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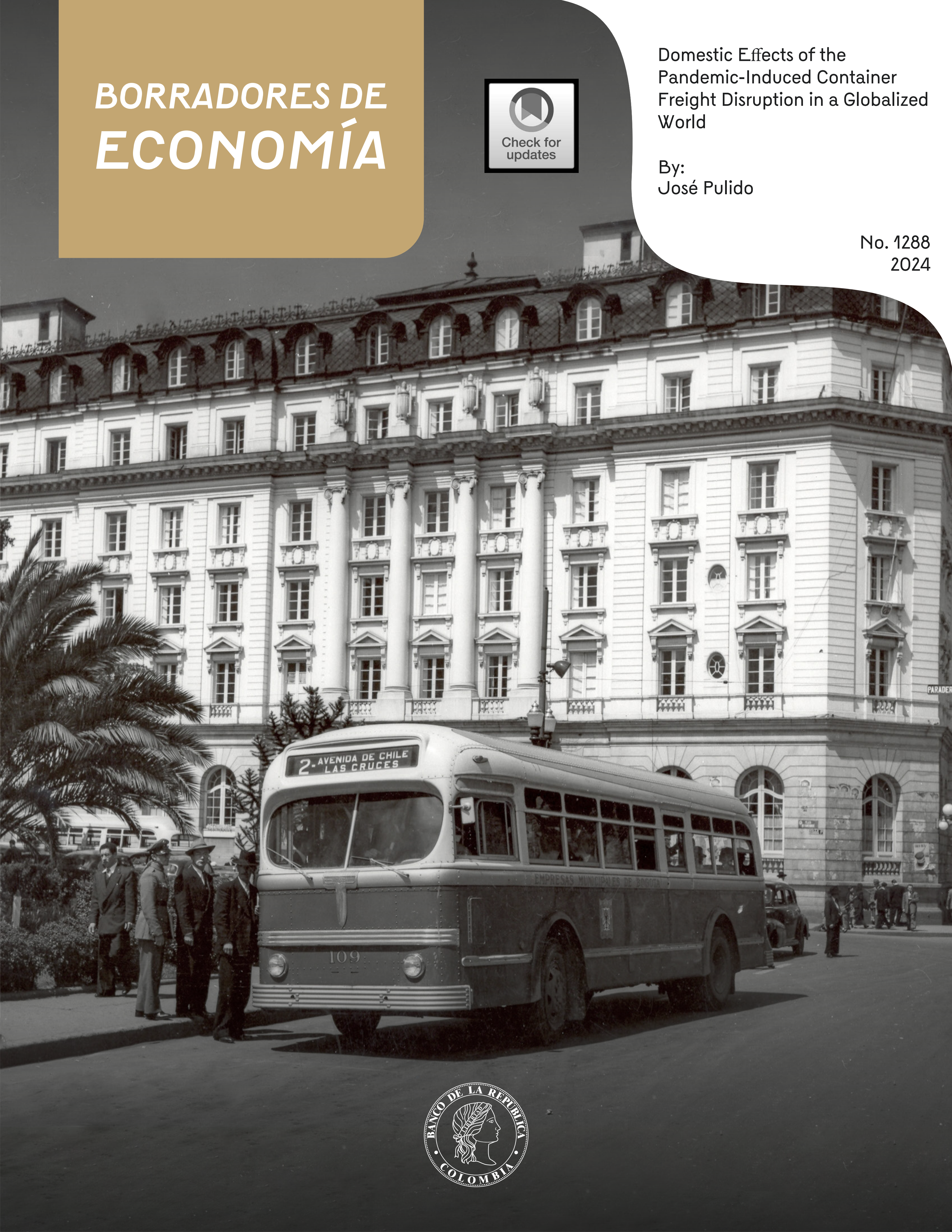

BANCO DE LA REPÚBLICA
COLOMBIA

Domestic Effects of the Pandemic-Induced Container Freight Disruption in a Globalized World*

José Pulido†

Abstract

The Covid-19 pandemic severely disrupted the maritime transportation industry, leading to historic surge in container freight rates, which only returned to normal in 2023. In this paper I examine the welfare effects on a particular country, Colombia, of the observed disruption in international freight rates during the 2020-2023 period. For this, I use a quantitative model of international trade with out-of-steady-state transitional dynamics and a global production network, along with an instrumental variable approach to estimate a trade elasticity to freight. I quantify both the direct effects of freight increases on goods transported to and from Colombia, as well as the indirect impact of heightened rates on routes across the rest of the world. The freight disruption caused a welfare loss of 0.4%, attributable solely to the direct effects, as the indirect impact simultaneously enhances Colombia's relative trade openness, thereby compensating for the increased shipping costs globally.

Keywords: Container freight, transportation costs, international trade, Covid-19.
J.E.L. Classification: F16, F62, F17

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Efectos Domésticos de los Ajustes en Fletes de Contenedores Marítimos por la Pandemia en un Mundo Globalizado*

José Pulido†

Resumen

La pandemia de Covid-19 afectó severamente a la industria del transporte marítimo, provocando un aumento histórico en los fletes de contenedores, los cuales retornaron a niveles previos solo en 2023. Este artículo estudia los efectos sobre el bienestar de Colombia del ajuste observado en las tarifas internacionales de fletes de contenedores durante el período 2020-2023. Para ello, se utiliza un modelo cuantitativo de comercio internacional con dinámicas de ajuste fuera del estado estacionario y una red de producción global, junto con una estrategía de variable instrumental para estimar la elasticidad de los flujos comerciales a los fletes. Se cuantifican tanto los efectos directos del aumento en los fletes de los bienes transportados desde y hacia Colombia, asi como el impacto indirecto del incremento en los fletes en las demás rutas internacionales. La disrupción en los fletes causó una pérdida de bienestar del 0,4 % atribuible únicamente a los efectos directos, ya que el aumento en los fletes en las demás rutas internacionales mejora simultáneamente el grado relativo de apertura comercial de Colombia, compensando los efectos de costos.

Palabras Clave: Fletes, contenedores, transporte marítimo, comercio,Covid-19.
Clasificación JEL: F16, F62, F17

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1 Introduction

One of the most well-established results in the international trade literature is the close connection between welfare and trade costs. Alongside natural and regulatory trade barriers, a substantial proportion of these costs arises from international transportation, which was profoundly disrupted by the Covid-19 pandemic. Notably, the sea transport industry, responsible for approximately 80% of total international trade (Heiland and Ulltveit-Moe, 2020*a*; UNCTAD, 2021*b*), encountered a confluence of intricate logistical and operational challenges, resulting in a historic surge in freight rates that began in late 2020 and persisted during three years. Thus, while the Covid-19 pandemic diminished welfare for various reasons, one of the channels through which welfare was affected was the impact on international trade and the global production networks resulting from the disruption in the maritime transport industry. Despite its importance, efforts to comprehensively quantify the significance of this channel have been relatively scarce.

In this study, I estimate the size of this welfare reduction for a specific country, Colombia. Given the increasing importance of global trade networks, I not only assess the effects of increased freight rates on the goods imported and exported by Colombia but also analyze the indirect impacts resulting from the rises in freight rates on all other international routes. For this, I use a quantitative model of international trade that encompasses multiple countries and sectors and uses an input-output structure similar to Caliendo and Parro (2015) to account for the global production network. In addition, given the dynamic nature of the shock, the model incorporates out-of-steady-state transitional dynamics and reallocation costs for workers, as in Caliendo, Dvorkin and Parro (2019) (hereafter CDP). Building on CDP, I model bilateral trade costs as a function of sector-specific duties and overall transportation costs. These transportation costs, in turn, depend on the observed freight rates (along with unobservable factors) and an elasticity of transportation costs with respect to freight.

The latter elasticity of transportation costs to freight, which is a key input for the quantification exercise, is estimated in a model-consistent way. Particularly, the gravity equation of the model suggests that this elasticity can be derived by combining two trade elasticities that are feasible to estimate: one related to freight and the other related to tariffs. Since bilateral freight rates are arguably endogenous to bilateral trade flows, I employ an instrumental variable (IV) approach to estimate the first elasticity. The instrument takes advantage of both the heterogeneous timing of lockdowns during the pandemic and the pre-existing conditions in port infrastructure. This empirical strategy yields a statistically significant trade elasticity to freight close to -1, falling within the range estimated in the relevant literature. By combining this elasticity with estimates of sectoral trade elasticities to tariffs obtained from recent studies, I obtain the elasticities of transportation costs to container freight. These elasticities, combined with a series of observed freight rates from 2019 to 2023, enable me to quantify the time series of shocks to transportation costs resulting from the pandemic.

With the obtained series of transportation cost shocks, I use the quantitative model of trade to evaluate the effects of these shocks in the domestic economy. For this, I start by constructing a quarterly baseline economy that begins in a pre-pandemic year with full availability of data (2018), and that, after that, evolves towards its steady state under the assumption that freight and other exogenous state variables (e.g., sectoral productivity levels, mobility costs across sectors, other bilateral international trade costs, etc.) remain constant. Subsequently, I analyze the implications for the allocation of labor, real wages, and welfare across various counterfactual scenarios, wherein I solely modify the transportation costs using my series of shocks. Those quantitative exercises are performed using the dynamic extension of the "exact-hat algebra" approach of Dekle, Eaton and Kortum (2008), recently proposed by CDP.

The results of the counterfactual exercises suggest that the observed global disruption in freight had a non-negligible impact on the allocation of Colombian workers and overall welfare. First, real wages declined across all economic sectors, depressing real consumption and consequently reducing the model-consistent measure of welfare by 0.39%. Second, the adjustment of wages relative to the option value of not working led to as much as 0.14% of the workforce (approximately 33.3 thousand workers) transitioning to non-employment at the peak of the disruption, while 0.04% of the workforce (9.2 thousand workers) remained permanently non-employed as a result of the entire shock. Although these shifts out of employment are significant in absolute terms, they are moderate compared to the patterns of labor reallocation exhibited by the baseline economy without shocks (i.e., the one transitioning towards its steady state). Third, within the employed population, there was a reallocation of workers toward non-tradable sectors, particularly services, at the expense of manufacturing, which lost a 0.32% employment share due to the shock.

As stated above, to understand the importance of global trade networks and the role of the country's degree of openness in shaping the latter results, I divide the full set of shocks into a subset that includes increases in freight rates only in routes that involve Colombia directly (i.e. freight rates for its imports and exports), and a subset with the increases in freight rates in all remaining routes. By doing so, the results of the corresponding counterfactuals show that the effects on the labor reallocation within the employed population work in opposite directions. This is because employment reallocations respond to changes in relative wages; and each subset of shocks triggers opposite impacts on the wages of tradable sectors relative to non-tradable sectors. While in the case of increasing freight only in routes that involve Colombia the country becomes relatively more closed with respect to the rest of the world, inducing a decrease on relative wages in tradable sectors, in the case in which freight increases only in routes that do not involve Colombia the country becomes relatively more open, and hence the opposite effect on relative wages occurs. Therefore, the employment reallocation effects obtained in the main counterfactual with the full set of shocks on, are the result of the sum of opposite forces on labor reallocation that partially offset each other.

Finally, concerning welfare, my findings indicate that the total welfare loss resulting from the disruption in the maritime transport industry can be solely attributed to the elevated freight rates on goods imported and exported by Colombia. Interestingly, while the increase in freight rates on other routes that do not involve Colombia, maintaining unchanged freight rates for goods crossing the Colombian border, does create a cost-push effect that impacts Colombia's productive structure, it also enhances the country's relative trade openness with respect to the rest of the world. This, in turn, allows the tradable sector to expand, generating gains from trade that effectively offset the effects of the increased shipping costs worldwide.

Related literature

This study belongs to a burgeoning literature in trade that uses quantitative Ricardian models to study transitional dynamics after a set of shocks hits an economy. The core structure of those models, built on the multi-sector version of the Eaton and Kortum's (2002) model of trade and its extension to consider I-O linkages of Caliendo and Parro (2015), is a workhorse framework in the trade literature, that, as opposed to older computable general equilibrium models, provides micro-theoretical foundations and a tight connection between theory and data. This type of models has been used extensively for quantitative analysis during the last decade –see Costinot and Rodríguez-Clare (2014) and Caliendo and Parro (2022) for a review, but mainly for the purpose of performing comparative static exercises (e.g., assessing the impact of trade policies or technology shocks, or the consequences of liberalization episodes). Instead, their use to study out-of-steady-state transitional dynamics is relatively recent.

