillovers and appropriately account for them in estimation.

We apply the methodology we develop in the context of a major natural disaster and recover an estimate of its aggregate cost. Such measures of the economic effect of environmental damages are of important economic interest, as they inform mitigation policies and estimates of the costs of climate change. However, our approach can be used to study a wide range of settings where spillover effects are suspected to be substantial.

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Appendix

A Proofs and additional theoretical results

A.1 Proof of Proposition 1

Unbiasedness. By the Frisch–Waugh–Lovell theorem, the OLS coefficient on z in regression (6) equals

$$\widehat{\theta} = \frac{z^\top M_X y}{z^\top M_X z}.$$

With $w = \left(\kappa_T^\top G^{-1} \kappa_T\right)^{-1} G^{-1} \kappa_T$,

$$z^\top M_X z = w^\top G w = \frac{\kappa_T^\top G^{-1} \kappa_T}{\left(\kappa_T^\top G^{-1} \kappa_T\right)^2} = \frac{1}{\kappa_T^\top G^{-1} \kappa_T},$$

and

$$\widehat{\theta} = \left(\kappa_T^\top G^{-1} E_T^\top M_X\right) y.$$

Using $y = E_T \beta_T + X\gamma + \varepsilon$ and $M_X X = 0$,

$$\begin{aligned}
\widehat{\theta} &= \kappa_T^\top G^{-1} E_T^\top M_X E_T \beta_T + \kappa_T^\top G^{-1} E_T^\top M_X \varepsilon \\
&= \kappa_T^\top \beta_T + \kappa_T^\top G^{-1} E_T^\top M_X \varepsilon \\
&= \theta + \kappa_T^\top G^{-1} E_T^\top M_X \varepsilon.
\end{aligned}$$

Under Assumption 1, $\mathbb{E}[\varepsilon \mid X, T] = 0$, hence

$$\mathbb{E}\left[\widehat{\theta} \mid X, T\right] = \theta.$$

So $\widehat{\theta}$ is unbiased.

Consistency. As ε^a and ε^y are orthogonal, $\mathrm{Var}(\varepsilon \mid X, E) = E\,\Sigma_a\,E^\top + \Sigma_y$. Then, as $\hat{\theta} - \theta = \kappa_T^\top G^{-1} E_T^\top M_X \varepsilon$,

$$\begin{aligned}
\mathrm{Var}(\hat{\theta} - \theta \mid X, E_T) &= (\kappa_T^\top G^{-1} E_T^\top M_X)\mathrm{Var}(\varepsilon \mid X, E)(M_X E_T G^{-1} \kappa_T) \\
&= \kappa_T^\top G^{-1} E_T^\top M_X E \Sigma_a E^\top M_X E_T G^{-1} \kappa_T + \kappa_T^\top G^{-1} E_T^\top M_X \Sigma_y M_X E_T G^{-1} \kappa_T.
\end{aligned}$$

The first term converges to zero. Indeed, set $A = E\Sigma_a E^\top$ and $B = M_X E_T G^{-1/2}$ ($G^{-1/2}$ exists because G is positive definite). A is positive semidefinite. Indeed, Σ_a is positive semidefinite because it is a covariance matrix, and for any vector v, $v^\top E\Sigma_a E^\top v = \left(E^\top v\right)^\top \Sigma_a \left(E^\top v\right) \geq 0$. Furthermore, as $G = E_T^\top M_X E_T$, we have $B^\top B = I$. Let $x = G^{-1/2}\kappa_T$.

Then

$$\begin{aligned}
\kappa_T^\top G^{-1} E_T^\top M_X E \Sigma_a E^\top M_X E_T G^{-1} \kappa_T &= \kappa_T^\top G^{-1} E_T^\top M_X A M_X E_T G^{-1} \kappa_T \\
&= x^\top B^\top A B x \\
&\leq \|A\|_{\text{op}}\, x^\top B^\top B x \\
&= \|A\|_{\text{op}}\, \kappa_T^\top G^{-1} \kappa_T.
\end{aligned}$$

By Assumption 3(ii), $\|A\|_{\text{op}} \leq \|E\|_{\text{op}}^2 \|\Sigma_a\|_{\text{op}} \leq C_E^2 C_a < \infty$. By Assumption 3(i), $\kappa_T^\top G^{-1} \kappa_T \to_p 0$. Hence the product converges to zero in probability by Slutsky's theorem.