To the best of my knowledge, the only papers that incorporate these types of dynamics into a multi-sector, multi-factor model of international trade with I-O linkages are CDP, Rodríguez-Clare, Ulate and Vásquez (2022), Dix-Carneiro et al. (2023), Caliendo et al. (2021), and Ulate, Vasquez and Zarate (2023)[1]. In the first three cases, the models also incorporate spatial frictions between regions (a dimension that I abstract from) to study the implications of the "China" trade shock in the the US (CDP and Rodríguez-Clare, Ulate and Vásquez, 2022), and the effects of the 2004 European Union enlargement (Caliendo et al., 2021). In the fourth case, their model instead adds consumption-saving decisions and labor market frictions within sectors to examine the response of labor markets in six countries to technology, trade and preference shocks. Finally, in the concurrent study by Ulate, Vasquez and Zarate (2023), which is the most closely related to this research, the model developed by Rodríguez-Clare, Ulate and Vásquez (2022) is used to explore the effects of temporary increases in iceberg trade costs on the U.S. labor market, aiming to simulate the global supply chain disruptions during the pandemic. One of the main differences between their study and mine is my additional effort to link the observed evolution of container freight rates across different shipping routes with model-specific transportation cost shocks, through the estimation of the relevant trade

[1] Kleinman, Liu and Redding (2023) also uses a model of trade with out-of-steady-state transitional dynamics and choices of migration, that include forward-looking investment decisions, but, in their baseline specification, with a single sector.

elasticities.

My research is also related to the literature that estimates trade elasticities to transportation costs, particularly the papers of Limão and Venables (2001), Martínez-Zarzoso and Suárez-Burguet (2005), Jacks and Pendakur (2010), Shapiro (2016) and Fraser (2018). Usually, transportation costs are measured either in a direct way using available freight rates for particular routes (as in Limão and Venables, 2001; Martínez-Zarzoso and Suárez-Burguet, 2005; Jacks and Pendakur, 2010; or in my case) or in an indirect way based on CIF/FoB ratios[2] that are collected from the same reporter, given the issues raised by Hummels and Lugovskyy (2006) of comparing data from different reporters.[3] The empirical strategies are usually based on the estimation of a gravity-type of equation, and, in similar way as here, some of those use IV approaches to address the problem of endogeneity between freight rates and trade flows (Martínez-Zarzoso and Suárez-Burguet, 2005; Jacks and Pendakur, 2010; Shapiro, 2016). Except for Jacks and Pendakur (2010), all the cited studies estimate trade elasticities to transportation costs that are significant and of the expected negative sign. The estimated elasticities range from -0.42 in the case of Fraser (2018) and -7.91 in the case of Shapiro (2016), so my estimated elasticity of -1.04 in my preferred specification lies inside that range.

This study also contributes to the extensive body of literature examining the implications of the Covid-19 pandemic across various dimensions. Specifically, it aligns with research that analyzes the evolution of the international maritime transportation industry during the crisis (Heiland and Ulltveit-Moe, 2020*a*,*b*; UNCTAD, 2021*b*) and the effects of the pandemic and its aftermath on global container shipping and ports (Hou, Shi and Guo, 2022; Yang, Liu and Chang, 2023). Furthermore, it relates to studies assessing the macroeconomic impacts of the pandemic on the Colombian economy, particularly in terms of trade flows (Graziano and Tian, 2023), real consumption (Acevedo et al., 2022) and the sectoral allocation of employment (Morales et al., 2022; Bonilla-Mejía et al., 2023).

Finally, considering my results regarding the increase in freight rates in routes not involving Colombia, that indicate that Colombia's relative position improves as other countries fare worse, there is a potential link between this study and the existing literature on unilateral trade protection. Relevant papers in this strand include Brander and Spencer (1981), Venables (1987), Ossa (2011), and Tobal (2017), among others.

The organization of this paper is as follows. Section 2 presents my empirical motivation, by examining the evolution of the container freight rates during the Covid-19 pandemic. Section 3 introduces the dynamic model of trade with observable freight rates. Section 4 discusses the procedure that allows me to infer the magnitude of the transportation cost shocks in the model, particularly by estimating the trade elasticity to freight rates. Section 5 performs the

[2]CIF: Cost, Insurance and Freight; FoB: Free on Board. Since CIF is the sum of FOB and transport costs, CIF/FOB equals one plus the ad valorem freight and insurance rate.

[3]Because of this, the advantage of the use of direct freight rates is that they are often considered to be of better quality (Gaulier et al., 2008)

results of the counterfactual exercises of adding the inferred transportation costs shocks to the baseline economy. I also perform some robustness checks to the baseline results. Finally, Section 6 concludes.

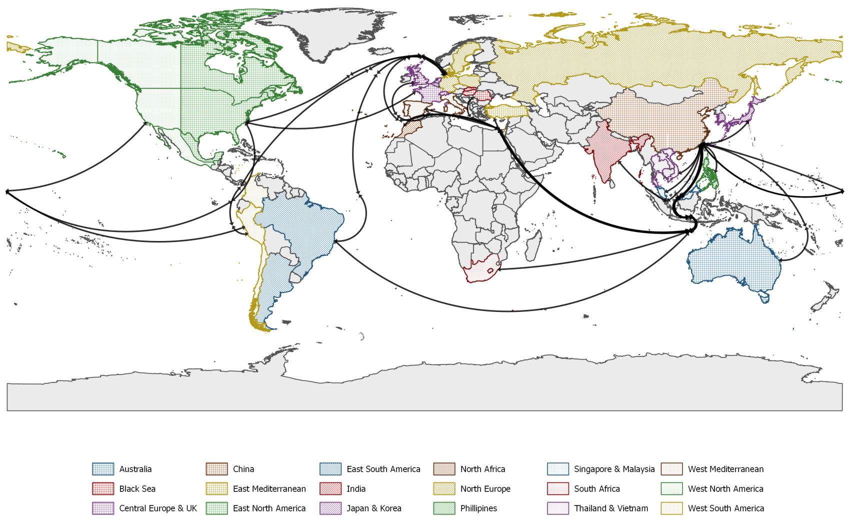
2 Container freight rates during the Covid-19 pandemic

As the world economy emerged from the severe and abrupt decline in economic activity caused by the Covid-19 pandemic in early 2020, a combination of various factors triggered a significant increase in container freight rates worldwide, beginning in late 2020. These factors included congestion and delays at ports resulting from lockdowns and other sanitary measures, bottlenecks faced by many manufacturing sectors due to supply chain disruptions, logistical challenges in meeting the rapid recovery in demand compared to anticipated levels, and even some exogenous shocks such as the obstruction of the Suez Canal (see Brooks, Fortun and Pingle 2020*a*,*b*; UNCTAD, 2021*a* for summaries). Although initially perceived as transitory, most of these factors persisted longer than expected, leading to historically high delivery times and freight rates in 2021 and 2022. Only in 2023, following the aftermath of the pandemic and the recovery of the global economy, the industry gradually returned to normalcy.

To study the evolution of container freight rates during the pandemic, I collect available time series for different routes all around the world from three different data providers: Drewry, Freightos/Baltic Exchange and Ningbo. Each of those sources collect real-time information of spot carry rates from different freight forwarders, and aggregate them to construct representative rates for individual shipping routes.[4] Table C.1 in the Appendix shows the 36 routes with available information from any of the three data providers. Those routes involve trade between 18 different worldwide regions, displayed in Figure 1, that are either shipping destinations, shipping origins or both.

[4]All rates are reported in USD per forty foot container, so the resulting measures are comparable.

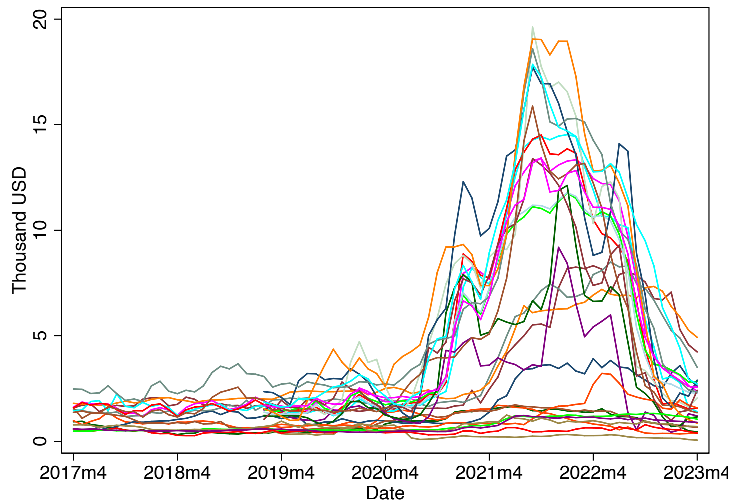
Figure 1 – Routes and Regions with Available Information of Container Freight



Note: The sources for each route are indicated in Table C.1, and the countries that belong to each of the displayed regions are listed in Table C.2.

Figure 2 jointly depicts the monthly evolution of all available container freight rates since 2017. Most of the series display a noticeable increase, starting by late 2020. In 2021, worldwide freight rates increased on average to four times their 2019 levels (306%). However, the increases were largely heterogeneous. By splitting the routes between origins and destinations that depart or arrive from Asia (East) or otherwise (West), Figure 3 shows that the increases were more striking in the routes departing from locations in the East (first row). This asymmetry is even present when observing freight rates between the same pair of regions. For instance, the 2021 average container freight for shipping from China to East North America increased 323% relative to their 2019 average level, whereas shipping the other way round was only 34% more expensive in 2021 compared to 2019.

Figure 2 – Container Freight Rates During the Covid-19 Pandemic



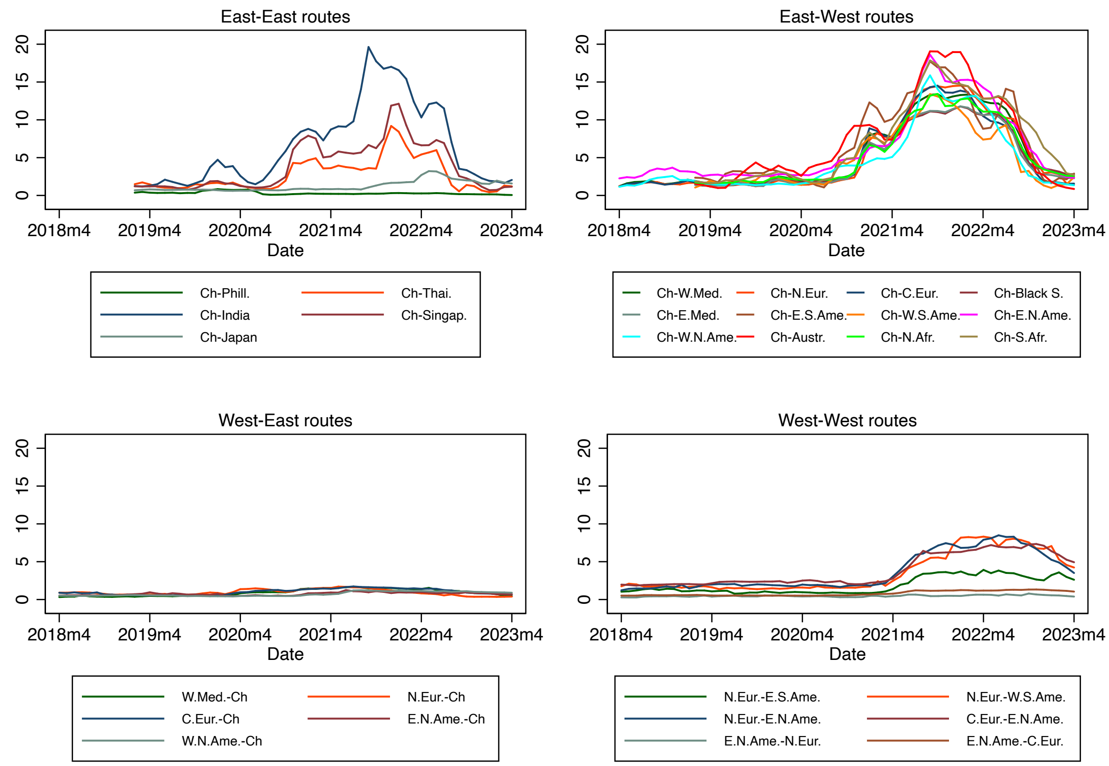
Note: All rates are reported in thousand USD per forty foot container. Sources: Drewry, Freightos and Ningbo container indexes.

The latter set of facts poses a challenge to the standard approach in which transportation costs are introduced in quantitative trade models. Commonly, under the assumption of a full pass-through of tariffs to consumers, the consumer price of a good from sector j in country n originated in country i at time t, is modeled as a function of the before-duty and transport-cost price at country i's border (FOB price) $p_t^{i,j}$ as:

$$p_t^{ni,j} = \left(1 + \tau_t^{ni,j}\right) \psi^{ni,j} p_t^{i,j} \tag{1}$$

where $\psi^{ni,j} > 1$ is the (iceberg) transportation cost component, that includes freight and insurance, and $\tau_t^{ni,j}$ is the ad-valorem tariff on the CIF price ($\psi^{ni,j} p_t^{i,j}$). Usually $\psi^{ni,j}$ is unobservable and is modeled simply as a function of distance between the pair of countries, (e.g. Hummels, 2007; Fontagné, Guimbard and Orefice, 2022); or as function of distance and other time-invariant country-pair characteristics representing both natural barriers (adjacency, land border) and cultural barriers (common language, colonial background); or simply as a time-invariant importer-exporter fixed effect. In any of the latter cases, the approach is at odds with the behavior of freight in the aftermath of the Covid-19 pandemic. First, freight were clearly time-variant as Figure 2 shows. And second, even in a cross-section, the distance effect was asymmetric between West and East inbound and outbound routes (Figure 3). To address these issues, in the next section I introduce in an otherwise standard model of international trade a more general representation of transportation costs. Particularly, I make $\psi^{ni,j}$ time-variant and use observable container freight rates from country i to n (F_t^{ni} hereafter) to inform the model about its temporal evolution.