The second term also converges to zero, as

$$\begin{aligned}
\kappa_T^\top G^{-1} E_T^\top M_X \Sigma_y M_X E_T G^{-1} \kappa_T &\leq \|\Sigma_y\|_{\text{op}}\, \|M_X E_T G^{-1} \kappa_T\|_2^2 \\
&= \|\Sigma_y\|_{\text{op}} \kappa_T^\top G^{-1} \kappa_T \\
&\to_p 0.
\end{aligned}$$

Conditional Chebyshev yields $\hat{\theta} - \theta \to_p 0$ given (X, E_T).

A.2 Efficiency

Proposition 2 (BLUE under homoskedasticity)**.** *Under homoskedasticity and Assumptions 1-2, the estimator*

$$\widehat{\theta} = \kappa_T^\top \widehat{\beta}_T = \kappa_T^\top (E_T^\top M_X E_T)^{-1} E_T^\top M_X y \tag{S.1}$$

is the Best Linear Unbiased Estimator (BLUE) of $\theta = \kappa_T^\top \beta_T$ among all linear unbiased estimators that are functions of (X, T). Moreover,

$$\widehat{\theta} = a^{\star\top} y \quad \textit{with} \quad a^\star = M_X E_T (E_T^\top M_X E_T)^{-1} \kappa_T, \tag{S.2}$$

and

$$\text{Var}(\widehat{\theta} \mid X, T) = \sigma^2 \kappa_T^\top (E_T^\top M_X E_T)^{-1} \kappa_T, \tag{S.3}$$

where $\text{Var}(\varepsilon \mid X, T) = \sigma^2 I_N$.

Proof. Consider linear estimators of the form $\tilde{\theta} = a^\top y$ with $a = a(X, T) \in \mathbb{R}^N$. Unbiasedness for all γ and β_T requires

$$a^\top X = 0 \qquad \text{and} \qquad a^\top E_T = \kappa_T^\top, \tag{S.4}$$

since $\mathbb{E}[y \mid X, T] = E_T \beta_T + X\gamma$. Under homoskedasticity, $\text{Var}(\tilde{\theta} \mid X, T) = \sigma^2 a^\top a$. Thus, the BLUE estimator can be found by solving the following problem:

$$\min_{a \in \mathbb{R}^n} a^\top a \quad \text{s.t.} \quad a^\top X = 0, a^\top E_T = \kappa_T^\top.$$

Form the Lagrangian $\mathcal{L}(a, \mu, \nu) = a^\top a + \mu^\top (a^\top E_T - \kappa_T^\top) + \nu^\top a^\top X$. The first-order condition

is $2a + E_T\mu + X\nu = 0$, so
$$a = -\tfrac{1}{2}(E_T\mu + X\nu). \tag{S.5}$$
Premultiplying by $X^\top$ and imposing $a^\top X = 0$ yields $X^\top X\nu = -X^\top E_T\mu$, hence $\nu = -(X^\top X)^{-1}X^\top E_T\mu$. Substituting into (S.5) gives $a = -\frac{1}{2}\big[I - X(X^\top X)^{-1}X^\top\big]E_T\mu = -\frac{1}{2}M_X E_T\mu$. Let $b \equiv -\frac{1}{2}\mu$. Then any optimizer has the form
$$a = M_X E_T b. \tag{S.6}$$
Imposing the second unbiasedness restriction in (S.4) gives $\kappa_T^\top = a^\top E_T = b^\top E_T^\top M_X E_T = b^\top G$. By Assumption 2, G is invertible, so the unique solution is $b = G^{-1}\kappa_T$. Plugging this into (S.6) yields
$$a^\star = M_X E_T G^{-1}\kappa_T,$$
which proves (S.2). The variance at the optimizer is $\mathrm{Var}(\widehat{\theta} \mid X, T) = \sigma^2 a^{\star\top}a^\star = \sigma^2\kappa_T^\top G^{-1}\kappa_T$, which is (S.3). $\square$

Proposition 3 (GLS estimator)**.** *Assume a known error covariance,* $\mathrm{Var}(\varepsilon \mid X, T) = \Omega$, *where* Ω *is symmetric positive definite and known. Define the* Ω*-weighted residual-maker and Gram matrix*
$$M_{X,\Omega} \equiv I - X(X^\top\Omega^{-1}X)^{-1}X^\top\Omega^{-1}, \qquad G_\Omega \equiv E_T^\top\Omega^{-1}M_{X,\Omega}E_T. \tag{S.7}$$
Assume $X^\top\Omega^{-1}X$ *and* G_Ω *are nonsingular. Define*
$$w_\Omega \equiv \frac{G_\Omega^{-1}\kappa_T}{\kappa_T^\top G_\Omega^{-1}\kappa_T}, \qquad z_\Omega \equiv E_T w_\Omega. \tag{S.8}$$
Let $\widehat{\theta}_{GLS}$ *be the GLS coefficient on* z_Ω *from*
$$y = \theta z_\Omega + X\gamma + \varepsilon, \quad \textit{estimated with weight matrix } \Omega^{-1}. \tag{S.9}$$
It is equal to
$$\widehat{\theta}_{\mathrm{GLS}} = \big(z_\Omega^\top\Omega^{-1}M_{X,\Omega}z_\Omega\big)^{-1}z_\Omega^\top\Omega^{-1}M_{X,\Omega}y. \tag{S.10}$$
$\widehat{\theta}_{\mathrm{GLS}}$ *is finite-sample unbiased for* $\theta = \kappa_T^\top\beta_T$ *and is BLUE among linear unbiased estimators of* θ. *Moreover,*
$$\mathrm{Var}\big(\widehat{\theta}_{\mathrm{GLS}} \mid X, T\big) = \kappa_T^\top G_\Omega^{-1}\kappa_T. \tag{S.11}$$
In the special case of WLS with weights ω, $\Omega = \sigma^2 W^{-1}$, *where* $W = \mathrm{diag}(\omega_i)$.

Proof. Set $y^\star = \Omega^{-1/2}y$, $X^\star = \Omega^{-1/2}X$, $E_T^\star = \Omega^{-1/2}E_T$, and $\varepsilon^\star = \Omega^{-1/2}\varepsilon$. Then $\mathrm{Var}(\varepsilon^\star \mid X, T) = I$. With $M_{X^\star} = I - X^\star(X^{\star\top}X^\star)^{-1}X^{\star\top}$,
$$G^\star \equiv E_T^{\star\top}M_{X^\star}E_T^\star = E_T^\top\Omega^{-1}\Big(I - X(X^\top\Omega^{-1}X)^{-1}X^\top\Omega^{-1}\Big)E_T = G_\Omega. \tag{S.12}$$

Apply the homoskedastic result to the transformed problem $(y^\star, X^\star, E_T^\star)$, with weight w_Ω from (S.8) (since $G^\star = G_\Omega$). OLS on $y^\star = \theta z_\Omega^\star + X^\star\gamma + \varepsilon^\star$, where $z_\Omega^\star \equiv E_T^\star w_\Omega$, is unbiased and BLUE. GLS on (S.9) equals that OLS, so $\widehat{\theta}_{\mathrm{GLS}}$ is unbiased and BLUE. Finally, in the transformed regression with unit error variance,

$$\begin{aligned}\operatorname{Var}\left(\widehat{\theta}_{\mathrm{GLS}} \mid X, T\right) &= \left(z_{\Omega}^{\star\top} M_{X^\star} z_{\Omega}^{\star}\right)^{-1} = \left(w_{\Omega}^{\top} G^{\star} w_{\Omega}\right)^{-1} \\ &= \left(\frac{\kappa_T^{\top} G_{\Omega}^{-1} \kappa_T}{\left(\kappa_T^{\top} G_{\Omega}^{-1} \kappa_T\right)^2}\right)^{-1} = \kappa_T^{\top} G_{\Omega}^{-1} \kappa_T,\end{aligned}$$

using $w_{\Omega} = G_{\Omega}^{-1}\kappa_T / (\kappa_T^{\top} G_{\Omega}^{-1} \kappa_T)$ and $G^{\star} = G_{\Omega}$. □

B Measures of exposure

In this section, we describe how to extend the results of Section 4 to a larger class of models, including inefficient economies and economies where production and consumption nodes are not CES. We also show how to compute first-order changes to Domar weights following shocks to wedges, factor supplies, and the factor ownership matrix. These results are either derived in Baqaee and Farhi (2019b) or are natural extensions of their framework.