Figure 3 – Container Freight Rates by West/East Direction of the Route



*All rates are reported in thousand USD per forty foot container. Sources: Drewry, Freightos and Ningbo container indexes.

3 A quantitative dynamic trade model with freight rates

In what follows I present a standard quantitative Ricardian model of international trade with multiple sectors and an input-output structure as in Caliendo and Parro (2015), extended to consider transitional dynamics in multiple periods as in CDP. The model closely resembles an economy that is similar to the one depicted by CDP's model, but abstracting from spatial (regional) dynamics within the studied country for simplicity. The main difference is that international trade costs are divided into sector-specific duties and international transportation costs, which in turn are a function of observed freight rates. The key elasticity of trade costs to freight rates, that is estimated below, links the observed increases in freight rates to transportation costs shocks in the model. In the following I denote time periods by $t = 1, 2, ...$ sectors by $j, k = 1, 2, ..., J$ and countries by $i, n = 1, 2, ..., N$.

3.1 Consumers

Consumers in each country are forward looking and have perfect foresight and a discount rate $\beta \geq 0$. They can be either employed or non-employed, in the latter case consumption is obtained from the country-specific exogenous home production $b^n > 0$. In our country of interest, call it n, the labor market is segmented, with barriers to mobility across sectors,[5] represented by a time-invariant sector-pair specific labor relocation cost $\zeta^{n,jk}$ measured in terms of utility.[6] Thus, workers in sector j supply a unit of labor inelastically and receive a sector-specific competitive market wage $w_t^{n,j}$. The total consumption of those individuals is represented by $C_t^{n,j}$, which is a Cobb–Douglas aggregator of the final goods purchased from each other sector, i.e. $C_t^{n,j} = \prod_{k=1}^{J}(c_t^{n,jk})^{\alpha^{n,k}}$ where $\alpha^{n,k}$ are the expenditure shares that add up to one. The aggregate price index is $P_t^n = \prod_{k=1}^{J}(P_t^{n,k}/\alpha^{n,k})^{\alpha^{n,k}}$ where $P_t^{n,k}$ is the price index of final goods purchased from sector k, defined below.

The consumers' problem is to decide in each period in which sector supply their labor in order to maximize their lifetime utility, subject to idiosyncratic shocks for each choice, denoted by ϵ_t^k (with zero mean), and the barriers to mobility across sectors ζ^{jk}. Denoting sector 0 as non-employment, the formal problem of a worker is:

$$\mathrm{v}_t^{n,j} = \ln C_t^{n,j} + \max_{\{k\}_{k=0}^{J}} \left\{\beta E\left[\mathrm{v}_{t+1}^{n,k}\right] - \zeta^{n,jk} + \nu\epsilon_t^k\right\}$$
$$\text{s.t. } C_t^{n,j} \equiv \begin{cases} b^n & \text{if } j=0 \\ w_t^{n,j}/P_t^n & \text{otherwise} \end{cases}$$

where $\mathrm{v}_t^{n,j}$ is the lifetime utility, and ν quantifies the variance of the idiosyncratic shocks. Once a distributional assumption on the shocks ϵ_t^k is imposed (Type-I extreme value), it is possible to obtain closed-form solutions for both the expected lifetime utility for working in a given sector j and the transitions of labor across sectors.[7] Particularly, denoting the expected lifetime utilities by $V^{n,j} \equiv E\left[\mathrm{v}_{t+1}^{n,j}\right]$, these are given by:

$$V^{n,j} = \ln C_t^{n,j} + \nu \ln\left[\sum_{h=0}^{J} \exp\left(\beta V_{t+1}^{n,h} - \zeta^{n,jh}\right)^{1/\nu}\right] \quad (2)$$

so the expected lifetime utilities depend on both the current utility derived from working in the current sector and the option value to move to any other sector. Finally, the share of

[5]The existence of barriers of mobility across sectors even for workers that do not migrate from their initial locations has been well documented in the literature. See for instance Alvarez-Cuadrado, Amodio and Poschke (2021) or Pulido and Święcki (2020) for the case of barriers between agriculture and non-agriculture.

[6]For simplicity and to avoid larger data requirements, for the remaining countries a non-segmented labor market is assumed; i.e. with free labor mobility and the same wage across sectors.

[7]These solutions are standard in discrete choice models, see CDP for the full derivations.

workers in the studied country n that relocate from sector j to k in time t, can be written as:

$$\mu_t^{n,jk} = \frac{\exp\left(\beta V_{t+1}^{n,k} - \zeta^{n,jk}\right)^{1/\nu}}{\sum_{h=0}^{J} \exp\left(\beta V_{t+1}^{n,h} - \zeta^{n,jh}\right)^{1/\nu}} \tag{3}$$

Notice that in (2) and (3), $1/\nu$, the inverse of the standard deviation of the idiosyncratic shocks, plays the role of a inter-sectoral relocation elasticity. Further, equation (3) helps to characterize the evolution over time of sectoral employment in country n, since employment in sector j in time $t+1$ can be expressed simply as:

$$L_{t+1}^{n,j} = \sum_{k=0}^{J} \mu_t^{n,kj} L_t^{n,k}. \tag{4}$$

3.2 Firms

A continuum of firms of country n in each sector j produce varieties of intermediate goods. Firms use as inputs labor ($l_t^{n,j}$) and structures ($h_t^{n,j}$) as primary factors and a bundle of materials from all the sectors of the economy, $\prod_{k=1}^{J}(M_t^{n,jk})^{\gamma^{n,jk}}$, where $\gamma^{n,jk}$ is the share of materials from sector k in the production of sector j. Their total factor productivity depends on a common sectoral component ($A^{n,j}$) and a firm-specific component ($z^{n,j}$). As usual, I assume that the latter component is the realization of a Fréchet distribution with a shape parameter that varies by sector, θ^j.[8] Finally, firms' technology displays constant returns to scale, and takes the form:

$$q_t^{n,j} = z^{n,j}(A_t^{n,j}(h_t^{n,j})^{\xi^n}(l_t^{n,j})^{1-\xi^n})^{\gamma^{n,j}} \prod_{k=1}^{J}(M_t^{n,jk})^{\gamma^{n,jk}}$$

where $\gamma^{n,j} \geq 0$ is the share of value added in output,[9] ξ^n the share of structures in value added and $q_t^{n,j}$ the units of the variety produced. Cost minimization in perfect competition implies that firms price at their unit cost, $x_t^{n,j}/z^{n,j}(A_t^{n,j})^{\gamma^{n,j}}$, where $x_t^{n,j}$ is the standard Cobb-Douglass unit price of an input bundle, given by:

$$x_t^{n,j} = B^{n,j}((r_t^{n,j})^{\xi^n}(w_t^{n,j})^{1-\xi^n})^{\gamma^{n,j}} \prod_{k=1}^{J}(P_t^{n,k})^{\gamma^{n,jk}} \tag{5}$$

where $r_t^{n,j}$ is the rental price of structures in sector j of country n and $B^{n,j}$ is a constant. In this way, the price of any variety depends on the aggregate price of all intermediate goods,

[8] Here the location parameter is normalized to 1, but this parameter is isomorphic to the sectoral component of firm-productivity, $\left(A_t^{n,j}\right)^{\gamma^{n,j}}$.

[9] Constant returns to scale implies that $\gamma^{n,j} + \sum_{k=1}^{J} \gamma^{n,jk} = 1$

implying that a shock in any single sector (as a transportation cost shock) will affect all the sectors in the economy, via the cost of the bundle of materials.

In each sector there are producers of composite intermediate goods that are used either as materials for the production of intermediate varieties or for final consumption. They supply in total $Q_t^{n,j}$ units of the good by purchasing intermediate varieties from the lowest cost suppliers across countries.[10] Varieties purchased from other countries are subject to international trade costs $\kappa_t^{in,j}$. These costs are composed of transport costs and sector-specific ad-valorem tariffs $\zeta_t^{in,j}$. Transport costs are of the "iceberg" type, such that to obtain in country n an unit of the variety shipped from country i requires producing $\psi_t^{ni,j} \geq 1$ units in country i. I assume that observable container freight rates F_t^{ni} between the origin country i and the destination country n are informative about the evolution of $\psi_t^{ni,j}$. Particularly, $\psi_t^{ni,j}$ and F_t^{ni} are related through:

$$\psi_t^{ni,j} = \Upsilon^{ni,j} \left(F_t^{ni}\right)^{\rho_F^j} \varepsilon_t^{ni,j}$$

where $\Upsilon^{ni,j}$ represents any time-invariant determinant of transportation costs between n and i for sector j (e.g. transactions costs due to language, etc. or the distance effect that is not accounted by freight), that I call non-freight barriers; $\varepsilon_t^{ni,j}$ collapses other time-variant determinants of transportation costs apart from container freight and orthogonal to them, plus mean-zero measurement errors; and ρ_F^j is the key elasticity of transportation costs to observable freight rates. In this way, the wedge between the before-duty and transport-cost price at country i's border and the final price that is paid by producers of the composite good in country n is given by:

$$\kappa_t^{ni,j} = \left(1 + \tau_t^{ni,j}\right) \psi_t^{ni,j} = \left(1 + \tau_t^{ni,j}\right) \Upsilon^{ni,j} \left(F_t^{ni}\right)^{\rho_F} \varepsilon_t^{ni,j} \tag{6}$$

with $\psi_t^{ni,j} = \kappa_t^{ni,j} = \infty$ for non-tradable sectors j and $\kappa_t^{ni,j} = 1 \ \wedge \ \tau_t^{ni,j} = 0$ for $n = i$. Thus, the price paid by producers of the sectoral aggregate good for a particular variety is given by the minimum unit cost across all countries, taking into account trade costs:

$$p_t^{n,j} = \min_{\{i\}_{i=i}^N} \left\{ \frac{\kappa_t^{ni,j} x_t^{i,j}}{z^{i,j} (A_t^{i,j})^{\gamma^{i,j}}} \right\}$$

with $\kappa_t^{ni,j}$ as in (6). By solving for $p_t^{n,j}$, standard properties of the Fréchet distribution over $z^{i,j}$ imply that the price of the sectoral aggregate good has a closed form solution, equal to:

$$P_t^{n,j} = \Gamma^{n,j} \left[\sum_{i=1}^{N} \left(x_t^{i,j} \kappa_t^{ni,j} \right)^{-\theta^j} \left(A_t^{i,j} \right)^{\theta^j \gamma^{i,j}} \right]^{-1/\theta^j} \tag{7}$$

[10] In particular, $Q_t^{n,j}$ is a CES aggregator of the different quantities demanded of intermediate goods of a given variety.

and that the share of total expenditure in country n on goods j from market i is equal to:

$$\pi_t^{ni,j} = \frac{(x_t^{i,j}\kappa_t^{ni,j})^{-\theta^j}(A_t^{i,j})^{\theta^j\gamma^{i,j}}}{\sum_{m=1}^{N}(x_t^{m,j}\kappa_t^{nm,j})^{-\theta^j}(A_t^{m,j})^{\theta^j\gamma^{m,j}}} = \frac{(x_t^{i,j}\kappa_t^{ni,j})^{-\theta^j}(A_t^{i,j})^{\theta^j\gamma^{i,j}}}{\Psi_t^{n,j}} \tag{8}$$

with $\pi_t^{ni,j} \equiv \frac{X_t^{ni,j}}{X_t^{n,j}}$. Equation (8) is the gravity equation of the model, and it guides my estimation of ρ_F.

3.3 Markets clearing

The model is closed with standard goods and factors market-clearing conditions. By one side, goods market-clearing requires that the total expenditure on a good of a given sector in a country be equal to the value of the total demand for the good used as materials in all sectors in the economy, plus the value of its final demand. The final demand is a constant share ($\alpha^{n,j}$) of the total income of workers and rentiers of structures. To deal with trade imbalances, following CDP, it is assumed that rentiers of structures send all their local rents to a global portfolio, which in return receive a constant share ι^n from it (here ι^n is disciplined by observed trade imbalances in the initial period).[11] By the other side, the labor and structures market-clearing conditions requires that the total expenditure of both workers and rentiers of structures to be equal to their respective incomes. Since these conditions are essentially the same as in CDP, their equations (B.1-B.3) are relegated to Appendix B.1.

3.4 Equilibrium

The equilibrium of the model is a sequential competitive equilibrium that can be formulated as follows. Given an initial distribution of workers $\{L_0^{n,j}\}_{n=1,j=1}^{N,J}$, constant exogenous state variables $\{\zeta^{n,jk}, b^n, \Upsilon^{ni,j}, H^{n,j}\}_{n=1,i=1j=1,k=1}^{N,N,J,J}$, time-varying exogenous state variables $\{A_t^{n,j}, \tau_t^{ni,j}, \varepsilon_t^{ni,j}\}_{n=1,i=1,j=1,t=0}^{N,N,J,\infty}$, parameters $\{\gamma^{n,j}, \gamma^{n,jk}, \xi^n, \alpha^{n,j}, \iota^n\}_{n=1,j=1,k=1}^{N,J,J}$, elasticities $\{\theta^j\}_j^J$, ν and ρ_F and discount factor β; a sequential competitive equilibrium of the dynamic model under freight $\{F_t^{ni}\}_{n=1,i=1,t=0}^{N,N,\infty}$ is characterized by a sequence of labor prices $\{w_t^{n,j}\}_{n=1,j=1,t=0}^{N,J,\infty}$, sectoral reallocation shares $\{\mu_t^{n,jk}\}_{n=1,j=1,k=1,t=0}^{N,J,J,\infty}$, lifetime utilities $\{V_t^n\}_{n=1,t=0}^{N,\infty}$ and labor $\{L_t^n\}_{n=1,t=0}^{N,\infty}$, that satisfies equilibrium conditions (2), (3), (4), (5), (7), (8), (B.1), (B.2) and (B.3) for all countries i,n sectors j, k and time periods t.

[11] In the subsequent periods, the difference between the remittances and the income rentiers receive generates imbalances, and the the price of the infrastructures in each period match those imbalances to the trade deficits or superavits. In this way, trade imbalances become endogenous in the model.

3.5 Model solution

I use the dynamic version of "exact hat algebra" (developed in CDP, built on the static version of Dekle, Eaton and Kortum, 2008), to solve the model in relative time differences and to evaluate counterfactuals. The main advantage of the technique is that it does not require to have information about any of the exogenous state variables of the model (see the list of variables in the definition of equilibrium above). Further, the method allows the model to perfectly match the sector-level input-output and trade observable data, and reduces the computational burden considerably.

In summary, dynamic exact hat algebra first requires to express the system of equations that define the equilibrium of the model in relative time differences, which is done in Appendix B.3. Then, for each period t, the new system can be used to solve for the quantities of interest (factor prices, sectoral reallocation shares, lifetime utilities and labor) given the variables that are already known from the previous period $t-1$, and an assumption on the relative changes in the time-varying exogenous state variables, that I call hereafter fundamentals, and in freight. Thus, starting at $t=1$, and by iterating, it is possible to solve for the full time paths of all variables of interest with observed information on a base year $t=0$ and an anticipated convergent sequence of changes in fundamentals and freight. Thus, besides the set of parameters, elasticities and discount factor, the only pieces of information required for solving the model for a given sequence of changes in fundamentals and freight rates, are the allocation of labor in the base year $t=0$, the transition matrix with the sectoral reallocation shares for the same year, and, in order to solve for factor prices in $t=0$, the bilateral trade shares and sectoral output for the same year. Notice that the system at the base year is not necessarily in steady state, and hence even with constant fundamentals and freight, the economy can have transitional dynamics.

Once the paths of the endogenous state variables are found for a given sequence of changes in fundamentals and freight –call those paths as the "baseline economy"– it is possible to evaluate counterfactual scenarios. For this, the whole system in relative time differences representing the baseline economy can be re-expressed relative to a new system in relative time differences that represents the counterfactual one, which is done in Appendix B.4. With this new set of equations, it is possible to compute the impact of a given change in the initial sequence of relative changes in fundamentals and freight rates on the relative time differences of the real endogenous variables. The only additional piece of information needed is then the relative change in the sequences of fundamentals and freight rates between the baseline economy and the counterfactual one.

In order to isolate the impact derived from rises in transportation costs from other effects from the pandemic, in my empirical implementation I start by constructing a quarterly baseline economy that begins in a pre-pandemic year with available data (2018) and constant fundamentals and freight thereafter. Next, for the counterfactual economy, I change the paths of transportation costs according to the observable variation in freight rates during the pandemic, and keep constant the remaining set of fundamentals. Therefore, to evaluate the impact on the relative time differences of the endogenous variables the only extra information needed is the relative change in the sequences of transportation costs between the baseline economy and the counterfactual one, i.e.:

$$\frac{\left\{\frac{\kappa_t^{ni,j}}{\kappa_{t-1}^{ni,j}}\right\}_{t=1,counterfactual}^{\infty}}{\left\{\frac{\kappa_t^{ni,j}}{\kappa_{t-1}^{ni,j}}\right\}_{t=1,baseline}^{\infty}} = \left\{\frac{\kappa_t^{ni,j}}{\kappa_{t-1}^{ni,j}}\right\}_{t=1}^{\infty} = \left\{\frac{\left(F_t^{ni}\right)^{\rho_F^j}}{\left(F_{t-1}^{ni}\right)^{\rho_F^j}}\right\}_{t=1}^{\infty} \tag{9}$$

where the first equality follows from the fact that in the baseline economy fundamentals are constant, and the second one because the determinants of transportation costs other than freight rates do not change. The next section presents a procedure to compute (9), the main input for the counterfactual exercises, and Section 5 presents the results of the counterfactuals.

4 Identifying transportation costs shocks

In order to derive the paths of transportation costs shocks as a result of the Covid-19 pandemic, equation (9) requires estimates of ρ_F^j as well as values of F_t^{ni} for those country-pairs where freight rates are not available. Hence, in what follows I first present a model-consistent empirical strategy to estimate ρ_F^j and next a simple procedure to impute values of F_t^{ni} for those country-pairs with missing information on freight.

By taking logs of the gravity equation (8), the determinants of the bilateral sectoral flows can be rewritten in a linear form. The coefficients on the resulting linear equation can be estimated by the following regression of log-freight rates on log-bilateral flows, controlling for tariffs and the usual set of fixed effects:

$$\ln X_t^{ni,j} = \delta_t^{i,j} + \delta_t^{n,j} + \delta^{ni,j} + \beta_F \ln F_t^{ni} + \beta_\tau \ln\left(1 + \tau_t^{ni,j}\right) + \varepsilon_t^{ni,j} \tag{10}$$

In this equation, the exporter-industry-time fixed effect, $\delta_t^{i,j}$, absorbs $-\theta^j \ln x_t^{i,j} + \theta^j \gamma^{i,j} \ln A_t^{i,j}$, i.e. the sources of comparative advantage of the exporter; the importer-industry-time fixed effect, $\delta_t^{n,j}$, captures $\ln X_t^{n,j} - \ln \Psi_t^{n,j}$, i.e. importer's total demand and the resistance term for the importer; and the exporter-importer-industry fixed effect, $\delta^{ni,j}$, collapses $-\theta^j \ln \Upsilon^{ni,j}$, i.e. time-invariant bilateral trade frictions (see Appendix B.2 for the proof). Further, the estimated coefficient $\hat{\beta}_\tau$ on tariffs identifies $\left(-\theta^j - 1\right)$, whereas the estimated coefficient $\hat{\beta}_F$ on freight rates identifies $-\theta^j \rho_F^j$. Thus, by estimating (10), it is possible to obtain values of $-\theta^j$ and ρ_F^j that are both grounded in the theoretical model and appropriate for the selected set of countries and industries.

Regarding the estimation of (10), it has been established in the related literature (Martínez-

Zarzoso and Suárez-Burguet, 2005; Jacks and Pendakur, 2010; Shapiro, 2016) that using OLS could deliver biased estimates, since container freight rates are arguably endogenous to bilateral flows. This is because container freight rates are nothing but the prices for shipping services, and as such, are a function of the supply of containers and the volume of trade demanded. This means that trade flows and container freight rates are simultaneously determined. Therefore, for dealing with this endogeneity, in what follows I estimate equation (10) using an IV strategy.

To exploit the temporal variation in freight rates across a period encompassing both 'normal' times and the pandemic, I utilized monthly sectoral trade data spanning from January 2017 to September 2021, for the selection of 40 countries (see Table A.1 in Appendix A) and 15 tradable industries (Table A.2) , which are incorporated into the model. Given that freight data is available only for the 18 regions displayed in Figure 1, I assign the 40 selected countries to the geographically closest available region as it shown in Table C.2.[12] Furthermore, since monthly tariff data are not available, I instead use annual data to control for tariffs. However, given their limited temporal variation during the sample period, I opt not to use the estimates of $\hat{\beta}_{\tau}$ to derive the structural parameters θ^j. Instead, as discussed below, I utilize recent estimates of θ^j from the literature available for the same 15 tradable industries, and focus the structural interpretation of my results only on the estimation of $\hat{\beta}_F$.

Regarding the instrument, it takes advantage of the heterogeneous timing of the lockdowns during the pandemic and of the pre-existent conditions in port infrastructure. Particularly, I construct a metric that interacts a combination of pre-pandemic measures of port infrastructure quality for both countries in each country-pair, with an indicator of whether both countries had lockdowns in a particular month. More specifically, the instrument Z_t^{ni} is given by:

$$Z_t^{ni} = PortQua_{2019}^n * PortQua_{2019}^i * \mathbb{D}_t^{ni}, \; with \; \mathbb{D}_t^{ni} \begin{cases} 0 & n \wedge i \; are \; in \; lockdown \; in \; t \\ 1 & otherwise \end{cases}$$

where $PortQua_{2019}^n$ is the index of quality of port infrastructure in 2019 of country n, collected from the World Economic Forum (WEF),[13] see Figure D.1 in Appendix D for the

[12] Admitted not ideal, this imputation is necessary given the limitations of the data on freight rates. As a sensitivity test, I performed robustness checks by grouping bilateral trade data into 18 regions, with no significant differences in the results. It is worth noting that, since I have different freight rates for routes departing from or arriving at each coast in North America, I divide North American countries into western and eastern sub-regions according to the share that an aggregate of all western or eastern states or provinces has in the national annual trade flows. See Appendix A for more details about this procedure.

[13] The index is collected from the 2019 Global Competitiveness Report of the WEF, in which several metrics of countries' competitiveness are constructed based on the perceptions of a large number of business executives (16936 in 2019) from 139 countries. The index range from 1 (port infrastructure considered extremely underdeveloped) to 7 (port infrastructure considered efficient by international standards); so $PortQua_{2019}^n * PortQua_{2019}^i$ ranges from 1 to 49. For landlocked countries the question changes to how accessible are port facilities. See Klaus (2019) for more details.

variation of its values across the selected countries.[14] Formulated in this way, the routes in which the ports of the origin/destination of the ships' journey have a larger measured quality, a mutual lockdown in both trade partners have a larger decrease in the value of Z_t^{ni} due to the lockdowns. Further, in absence of lockdowns, the only variation in the value of Z_t^{ni} across country-pairs is the combined measure of the quality of the ports involved in the route.

Table 1 shows the baseline results using Z_t^{ni} as instrument under two different specifications for non-freight barriers $\Upsilon^{ni,j}$. In the first specification (columns 1-3) $\Upsilon^{ni,j}$ is included as a set of observable time-invariant geographical and cultural barriers, such as distance and indicators for having a common language, a common land border and a past colonial relationship. [15] This is a common specification in the gravity literature, and the estimated elasticity is computed exploiting the variation in freight both over time and between country-pairs (conditional on observables). In the second specification (columns 4-6) $\Upsilon^{ni,j}$ is modeled as an exporter-importer-industry fixed effect, exactly as it is specified in the theoretical model. In this case, the estimated elasticity is computed exploiting the variation in freight rates only over time for each country-pair. All regressions control for average sectoral tariffs, for exporter-industry-time fixed effects (the exporter's time-varying comparative advantage) and importer-industry-time fixed effects (the importer's time-varying common demand). Moreover, the regressions exclude industries where tankers or bulk dry ships are the main transportation modes instead container ships (oil, chemicals, pharmaceutical and agriculture/food).

Table 1 – IV Baseline results

	$\Upsilon^{ni,j}$ = observables			$\Upsilon^{ni,j}$ = Exp x Imp x Ind FE		
	(1)	(2)	(3)	(4)	(5)	(6)
	IV	First stage	Reduced form	IV	First stage	Reduced form
Dependent variable	ln(Trade)	ln(Freight)	ln(Trade)	ln(Trade)	ln(Freight)	ln(Trade)
ln(Freight)	-5.514***			-1.035**		
	(0.772)			(0.508)		
Instrument		-0.020***	0.109***		-0.014***	0.014**
		(0.002)	(0.011)		(0.001)	(0.007)
Importer x Industry x Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Exporter x Industry x Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes			
Exporter x Importer x Industry FE				Yes	Yes	Yes
Observations	81,200	81,200	81,200	81,200	81,200	81,200
F first stage (Kleibergen-Paap)		117.4			101.0	

*All regressions control for tariffs. Additional controls include distance and dummies for a common language, a common land border and a past colonial relationship. Industries where tankers or bulk dry ships are the main transportation modes are excluded (oil, chemicals, pharmaceutical and agriculture/food). Heteroskedasticity robust errors in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

The results in Table 1 show that the estimated trade elasticities to container freight rates

[14] Further, Figure D.2 in Appendix D shows the months in which each country had a lockdown.