B.1 Inefficient economies

The profits generated by wedges in the economy can be viewed as income from an additional factor that Baqaee and Farhi describe as "ficticious". In what follows, we denote the set of "real" factors by F and the set of all factors (both real and fictitious) by F^*.

In the presence of distortions, elements of the exposure matrix can be expressed as:

$$\begin{aligned}\frac{\mathrm{d}\log\lambda_i}{\mathrm{d}\log A_j} = &\sum_{k\in C,N} \frac{\lambda_k}{\lambda_i}\frac{(\theta_k - 1)}{\mu_k}\operatorname{Cov}_{\tilde{\Omega}^{(k)}}\left(\Psi_{(i)}, \tilde{\Psi}_{(j)}\right) \\ &- \sum_{f\in F}\sum_{k\in C,N} \frac{\lambda_k}{\lambda_i}\frac{(\theta_k - 1)}{\mu_k}\operatorname{Cov}_{\tilde{\Omega}^{(k)}}\left(\Psi_{(i)}, \tilde{\Psi}_{(f)}\right)\frac{\mathrm{d}\log\Lambda_f}{\mathrm{d}\log A_j} \\ &+ \frac{1}{\lambda_i}\sum_{f\in F^*}\sum_{c\in C}\left(\lambda_i^c - \lambda_i\right)\Phi_{cf}\Lambda_f\frac{\mathrm{d}\log\Lambda_f}{\mathrm{d}\log A_j}\end{aligned} \tag{S.13}$$

Again, computing these entries necessitates the inversion of the following system of equations for different values of j to obtain the $\frac{\mathrm{d}\log\boldsymbol{\Lambda}}{\mathrm{d}\log\boldsymbol{A}}$ matrix.

$$\begin{aligned}\frac{\mathrm{d}\log\Lambda_n}{\mathrm{d}\log A_j} = &\sum_{k\in C,N}\frac{\lambda_k}{\Lambda_n}\frac{(\theta_k-1)}{\mu_k}\mathrm{Cov}_{\tilde{\Omega}^{(k)}}\left(\Psi_{(n)},\tilde{\Psi}_{(j)}\right)\\ &-\sum_{f\in F}\sum_{k\in C,N}\frac{\lambda_k}{\Lambda_n}\frac{(\theta_k-1)}{\mu_k}\mathrm{Cov}_{\tilde{\Omega}^{(k)}}\left(\Psi_{(n)},\tilde{\Psi}_{(f)}\right)\frac{\mathrm{d}\log\Lambda_f}{\mathrm{d}\log A_j}\\ &+\frac{1}{\Lambda_n}\sum_{f\in F^*}\sum_{c\in C}\left(\Lambda_n^c-\Lambda_n\right)\Phi_{cf}\Lambda_f\frac{\mathrm{d}\log\Lambda_f}{\mathrm{d}\log A_j}\end{aligned} \tag{S.14}$$

B.2 Shocks to factor supplies

While Baqaee and Farhi (2019b) focus on the ripple effects of productivity shocks, their results can be extended to other types of shocks. Consider, for instance, changes to the supply of a given factor (e.g., inflows of capital through FDI, increases in the amount of agricultural land through deforestation, or increases in the labor supply following migration shocks). The following equations give the first-order effects of such changes in factor supply:

$$\begin{aligned}\frac{\mathrm{d}\log\lambda_i}{\mathrm{d}\log L_j} = &\sum_{k\in C,N}\frac{\lambda_k}{\lambda_i}\frac{(\theta_k-1)}{\mu_k}\mathrm{Cov}_{\tilde{\Omega}^{(k)}}\left(\Psi_{(i)},\tilde{\Psi}_{(j)}\right)\\ &-\sum_{f\in F}\sum_{k\in C,N}\frac{\lambda_k}{\lambda_i}\frac{(\theta_k-1)}{\mu_k}\mathrm{Cov}_{\tilde{\Omega}^{(k)}}\left(\Psi_{(i)},\tilde{\Psi}_{(f)}\right)\frac{\mathrm{d}\log\Lambda_f}{\mathrm{d}\log L_j}\\ &+\frac{1}{\lambda_i}\sum_{f\in F^*}\sum_{c\in C}\left(\lambda_i^c-\lambda_i\right)\Phi_{cf}\Lambda_f\frac{\mathrm{d}\log\Lambda_f}{\mathrm{d}\log L_j}\end{aligned} \tag{S.15}$$