[15] All these variables are taken from the CEPII Gravity dataset (Conte, Cotterlaz and Mayer, 2022).

are significant, of the expected negative sign and economically meaningful. Both the F statistics and the estimated coefficients of the first stages suggest that the instrument is relevant in both specifications. I find a elasticity close to -5.5 when $\Upsilon^{ni,j}$ is modeled as a set of observables and close to -1 when it is included as an exporter-importer-industry fixed effect. Both elasticities lie inside the range found in the literature, that is between -0.42 in Fraser (2018) and -7.91 in Shapiro (2016) (see the literature review section for more details). The difference in their magnitudes would suggest that there are country-pair specific time-invariant omitted variables that are determinants of the trade flows and are correlated with freight, causing a bias in the estimation of the first specification. For this reason, and to keep the estimation the closest possible to the specification in the trade model, I consider as my baseline the estimated value of -1.03. However, it is worth noting that in my quantitative exercises with the structural model, I will provide robustness checks using the bounds of the 95% confidence interval for this estimated value.

As a sensitivity analysis of these results, I explore the influence of zeros in the data and the robustness of standard errors. First, zeros in bilateral flows are unlikely to be random, and without accounting for these observations, they may introduce sample selection bias.[16]The usual approach in the literature is to use the Poisson pseudo-maximum-likelihood (PPML) estimator proposed by Silva and Tenreyro (2006) that can be implemented in the balanced panel. However, in the presence of fixed effects, estimating a Poisson regression with an IV approach could suffer from the incidental parameters problem, so it does not guarantee consistent estimators. Instead, a feasible test to gauge the influence of zeros is to compare the results of the reduced-forms estimated by OLS (as in IV) and those estimated by PPML. This is done in Table C.3 in Appendix C, where it is shown that the estimated coefficient on the instrument is barely affected. An additional check consists in estimating the IV regression with a linear probability model (LPM) to assess the importance of the extensive margin in the results. This is, I replace $\ln X_t^{ni,j}$ by a dummy indicator that takes the value of 1 for positive values of $X_t^{ni,j}$ and 0 otherwise; and next I re-estimate equation (10) by IV. The results of the LPM are shown in Table C.4 in Appendix C, with the baseline IV results for comparison. The coefficient on freight rates estimated by the LPM is close to zero and not significant, meaning that the extensive margin does not play a role in the determination of the trade elasticities to container freight rates. A similar result is obtained for the reduced form estimated by the LPM.

Second, Table C.4 in Appendix C shows a re-computation of standard errors and first-stage F tests by clustering at different levels. First, I cluster standard errors at the importer-exporter-industry level, to allow for auto-correlations within trade-partners; and next at the exporter's region-importer's region-industry level, to allow for correlations within regions,

[16]In the IV strategy above, I simply replaced those values either with the minimum value of the panel or with random numbers between zero and that minimum value. The results do not change significantly between the two options.

besides auto-correlations. The baseline computed trade elasticity remain significant in both cases.

Now, in order to obtain ρ_F from the above results, I require a value for θ^j, since the estimated coefficient $\hat{\beta}_F$ on freight rates identifies $-\theta^j \rho_F$. As stated earlier, given the unavailability of monthly tariff data, I rely on values of θ^j derived from recent trade literature. Particularly, I use the trade elasticities obtained by Fontagné, Guimbard and Orefice (2022), who estimate θ^j based on product-level data by exploiting annual variation in bilateral tariffs for a large set of country-pairs (152 importing and 189 exporting countries) over the 2001-2016 period. More specifically, Fontagné, Guimbard and Orefice (2022) pool all HS6 products within each of my considered industries (we use the same OECD's Trade in Valued Added - TiVA aggregation) and obtain θ^j as the average tariff elasticity in sector j. Table C.6 in Appendix C shows the obtained elasticities. Using those elasticities, I finally make ρ_F sector-specific using $\rho_F^j = \hat{\beta}_F / \theta^j$.

Lastly, to construct the increases in transportation costs induced by the pandemic for each country-pair in my dataset, I need to deal with missing information on freight rates. For this, I fit a model of observable container freight rates on bilateral maritime distance D^{ni} (number of days to take a ship make a round trip between the primary port for each country, constructed by Feyrer, 2021) to fill missing information. Particularly, I fit the model:

$$F_t^{ni} = A_t^D \left(D^{ni}\right)^{\beta_{it}^D} \varepsilon_{ni,t}^D \; with \; \beta_{it}^D = \begin{cases} \beta_{E,t}^D & if \; i \in East \\ \beta_{W,t}^D & if \; i \in West \end{cases} \tag{11}$$

with A_t^D a common monthly shifter for all routes, that captures the overall monthly impact of the pandemic on the whole maritime transportation industry; β_{it}^D an elasticity of freight on distance, that, given the evidence commented in Section 2, I make time-variant and heterogeneous depending on the location of the exporter country (West/East); and $\varepsilon_{ni,t}^D$ a term that collapses other time-variant determinants of container freight apart from distance, and that I assume is, in logs, mean-zero and orthogonal to it. I estimate equation (11) in logs by OLS using time FE and the triple-difference $D^{ni} \times time \times \mathbb{I}_{i \in east}$. Figure D.3 in Appendix D shows the in-sample performance of the model, by comparing the model's predicted freight rates against their actual values, a plot that depicts a reasonable good fit. Some out-of-sample predictions are shown in Figure D.4 in Appendix D, where it can been seen that the model is able to replicate the heterogeneous behavior of freight rates depending on the region of departure, even for the same route.

Armed with F_t^{ni} for all country-pairs and the estimated values of ρ_F^j, it is possible to compute (9) to evaluate counterfactuals. The next section delivers the main results of these exercises.

5 Model results

In what follows I present the implementation of the dynamic trade model outlined in Section 3, the results from the counterfactual exercises and several robustness checks. I first show how the baseline economy with constant fundamentals is constructed, describing the data requirements and assumptions concerning the structure of labor markets in both the studied country (Colombia) and abroad. Next, I show the impacts on relative prices, labor reallocation and welfare of a similar economy that only faces the increase in worldwide freight as observed between 2020 and 2023, my principal findings. To understand the mechanisms behind those results, I subsequently present the outcomes for the counterfactual economies with the following sets of shocks: i) the same increase in freight but restricted to routes involving Colombia as the origin or destination; ii) an increase in freight across all routes excluding those involving Colombia; iii) an increase in worldwide freight observed until the peak of the disruption. Finally, I conduct a sensitivity analysis of these results to variations in the calibrated parameters.

5.1 Baseline economy

As stated above, I set 2018 as my pre-pandemic base-year, and construct the baseline economy at a quarterly frequency with constant fundamentals from 2018 onwards. To do this, besides the set of constant parameters, I require data on the initial sectoral allocation of labor $L_{2018}^{n,j}$ and its associated transition matrix $\mu_{2017}^{n,jk}$, plus the initial bilateral trade shares $\pi_{2018}^{ni,j}$ and sectoral outputs $X_{2018}^{n,j}$. Following CDP, I assume that there is not labor migration across countries and that the only segmented labor market is that of the studied country, i.e. Colombia. This means that the labor transition matrix, the most challenging object among the data requirements, and the initial allocation of labor, are inputs that are only needed for Colombia.

Therefore, the collected dataset consists on: i) the matrices $\left\{\pi_{2018}^{ni,j}, X_{2018}^{n,j}\right\}$ for the same 40 countries and 15 tradable industries considered in the estimation of ρ_F^j, plus 17 non-tradable-sectors (see Tables A.1 and A.2 in Appendix A), that are obtained from the OECD's Inter-Country Input-Output (ICIO) tables and the TiVA database; ii) $L_{2018}^{Col,j}$, that is derived from the GEIH (Colombia's household survey), limiting the computations only for individuals between 25 and 65 years of age (around 23.8 millions of persons); and iii) $\mu_{2017}^{Col,jk}$ the matrix of transition probabilities across sectors between 2017 and 2018, that is estimated from PILA, the Colombian social security administrative data, that has full coverage of formal workers.[17] For more details on the construction of the dataset, see Appendix A.

The set of constant parameters is obtained as follows. Technological parameters are the

[17] Here an implicit assumption is that the transition probabilities across sectors behave similar between the formal and informal segments of the labor market. Admitted not ideal, this assumption is necessary given the lack of the data on transitions among informal workers.

I-O coefficients ($\gamma^{n,jk}$) and the value added shares ($\gamma^{n,j}$), that are collected from OECD's ICIO tables and the TiVA dataset for 2018 –so they match exactly the trade and output data above–; plus the shares of structures in value added (ξ^n), collected from the Penn World Tables (PWT) for 2018. Trade elasticities θ^j and transportation costs elasticities ρ_F^j are the same as in Section 4. Finally the only calibrated parameters are the quarterly discount factor $\beta = 0.99$ and the (inverse of) sectoral reallocation elasticity $\nu = 5.34$; both values come from CDP. In Section 5.4 I present robustness checks to variations in these calibrated parameters.

Once all data requirements are gathered, I construct the baseline economy following the procedure described in Section 3.5. It is worth to emphasize that the fact that I use constant fundamentals does not imply that there is not transitional dynamics in the baseline economy. Since the economy in 2018 is not in its steady state, the baseline economy delivers both reallocation of workers across sectors and adjustments in relative prices over time until it reaches its steady state. For example, Figure D.5 in Appendix D show the dynamics of labor reallocation in Colombia in the baseline economy for an aggregation of the main five sectors in the economy plus non-employment. Compared to its steady state, the fraction of the Colombian workforce in 2018 in services and non-employment is larger, generating thus a decreasing path in the labor share of those two segments over time; as opposed to what happens in agriculture.

5.2 Impacts of the freight disruption as observed until 2023

I start by solving for the dynamic impact on the variables of interest of a counterfactual in which container freight increases for all routes in the world as observed between 2019Q1 and 2023Q2, and are constant afterwards. That is, denoting by $\hat{y}_t \equiv \left(\frac{\dot{y}_t'}{\dot{y}_t}\right)$ the change in the relative time difference of a variable y_t between the counterfactual and the baseline (where y_t' corresponds to the value of the variable y_t in the counterfactual), I solve for equations (B.14)-(B.21) in Appendix B.4 using:

$$\hat{\kappa}_t^{ni,j} = \left\{ \frac{\left(F_t^{ni}\right)^{\rho_F^j}}{\left(F_{t-1}^{ni}\right)^{\rho_F^j}} \right\}_{t=2019Q1}^{2023Q2}$$

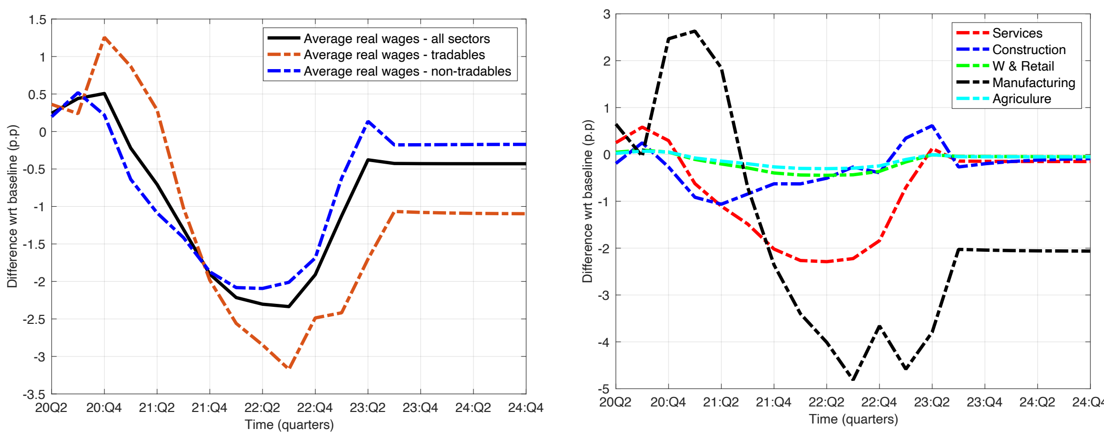
and $\hat{\kappa}_t^{ni,j} = 1$ for t after 2023Q2.[18]

The series of transportation cost shocks generates effects on both relative prices and labor allocations. Concerning the former, Figure 4 illustrates the differences in real wages between the economy subjected to transportation cost shocks and the baseline economy. The comparison is presented for both the division between tradable and non-tradable sectors (Panel

[18] Note that in the economy experiencing transportation shocks, freight rates began to fluctuate before the pandemic. These variations will result in some differences in the trajectories of variables between the baseline and counterfactual economies even before the pandemic; however, these differences are relatively minor compared to those caused by the disruption following the onset of the COVID-19 pandemic.

A) and the aggregation of the five main sectors (Panel B). Due to the disruption, real wages across all sectors declined until the third quarter of 2022, at which point they began to recover. However, they did not return to the levels that would have been observed in the absence of the shock. Tradable sectors, particularly manufacturing, experienced the most substantial real wage losses. It is important to note that since all real wages are deflated using the aggregate price index, variations in the paths of real wages across sectors are solely attributed to adjustments in relative wages. As I will explain in the next subsection, these adjustments in relative wages depend on the extent to which the shocks shift the country towards a more open or closed economy in relation to the rest of the world.

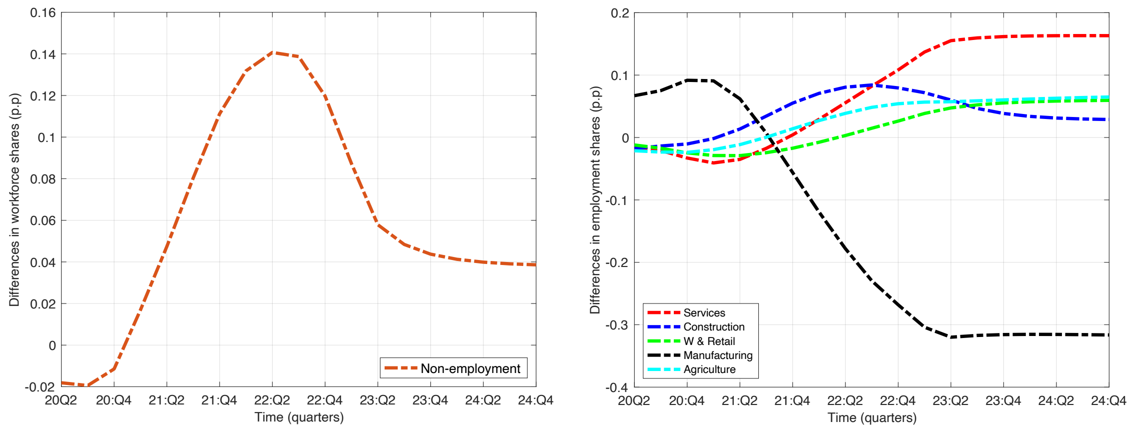
Figure 4 – Effects on the Levels of Real Wages



(a) Tradable and Non-tradable Sectors **(b)** Five Main Sectors

Regarding the employment effects, Figure 5 displays the absolute differences in the sectoral shares of Colombian workers between the counterfactual and baseline economies, illustrating the impact of transportation cost shocks on worker reallocation. First, the global increase in container freight rates led to 0.14% of the workforce (approximately 33.7 thousand workers) transitioning to non-employment at the peak of the disruption (Panel A of Figure 5). This effect is attributable to the overall decline in real wages, which increases the relative value of home production. After the peak, the share of non-employed individuals began to decrease compared with the economy without transportation cost shocks. However, even after the shocks abated, there was still a permanent effect; 0.04% of the workforce (9.2 thousand workers) remained out of employment compared to the baseline at the end of 2024. It is noteworthy that, compared to the magnitudes of the declining trend observed in the share of non-employees in the baseline economy (Panel A in Figure D.6 in the Appendix), that reflect the transitional dynamics of the economy towards its steady state, these impacts are somewhat moderate.

Figure 5 – Impacts of Increases in Worldwide Freight on the Reallocation of Workers



(a) Towards Non-Employment **(b)** Within Employment

Second, within the employed population, there is also a reallocation of workers from the affected tradable sectors (all in manufacturing) towards most of the non-tradable sectors. The main industry experiencing the largest increase in its employment share was services, which experienced a 0.16% increase relative to the baseline economy, approximately 31.2 thousand workers (Panel B of Figure 5). In turn, as a consequence for the entire disruption, the manufacturing employment share permanently dropped by 0.32%, approximately 61 thousand workers. When comparing these figures with the relocation of workers out of manufacturing in the baseline economy (Panel B in Figure D.6 in the Appendix), these impacts are not negligible: the freight shock more than doubled the expected decrease in the manufacturing employment share over the four years studied.

To quantify the impact on welfare, CDP show that in this type of dynamic trade models a measure of the change in welfare from a change in fundamentals that is model-consistent is the present discounted value of the expected change in real consumption relative to the change in the workers' option value, $\hat{\mu}^{n,jj}$, that is:

$$\hat{Welfare}^{Col,j} = \sum_{t=1}^{\infty} \beta^t \ln \left(\frac{\hat{C}_t^{Col,j}}{\left(\hat{\mu}^{Col,jj}\right)^{\nu}} \right) \tag{12}$$

Evaluating equation (12) by aggregating welfare by the initial share of workers in each sector j, the decrease in welfare as result of the increases in container freight rates all around the world is 0.39%, consistent with the obtained fall in real wages on average. Column (1) of Table 2 summarizes the main findings of this section, which will be compared with the results of the subsequent counterfactual exercises

Table 2 – Results of Counterfactual Exercises

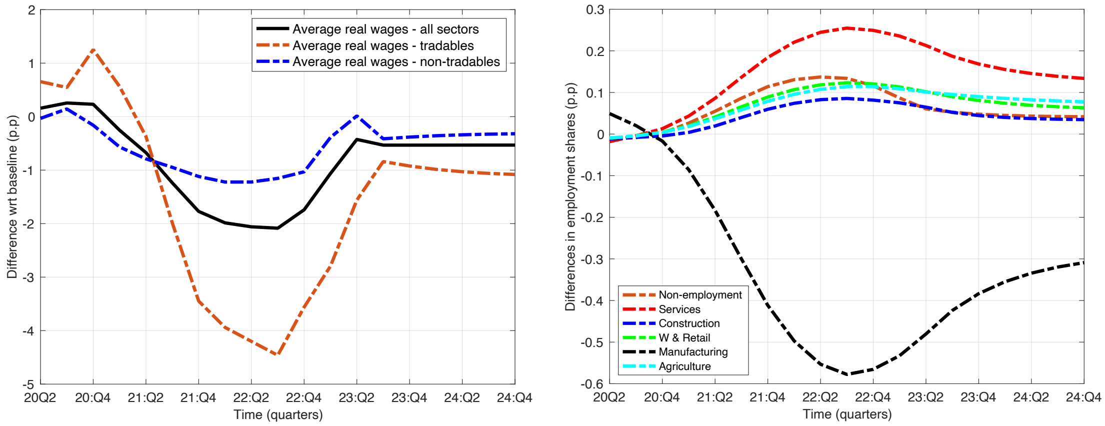
	(1) Worldwide disruption	(2) Only Colombia	(3) All routes except Colombia	(4) Permanent disruption
Permanent change in non-employment share	0.04	0.04	0.00	0.17
Maximum change in non-employment share	0.14	0.14	-0.01	0.17
Permanent change in manufacturing share	-0.32	-0.58	0.41	-0.28
Permanent change in services share	0.16	0.25	-0.20	0.09
Welfare impact	-0.39	-0.45	0.08	-1.81

Note: All values are in percentage points (%).

5.3 Other counterfactual exercises

To gain a deeper understanding of the mechanisms underlying the aforementioned results, I initially partition the complete set of shocks in worldwide container freight rates into two subsets: one comprising shocks in freight solely on routes directly involving Colombia, and another containing shocks on all other routes. Figure 6 depicts the effects on real wages (Panel A) and the allocation of labor (Panel B) resulting from the increase in freight rates solely for routes involving Colombia either as the destination or origin, while column (2) of Table 2 summarizes the main findings. In this case, the reallocation of workers is much stronger towards non-tradable sectors, with a much larger contraction of the employment in manufacturing (0.6% of total employment, 115 thousand workers). This is because in this case the Colombian economy becomes more closed relative to the rest of the world, so the usual general equilibrium effects of moving towards autarky (an increase in relative wages of non-tradable sectors that leads to a contraction of the tradable sectors) operate in this case. However, average real wages move very similar to the counterfactual with full set of shocks, leading to a job loss that is similar (0.14%) and to welfare implications that are in the same order of magnitude: a welfare loss of 0.45%.

Figure 6 – Impacts of Increases in Freight Only for Routes that Involve Colombia*

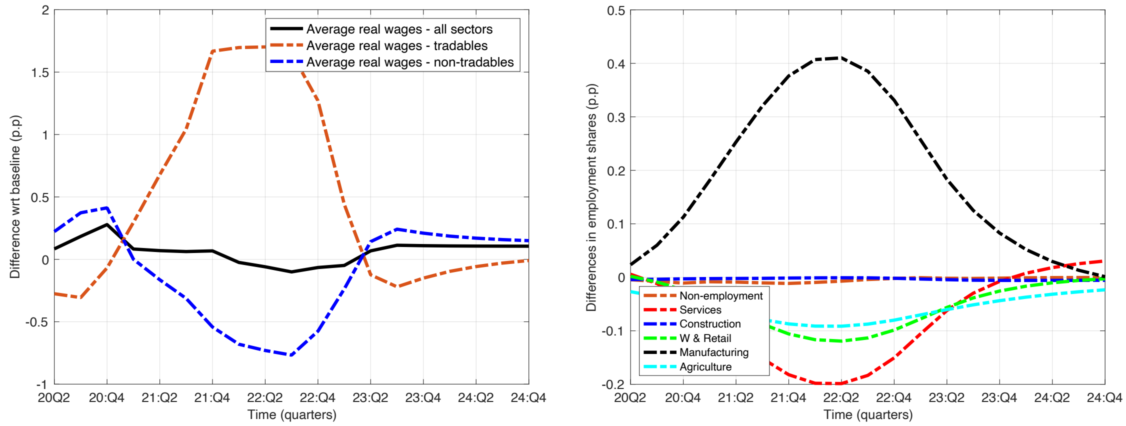


(a) Real Wages **(b)** Labor

*Note: In this case, the set of shocks $\hat{\kappa}_t^{ni,j}$ is restricted to have values different from one only for $n \vee i = Col$.

Figure 7 replicates the latter impacts, assuming instead that freight rates increase worldwide except for routes involving Colombia, and column (3) of Table 2 summarizes the main findings. In this counterfactual scenario, Colombia becomes relatively more open compared to the rest of the world, so the adjustment of relative wages takes an opposite direction to the previous case, and even the levels of real wages in the tradable sector rise. Consequently, manufacturing experiences significant expansion (similar in magnitude to the contraction observed in the previous case). This implies that the moderate effects on employment reallocation obtained in the counterfactual with the full set of shocks are the result of opposing forces on labor reallocation that partially offset each other. Furthermore, the increase in real wages in the tradable sector offsets the decline in real wages in the non-tradable sector. As a result, the average real wage undergoes minimal adjustment, leading to almost no reallocation of workers between employment and non-employment, and even a slight increase in welfare of approximately 0.08%.

Figure 7 – Impacts of Increases in Freight for Routes that do not Involve Colombia*

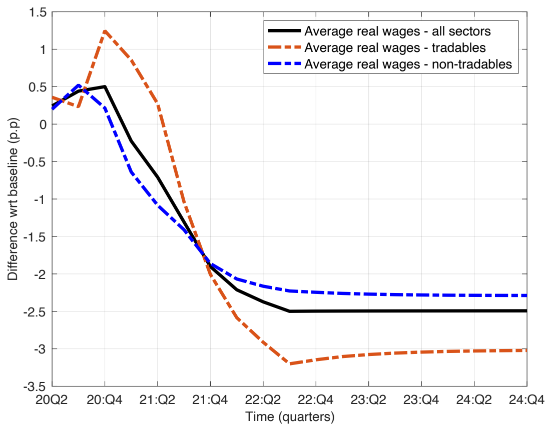


(a) Real Wages **(b)** Labor

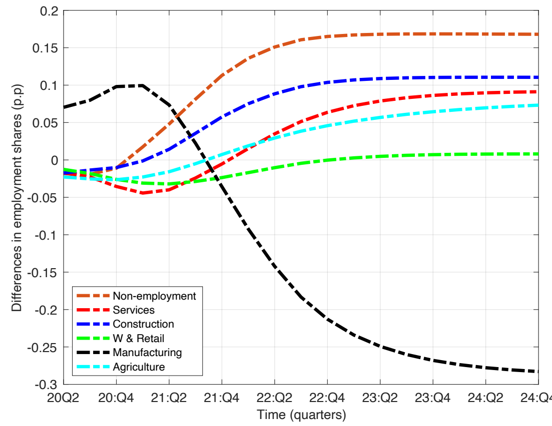
*Note: In his case, the set of shocks $\hat{\kappa}_t^{ni,j}$ is restricted to have values different from one only for $n \wedge i \neq Col$.