$$\begin{aligned}\frac{\mathrm{d}\log\Lambda_n}{\mathrm{d}\log L_j} = &\sum_{k\in C,N}\frac{\lambda_k}{\Lambda_n}\frac{(\theta_k-1)}{\mu_k}\mathrm{Cov}_{\tilde{\Omega}^{(k)}}\left(\Psi_{(n)},\tilde{\Psi}_{(j)}\right)\\ &-\sum_{f\in F}\sum_{k\in C,N}\frac{\lambda_k}{\Lambda_n}\frac{(\theta_k-1)}{\mu_k}\mathrm{Cov}_{\tilde{\Omega}^{(k)}}\left(\Psi_{(n)},\tilde{\Psi}_{(f)}\right)\frac{\mathrm{d}\log\Lambda_f}{\mathrm{d}\log L_j}\\ &+\frac{1}{\Lambda_n}\sum_{f\in F^*}\sum_{c\in C}\left(\Lambda_n^c-\Lambda_n\right)\Phi_{cf}\Lambda_f\frac{\mathrm{d}\log\Lambda_f}{\mathrm{d}\log L_j}\end{aligned} \tag{S.16}$$

B.3 Shocks to the allocation of factor income

Similarly, the framework of Baqaee and Farhi (2019b) allows us to study shocks to the factor ownership matrix $\boldsymbol{\Phi}$ (e.g., because of a shock to the allocation of government spending). The first-order effect of a shock to an entry Φ_{dg} of the factor ownership matrix is given by the following equations:

$$\frac{\mathrm{d}\log\lambda_i}{\mathrm{d}\Phi_{cf}} = -\sum_{g\in F}\sum_{k\in C,N}\frac{\lambda_k}{\lambda_i}\frac{(\theta_k-1)}{\mu_k}\mathrm{Cov}_{\tilde{\Omega}^{(k)}}\left(\Psi_{(i)},\tilde{\Psi}_{(g)}\right)\frac{\mathrm{d}\log\Lambda_g}{\mathrm{d}\Phi_{cf}} + \lambda_i^c\frac{\Lambda_f}{\lambda_i} \tag{S.17}$$

$$\frac{\mathrm{d}\log\Lambda_n}{\mathrm{d}\Phi_{cf}} = -\sum_{g\in F}\sum_{k\in C,N}\frac{\lambda_k}{\Lambda_n}\frac{(\theta_k-1)}{\mu_k}\mathrm{Cov}_{\tilde{\Omega}^{(k)}}\left(\Psi_{(i)},\tilde{\Psi}_{(g)}\right)\frac{\mathrm{d}\log\Lambda_g}{\mathrm{d}\Phi_{cf}} + \Lambda_n^c\frac{\Lambda_g}{\Lambda_n} \tag{S.18}$$

B.4 Shocks to wedges

Changes to the vector of wedges $\boldsymbol{\mu}$ also affect Domar weights. To the first order, we have

$$\begin{aligned}\frac{\mathrm{d}\log\lambda_i}{\mathrm{d}\log\mu_j} = &\sum_{k\in C,N}(1-\theta_k)\frac{\lambda_k}{\lambda_i}\mu_k^{-1}\mathrm{Cov}\left(\tilde{\Psi}_{(j)},\Psi_{(i)}\right)\\ &+\sum_{g\in F}\sum_{k\in C,N}(1-\theta_k)\frac{\lambda_k}{\lambda_i}\mu_k^{-1}\mathrm{Cov}\left(\tilde{\Psi}_g,\Psi_{(i)}\right)\frac{\mathrm{d}\log\Lambda_g}{\mathrm{d}\log\mu_j}\\ &-\frac{\lambda_j}{\lambda_i}\left(\Psi_{ji}-\mathbb{1}_{i=j}\right)+\sum_{c\in C}\sum_{g\in F^*}\chi_c\Phi_{cg}\Lambda_g\frac{\lambda_i^c}{\lambda_i}\frac{\mathrm{d}\log\Lambda_g}{\mathrm{d}\log\mu_j},\end{aligned} \tag{S.19}$$

where $\chi_c = \frac{\sum_{i=1}^N p_i c_{ci}}{\sum_{j=1}^N\sum_{d=1}^C p_j c_{di}} = \sum_{f\in F^*}\Phi_{cf}\Lambda_f$ is consumer c's share in aggregate revenue. Changes in factors' Domar weights $\frac{\mathrm{d}\log\Lambda_g}{\mathrm{d}\log\mu_j}$ is given for real factors by solving the following system of equations:

$$\begin{aligned}\frac{\mathrm{d}\log\Lambda_g}{\mathrm{d}\log\mu_j} = &\sum_{k\in C,N}(1-\theta_k)\frac{\lambda_k}{\Lambda_g}\mu_k^{-1}\mathrm{Cov}\left(\tilde{\Psi}_{(j)},\Psi_{(g)}\right)\\ &+\sum_{g\in F}\sum_{k\in C,N}(1-\theta_k)\frac{\lambda_k}{\Lambda_g}\mu_k^{-1}\mathrm{Cov}\left(\tilde{\Psi}_g,\Psi_{(g)}\right)\frac{\mathrm{d}\log\Lambda_g}{\mathrm{d}\log\mu_j}\\ &-\frac{\lambda_j}{\Lambda_g}\left(\Psi_{ji}-\mathbb{1}_{i=j}\right)+\frac{1}{\Lambda_g}\sum_{c\in C}\sum_{g\in F^*}\chi_c\Phi_{cg}\Lambda_g\left(\Lambda_g^c-\Lambda_g\right)\frac{\mathrm{d}\log\Lambda_g}{\mathrm{d}\log\mu_j},\end{aligned} \tag{S.20}$$

and for fictitious factors by

$$\frac{\mathrm{d}\log\Lambda_{i^*}}{\mathrm{d}\log\mu_j} = \mathrm{d}\log\lambda_i + \frac{1}{\mu_i-1}\mathbb{1}_{i=j}, \tag{S.21}$$

where Λ_{i^*} is the markup placed on the ith good.

B.5 Non-CES production and consumption nodes

While until now, we focused on consumption and production nodes that aggregate inputs with a constant elasticity of substitution, the formulas to compute the exposure matrix can be adjusted to accommodate arbitrary production functions. To do so, parameters of the form $(\theta_j - 1)\,\mathrm{Cov}_{\Omega^{(j)}}\left(\Psi_{(k)}, \Psi_{(l)}\right)$ need to be replaced with the input-output substitution operator, that Baqaee and Farhi (2019b) define as

$$\Xi_j\left(\Psi_{(k)}, \Psi_{(l)}\right) = -\sum_{x,y} \Omega_{jx}\left[\mathbb{1}_{xy} + \Omega_{jy}\left(\vartheta_j(x,y) - 1\right)\right]\Psi_{xk}\Psi_{yl}. \tag{S.22}$$

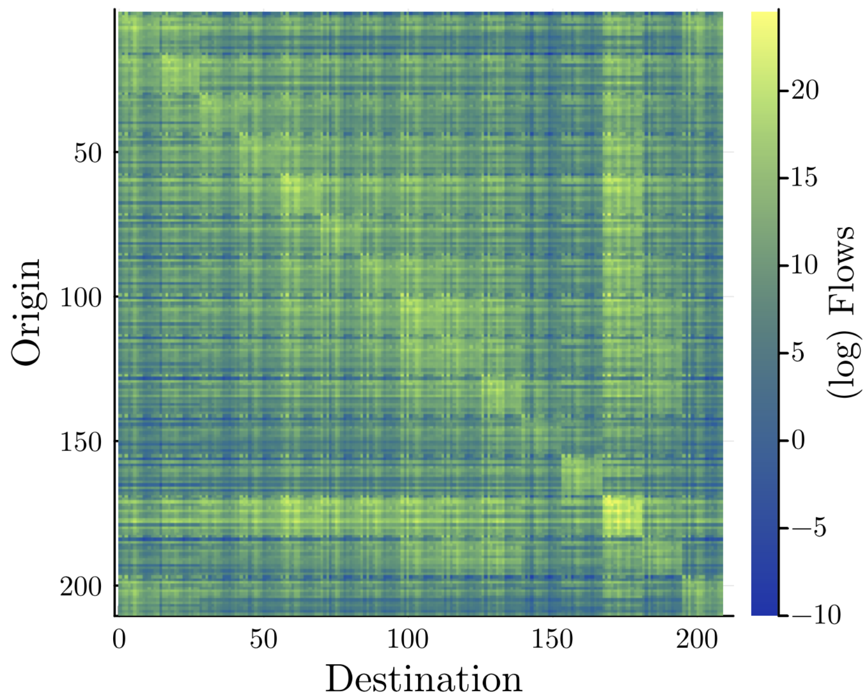
In this expression, $\vartheta_j(x,y)$ is the Allen-Uzawa elasticity of substitution between inputs x and y. Given the cost function C_j of producer j, this elasticity is given by