Finally, I explore the consequences of shifting the nature of the observed freight disruption from a transitory event to a permanent one. In this counterfactual scenario, each freight rate, after reaching its individual peak value in mid-2022, remains permanently at that level. Figure 8 shows the effects on real wages and the allocation of labor, while column (4) of Table 2 presents the main findings. In the case of a permanent transportation cost shock, welfare would have decreased by 1.8%, more than four times the impact of the observed transitory disruption. The total employment loss would have been 0.17%, corresponding to around 40 thousand workers—a permanent impact that exceeds the maximum impact of the transitory disruption of freight rates. Finally, the reallocation of workers within employment due to the shock follows a similar pattern (both qualitatively and quantitatively) as with the transitory disruption, with gains in the employment shares of non-tradable sectors (mainly in services) at the expense of losses in the manufacturing employment share.

Figure 8 – Impacts of Permanent Increases in Freight*



(a) Real Wages



(b) Labor

*Note: In his case, shocks $\hat{\kappa}_t^{ni,j}$ are constructed with the restriction $\dot{F}_t^{ni,j} = 1$ $for\ t > Max\{t\}$, with $Max\{t\}$ the time t where each freight rate $F_t^{ni,j}$ reached its maximum value.

5.4 Robustness checks

I now explore the robustness of the baseline results to alternative values of the calibrated parameters of the model, particularly the elasticities of transportation costs to freight ρ_F^j, the (inverse of the) sectoral reallocation elasticity ν, and the discount factor β. First, regarding ρ_F^j, the key input for calculating these elasticities was the estimated value of $\hat{\beta}_F$ in Section 4, the elasticity of trade flows to freight (since $\rho_F^j = \hat{\beta}_F/\theta^j$, with θ^j being the trade elasticities obtained by Fontagné, Guimbard and Orefice, 2022). Thus, to perform a sensitivity analysis of the baseline results to the values ρ_F^j, I account for the uncertainty in the estimation of $\hat{\beta}_F$, by computing ρ_F^j with the values derived from the lower and upper bounds of the 95% confidence interval obtained for $\hat{\beta}_F$,which, with a standard error of 0.508, ranges from -0.03 to -2.03.Columns (2) and (3) of Table 3 present the results using these two values for $\hat{\beta}_F$,respectively.

Table 3 – Counterfactual Results for Alternative Parameterizations

	(1) Baseline	(2) Low $\hat{\beta}_F$	(3) High $\hat{\beta}_F$	(4) Low ν	(5) High ν	(6) Low β	(7) High β
Parameters							
Elasticity of trade flows to freight* $\hat{\beta}_F$	-1.02	-0.03	-2.03	-1.02	-1.02	-1.02	-1.02
Sectoral reallocation elasticity ν	5.34	5.34	5.34	4.00	7.00	5.34	5.34
Discount factor β	0.99	0.99	0.99	0.99	0.99	0.95	1.00
Impacts (%)							
Permanent change in non-employment share	0.04	0.00	0.06	0.05	0.03	0.04	0.04
Maximum change in non-employment share	0.14	0.02	0.24	0.18	0.11	0.13	0.14
Permanent change in manufacturing share	-0.32	-0.01	-0.69	-0.38	-0.27	-0.29	-0.33
Permanent change in services share	0.16	0.01	0.32	0.18	0.14	0.15	0.17
Welfare impact	-0.39	-0.02	-0.59	-0.38	-0.40	-0.37	-0.37

*Note: The sectoral elasticities of transportation costs to freight are constructed as $\rho^j_F = \hat{\beta}_F/\theta^j$ with θ^j being the trade elasticities obtained by Fontagné, Guimbard and Orefice (2022), presented in Table C.6 in Appendix C.

As expected, columns (2) and (3) of Table 3 show that the welfare loss, the reallocation of workers toward non-employment and the recomposition effects toward non tradable sectors increase with the elasticity of transportation costs to freight, meaning that the freight disruption has larger impacts when freight constitutes a larger proportion of transport costs. Using the upper bound of the confidence interval for $\hat{\beta}_F$, the welfare loss reaches 0.59%, with 0.24% of the workforce (approximately 56.5 thousand workers) transitioning to non-employment at the peak of the disruption, and 0.06% of the workforce (14.6 thousand workers) remaining permanently out of employment compared to the baseline. In contrast, when using the lower bound of the confidence interval for $\hat{\beta}_F$, the transportation shocks result in a welfare loss of only 0.02%, and the employment effects are relatively small: 0.02% of the workforce (approximately two thousand workers) transitions to non-employment at the peak of the disruption, and there are negligible permanent effects.

Second, regarding ν, columns (4) and (5) of Table 3 present the results of the main counterfactual exercise when I consider $\nu = 4.0$ and $\nu = 7.0$ respectively, instead of the baseline value of 5.34. In the first case, a smaller value of ν indicates more reallocation of workers when relative wages change. Thus, larger job losses are expected for the same increase in freight. Column (2) of Table 3 shows that the new reallocation of labor follows this pattern. Job losses increase from 0.14% in the original counterfactual at the peak of the disruption to 0.18% in the counterfactual with a lower value of ν. However, the welfare impact of the disruption remains almost unchanged, implying that ν does not significantly affect the transmission of freight to average real wages.. Conversely, column (3) shows that a larger value of ν causes the opposite effect: smaller job losses but with nearly negligible effects on the welfare implications.

Finally, columns (6) and (7) of Table 3 present the results of the main counterfactual exercise when I consider $\beta = 0.95$ and $\beta = 1.0$ (in practice 0.9999), respectively, instead of the baseline value of 0.99. First, compared to the baseline, when workers are more patient (i.e., a larger β), they place more weight on future consumption and thus shift more between sectors in response to the same adjustments in future relative wages. When computing the welfare metric, the effect of the larger reallocation more than compensates for the fact that they value their (lower) future consumption more, resulting in a welfare loss that is marginally lower than in the baseline (0.37%). Conversely, more impatient workers (i.e., a smaller β) place more weight on present consumption and thus shift less between sectors. When computing the welfare metric, the fact that these workers value their unaffected present consumption more compensates for the effect of the smaller reallocation, resulting in a welfare loss that is also slightly lower than in the baseline, similar to that of the more patient workers (0.37%).

6 Conclusions

By utilizing a state-of-the-art quantitative model of international trade that incorporates a rich set of realistic features —such as input-output linkages, out-of-steady-state transitional dynamics, and barriers to sectoral mobility in labor markets— the general equilibrium effects of increases in international transportation costs, driven by variable container freight rates, on a specific country of interest can be comprehensively evaluated. In particular, the rigor of the dynamic trade model and the technique employed to solve for the model's equilibrium and evaluate counterfactuals (CDP's dynamic hat algebra) allow for a systematic and integrated evaluation, with relatively few data requirements and a low computational burden.

The results indicate that the temporary increase in container freight rates, driven by post-Covid-19 disruptions in the global maritime transportation industry, resulted in a welfare loss of 0.4% for the Colombian economy, alongside labor reallocations toward non-tradable sectors. While these quantifications are significant in their own right, the model offers further value by shedding light on the heterogeneous effects of transportation cost shocks on key variables of interest, depending on the degree of integration of the studied economy into the global production network and how each international shipping route is affected. Specifically, for the Colombian economy, my counterfactual exercises reveal that the direction of the impacts on employment reallocations depends primarily on the magnitude of freight rate increases on routes involving Colombia compared to the magnitudes of the increases on other routes. In other words, the reallocation effects are contingent upon whether the transportation cost shocks render the country relatively more open or closed in comparison to the rest of the world.

Several avenues for future research are worth noting. First, in the quantification exercise, I used information on comparable freight rates from different data providers. While these constitute a direct metric of freight costs, they suffer from incomplete information for several routes. A more granular analysis could be conducted by using CIF/FoB ratios to approximate freight costs, combining comparable customs data from multiple countries. Second, for tractability, I assumed in the quantitative analysis that fundamental variables other than transportation costs remained constant when constructing both the baseline and counterfactual economies. This assumption could be relaxed by incorporating time variation in these fundamentals and inferring their growth rates using data on job reallocation for all periods in which both economies are modeled. As a result, the evaluation presented here could be replicated for a country with quarterly data on job transitions within employment and between employment and non-employment in the aftermath of the pandemic, though this would limit the calculation of impacts to periods when such job transition data is available. Finally, the type of international trade models used here only allow for the evaluation of real effects. In addition to these real effects, the increase in container freight rates likely triggered inflationary pressures directly on tradable goods and indirectly on the rest of the economy via input-output linkages. A quantification of the inflationary impact of this disruption could be performed by incorporating nominal considerations into the model, such as price rigidities, allowing for a more comprehensive impact evaluation for policymakers.

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Appendix

A Data: Sources and selection of countries and sectors

A set of countries and sectors is selected to ensure both availability of the required variables of the model and relevance according to the routes where freight rates are available. Since value-added shares, input-output coefficients and gross output measures are required, the selection is based on the available countries and sectors in the OECD's Inter-Country Input-Output (ICIO) and Trade in Value Added (TiVA) databases (2021's release). Regarding countries, from the 65 available regions in ICIO-TiVA (64 countries plus an aggregate for the rest of the world), the 15 countries with the lowest participation in 2019-2021 Colombian trade flows were dropped. Further, since for the estimation of the trade elasticity to container freight (ρ_F) a dataset of monthly bilateral trade flows is required, an additional set of 10 countries was dropped for which monthly data was not available, or it was incomplete or with a significant publication lag. As a result, a set of 39 countries plus an aggregate for the rest of the world is selected, that is displayed with their corresponding ISO codes in Table A.1.

Table A.1 – List of Countries and ISO3 Codes

	Europe		**Asia**		**Americas**
BEL	Belgium	CHN	China	ARG	Argentina
DNK	Denmark	IND	India	BRA	Brazil
FRA	France	HKG	Hong Kong	CAN1,2	Canada
DEU	Germany	ISR	Israel	CHL	Chile
HUN	Hungary	JPN	Japan	COL	Colombia
ITA	Italy	KOR	Rep. of Korea	PER	Peru
ROU	Romania	MYS	Malaysia	MEX1,2	Mexico
NLD	Netherlands	PHL	Philippines	USA1,2	United States
POL	Poland	SGP	Singapore		
PRT	Portugal	THA	Thailand		**Africa / Oceania**
RUS	Russian Federation	TUR	Turkey	AUS	Australia
SVK	Slovak Republic	VNM	Vietnam	MAR	Morocco
ESP	Spain			ZAF	South Africa
SWE	Sweden				
CHE	Switzerland				**Other**
GBR	United Kingdom			ROW	Rest of the World

Regarding the set of sectors, it remains similar to the one used in ICIO-TiVA database, with a few aggregations. From the original 45 sectors involving the whole economy, five sectors are dropped that involve mining and activities of households as employers plus undifferentiated goods. From the remaining 40 sectors, 11 of them are aggregated into four categories according to the availability of monthly trade data and to ensure representativeness. Therefore, I use a total of 32 2-digit ISIC-rev. 4 sectors, that covers both tradable (15) and non-tradable industries. See Table A.2 for a description of the selected sectors.

Table A.2 – List of Sectors and ISIC codes

No.	2-dig ISIC*	Sector
		Tradable sectors
1	01 to 03	Agriculture, hunting, forestry, fishing and aquaculture
2	10 to 12	Food products, beverages and tobacco
3	13 to 15	Textiles, textile products, leather and footwear
4	16 to 18	Wood, products of wood and cork, paper products and printing
5	19	Coke and refined petroleum products
6	20	Chemical and chemical products
7	21	Pharmaceuticals, medicinal and chemical and botanical prod.
8	22 to 23	Rubber, plastics prod. and other non-methalic mineral prod.
9	24	Basic metals
10	25	Fabricated metal products
11	26	Computer, electronic and optical equipment
12	27	Electric equipment
13	28	Machinery and equipment, nec
14	29 to 30	Motor vehicles, trailers, and other transport equipment
15	31 to 33	Manufacturing nec; repair and installation of machinery equip.
		Non-Tradable sectors
16	35 to 39	Public serv. supply; sewerage, waste management
17	41 to 43	Construction
18	45 to 47	Wholesale and retail trade; repair of motor vehicles
19	49 to 53	Transport, warehousing, and postal/courier activities
20	55 to 56	Accommodation and food service activities
21	58 to 60	Publishing, audiovisual and broadcasting activities
22	61	Telecomunications
23	62 to 63	IT and other information services
24	64 to 66	Financial and insurance activities
25	68	Real estate activities
26	69 to 75	Professional, scientific and technical activities
27	77 to 82	Administrative and support services
28	84	Public administration and defense; compulsory s.s.
29	85	Education
30	86 to 88	Human health and social work activities
31	90 to 93	Arts, entertaiment and recreation
32	94 to 96	Other service activities