$$\vartheta_j(x,y) = \frac{C_j \frac{\mathrm{d}^2 C_j}{\mathrm{d}p_x \mathrm{d}p_y}}{\frac{\mathrm{d}C_j}{\mathrm{d}p_x} \cdot \frac{\mathrm{d}C_j}{\mathrm{d}p_y}} = \frac{\epsilon_j(x,y)}{\Omega_{jy}}, \tag{S.23}$$

where $\epsilon_j(x,y)$ denotes the elasticity of producer j's demand for input x with respect to p_y.

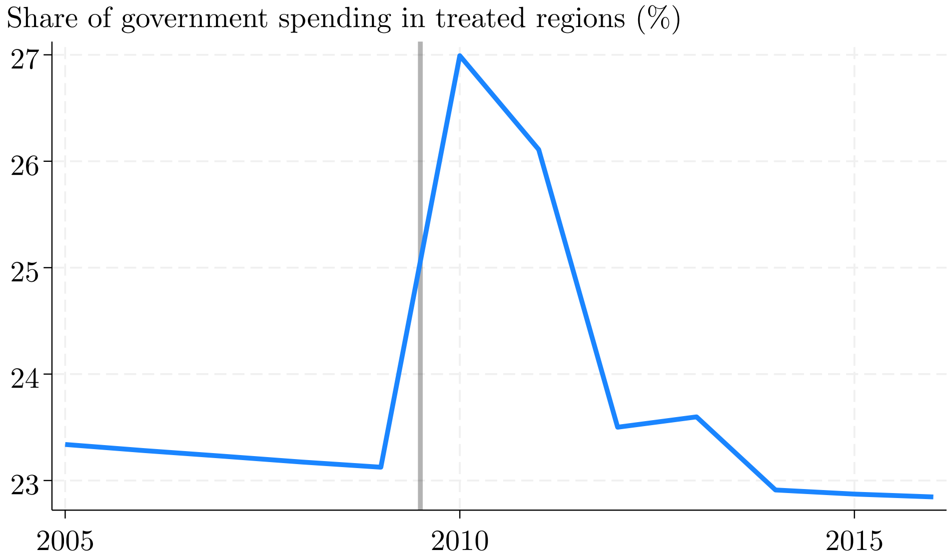
C Additional Figures

Figure S.1: IO matrix of the Chilean economy



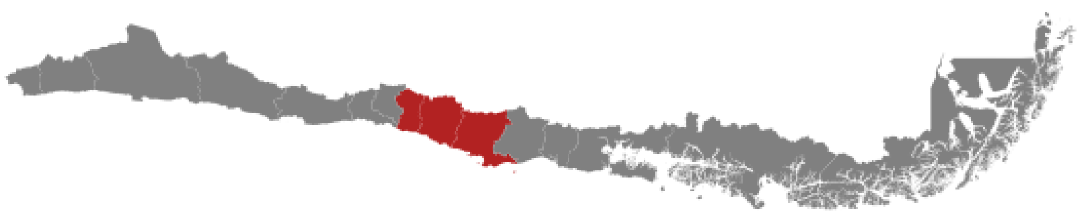
Notes: In this figure, we represent the IO matrix of the Chilean economy we built to implement the estimation procedure of Section 5.3. Each row (resp., column) of the matrix represents a separate node in our representation of the Chilean economy, i.e., a region × sector. When numbering nodes, we group nodes by region, and order them by sector. Node 1 hence corresponds to sector 1 (Agriculture, livestock, forestry and fishing) in region 1 (Tarapacá), and node 16 corresponds to sector 2 (Exploitation of mines and quarries) in region 2 (Antofagasta).

Figure S.2: Changes in government transfers after the shock



Notes: This figure shows the share of government spending that is allocated to regions in the treated area.

Figure S.3: Treatment area



Notes: This figure shows a map of the Chilean regions – those colored in red are the three that were declared in a state of catastrophic emergency in the aftermath of the shock and that constitute our treatment area.

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