*Revision 4 of ISIC

Once the set of countries and sectors is defined, two datasets are required: i) a panel of monthly bilateral trade flows for tradable sectors in order to estimate the trade elasticity to freight and hence to obtain ρ_F; and ii) a dataset with technology coefficients and the observable allocations of trade and labor in the initial period to perform the counterfactual exercise with the quantitative model. The first dataset is constructed for the period 2017m1 to 2021m9 with information from the UN-Comtrade and the ITC. As it is explained in the text, since for North America I have different freight rates for routes departing/arriving into each coast, I divide North American countries (particularly US and Canada) into west and east sub-countries according to the share that an aggregate of all western/eastern states or provinces has in the national annual trade flows. For the US, the western states are HI, AK, WA, OR, CA, NV, ID, MT, WY, UT, CO, AZ and NM; and for Canada the western provinces are BC, AB, SK, MB, YT, NT and NU. Mexico is not disaggregated given the absence of regional trade data to make the division; so it is excluded from the regression.[19]

The second dataset is constructed using the sources mentioned in the text: the OECD's Inter-Country Input-Output (ICIO) tables and the TiVA database to construct matrices $\left\{\pi_{2018}^{ni,j}, X_{2018}^{n,j}\right\}$ and to compute the I-O coefficients ($\gamma^{n,jk}$) and the value added shares ($\gamma^{n,j}$); the Penn World Tables (PWT) for 2018 to obtain the shares of structures in value added (ξ^n); the Colombian Wide-scale Integrated Household Survey (GEIH by its acronym in Spanish) to derive the initial sectoral allocation of labor $L_{2018}^{Col,j}$;[20] and PILA, the Colombian social security administrative data, to estimate the workers' probabilities of transition across sectors between 2017 and 2018 $\mu_{2017}^{Col,jk}$.[21]

B Derivations and Additional Procedures

B.1 Goods and Factors Market-Clearing Conditions

The goods market-clearing condition is:

$$X_t^{n,j} = \sum_{k=1}^{J} \gamma^{n,kj} \sum_{i=1}^{N} \pi_t^{in,k} X_t^{ik} + \alpha^j \left(\sum_{k=1}^{J} w_t^{nk} L_t^{nk} + \iota^n \sum_{i=1}^{N} \sum_{k=1}^{J} r_t^{i,k} H^{i,k} \right) \tag{B.1}$$

with ι^n the constant share that structure renters of country n obtain from a global portfolio where all the structure owners invest their local rents. The labor market-clearing condition is:

$$w_t^{n,j} L_t^{n,j} = \gamma^{n,j}(1-\xi^n) \sum_{i=1}^{N} \pi_t^{in,j} X_t^{i,j} \tag{B.2}$$

and the infrastructure market-clearing condition is:

$$r_t^{n,j} H^{n,j} = \gamma^{n,j} \xi^n \sum_{i=1}^{N} \pi_t^{in,j} X_t^{i,j} \tag{B.3}$$

B.2 Determinants of gravity equation (10)

First, notice that inserting (6) in (8) we obtain:

$$\frac{X_t^{ni,j}}{X_t^{n,j}} = \frac{p_t^{ni,j} q_t^{ni,j}}{X_t^{n,j}} = \frac{\left(x_t^{i,j} \left(1+\tau_t^{ni,j}\right) \Upsilon^{ni,j} \left(F_t^{ni}\right)^{\rho_F} \varepsilon_t^{ni,j} \right)^{-\theta^j} \left(A_t^{i,j}\right)^{\theta^j \gamma^{i,j}}}{\Psi_t^{n,j}} \tag{B.4}$$

[19] I also exclude Russia given the geographical difficulty to assign the country in one of the regions with available freight rates.

[20] The survey is produced by the National Administrative Department of Statistics (DANE by its acronym in Spanish), the official statistics bureau in Colombia. It is the largest monthly statistical operation in the country, with around 21 thousand face-to-face surveys per month in the 23 main metropolitan areas and a rural aggregate.

[21] These probabilities are estimated from the observable sectoral reallocations in job-to-job transitions and the allocations of new entries in the dataset, such that those reallocations satisfy the equations of the flows of workers between states (employment and non-employment).

Further, from equation (1) we have:

$$\frac{X_t^{ni,j}}{X_t^{n,j}} = \frac{p_t^{ni,j} q_t^{ni,j}}{X_t^{n,j}} = \frac{\left(1+\tau_t^{ni,j}\right) \psi_t^{ni,j} p_t^{i,j} q_t^{ni,j}}{X_t^{n,j}} \tag{B.5}$$

Now, notice that the estimation of equation (10) is performed using as bilateral trade flows the reported values of imports from each reporter country, which is a more reliable measure of the actual trade flows. According with UN-Comtrade, 92% of the countries in Comtrade report CIF values for imports. So, priced at CIF values (the CIF price is $\psi^{ni,j} p_t^{i,j}$), by combining (B.4) and (B.5), we obtain for the bilateral flows:

$$\frac{\psi_t^{ni,j} p_t^{i,j} q_t^{ni,j}}{X_t^{n,j}} = \frac{\left(x_t^{i,j}\left(1+\tau_t^{ni,j}\right) \Upsilon^{ni,j} \left(F_t^{ni}\right)^{\rho_F} \varepsilon_t^{ni,j}\right)^{-\theta^j} (A_t^{i,j})^{\theta^j \gamma^{i,j}} \left(1+\tau_t^{ni,j}\right)^{-1}}{\Psi_t^{n,j}}$$

$$\left(X_t^{ni,j}\right)^{CIF} = \left(x_t^{i,j} \Upsilon^{ni,j} \varepsilon_t^{ni,j}\right)^{-\theta^j} \left(1+\tau_t^{ni,j}\right)^{-\theta^j - 1} \left(F_t^{ni}\right)^{-\rho_F \theta^j} (A_t^{i,j})^{\theta^j \gamma^{i,j}} \left(\frac{X_t^{n,j}}{\Psi_t^{n,j}}\right) \tag{B.6}$$

By taking logs in (B.6) we derive the determinants of the fixed effects and the estimated coefficients mentioned in the text.

B.3 System in relative time differences

Denote $\dot{y}_{t+1} \equiv \left(\frac{y_{t+1}}{y_t}\right)$ the proportional change in a variable y_t. Let $u_t^{n,j} \equiv \exp\left(V_t^{n,j}\right)$ and the real wages $\omega_{t+1}^{n,j} = \frac{w_{t+1}^{n,j}}{P_{t+1}^{n}}$. The system of equations (2), (3), (5), (7), (8), (B.1), (B.2) can be written in relative time differences as:

$$\mu_{t+1}^{n,jk} = \frac{\mu_t^{n,jk} (\dot{u}_{t+2}^{n,k})^{\beta/\nu}}{\sum_{h=0}^{J} \mu_t^{n,jh} (\dot{u}_{t+2}^{n,h})^{\beta/\nu}} \tag{B.7}$$

$$\dot{u}_{t+1}^{n,j} = \dot{\omega}_{t+1}^{n,j} \left(\sum_{k=0}^{J} \mu_t^{n,jk} (\dot{u}_{t+2}^{n,k})^{\beta/\nu}\right)^{\nu} \tag{B.8}$$

$$\dot{x}_{t+1}^{n,j} = (\dot{L}_{t+1}^{n,j})^{\gamma^{n,j} \xi^n} (\dot{w}_{t+1}^{n,j})^{\gamma^{n,j}} \prod_{k=1}^{J} (\dot{P}_{t+1}^{n,k})^{\gamma^{n,jk}} \tag{B.9}$$

$$\dot{P}_{t+1}^{n,j} = \left(\sum_{i=1}^{N} \pi_t^{ni,j} (\dot{x}_{t+1}^{i,j} \dot{\kappa}_{t+1}^{ni,j})^{-\theta^j} (\dot{A}_{t+1}^{i,j})^{\theta^j \gamma^{i,j}}\right)^{-1/\theta^j} \tag{B.10}$$

$$\pi_{t+1}^{ni,j} = \pi_t^{ni,j} \left(\frac{\dot{x}_{t+1}^{i,j} \dot{\kappa}_{t+1}^{ni,j}}{\dot{P}_{t+1}^{n,j}}\right)^{-\theta^j} (\dot{A}_{t+1}^{i,j})^{\theta^j \gamma^{i,j}} \tag{B.11}$$

$$\dot{w}_{t+1}^{n,j} \dot{L}_{t+1}^{n,j} w_t^{n,j} L_t^{n,j} = \gamma^{n,j} (1-\xi^n) \sum_{i=1}^{N} \pi_{t+1}^{in,j} X_{t+1}^{i,j} \tag{B.12}$$

$$X_{t+1}^{nj} = \sum_{k=1}^{J} \gamma^{n,kj} \sum_{i=1}^{N} \pi_{t+1}^{in,k} X_{t+1}^{i,k} + \alpha^{j} \left(\sum_{k=1}^{J} \dot{w}_{t+1}^{n,k} \dot{L}_{t+1}^{n,k} w_{t}^{n,k} L_{t}^{n,k} + \iota^{n} \sum_{i=1}^{N} \sum_{k=1}^{J} \frac{\xi^{i}}{1-\xi^{i}} \dot{w}_{t+1}^{i,k} \dot{L}_{t+1}^{i,k} w_{t}^{i,k} L_{t}^{i,k} \right) \tag{B.13}$$

Adding equation (4), and noticing that equation is satisfied by Walras's law (B.3), equations (B.7)-(B.13) form a non-linear system that can be used to solved for the paths of labor prices $\{w_t^{n,j}\}_{n=1,j=1,t=0}^{N,J,\infty}$, sectoral reallocation shares $\{\mu_t^{n,jk}\}_{n=1,j=1,k=1,t=0}^{N,J,J,\infty}$, lifetime utilities $\{u_t^n\}_{n=1,t=0}^{N,\infty}$ and labor $\{L_t^n\}_{n=1,t=0}^{N,\infty}$. The system is solved using the numerical algorithm proposed by CDP.

B.4 System to solve for counterfactuals

Denote a variable y_t that belongs to the counterfactual solution as y_t', and $\hat{y}_t \equiv \left(\frac{\dot{y}_t'}{\dot{y}_t}\right)$ the proportional change in y_t in the counterfactual economy relative to the proportional change in the same variable in the baseline economy. As before, let $u_t^{n,j} \equiv \exp\left(V_t^{n,j}\right)$ and the real wages $\omega_{t+1}^{n,j} = \frac{w_{t+1}^{n,j}}{P_{t+1}^{n}}$. The system of equations that solves for the impacts in the endogenous state variables of moving from the baseline economy to the counterfactual one is:

$$\mu_t'^{n,jk} = \frac{\mu_{t-1}'^{n,jk} \dot{\mu}_t^{n,jk} \left(\hat{u}_{t+1}^{n,k}\right)^{\beta/\nu}}{\sum_{h=0}^{J} \mu_{t-1}'^{n,jh} \dot{\mu}_t^{n,jh} \left(\hat{u}_{t+1}^{n,h}\right)^{\beta/\nu}} \tag{B.14}$$

$$\hat{u}_t^{nj} = \hat{\omega}_t{}^{nj} \left(\sum_{i=1}^{N} \sum_{k=0}^{J} \mu_{t-1}'^{nj,ik} \dot{\mu}_t^{nj,ik} \left(\hat{u}_{t+1}^{ik}\right)^{\beta/\nu} \right)^{\nu} \tag{B.15}$$

$$L_{t+1}'^{nj} = \sum_{i=1}^{N} \sum_{k=0}^{J} \mu_t'^{ik,nj} L_t'^{ik} \tag{B.16}$$

$$\hat{x}_{t+1}^{n,j} = (\hat{L}_{t+1}^{n,j})^{\gamma^{n,j}\xi^{n}} (\hat{w}_{t+1}^{n,j})^{\gamma^{n,j}} \prod_{k=1}^{J} (\hat{P}_{t+1}^{n,k})^{\gamma^{n,jk}} \tag{B.17}$$

$$\hat{P}_{t+1}^{n,j} = \left(\sum_{i=1}^{N} \pi_t'^{ni,j} \dot{\pi}_{t+1}^{ni,j} (\hat{x}_{t+1}^{i,j} \hat{\kappa}_{t+1}^{ni,j})^{-\theta^j} (\hat{A}_{t+1}^{i,j})^{\theta^j \gamma^{i,j}} \right)^{-1/\theta^j} \tag{B.18}$$

$$\pi_{t+1}'^{n,ij} = \pi_t'^{ni,j} \dot{\pi}_{t+1}^{ni,j} \left(\frac{\hat{x}_{t+1}^{i,j} \hat{\kappa}_{t+1}^{ni,j}}{\hat{P}_{t+1}^{n,j}} \right)^{-\theta^j} (\hat{A}_{t+1}^{i,j})^{\theta^j \gamma^{i,j}} \tag{B.19}$$

$$\hat{w}_{t+1}^{n,k} \hat{L}_{t+1}^{n,k} = \frac{\gamma^{n,j}(1-\xi^n)}{w_t'^{n,k} L_t'^{n,k} \dot{w}_{t+1}^{n,k} \dot{L}_{t+1}^{n,k}} \sum_{i=1}^{N} \pi_{t+1}'^{in,j} X_{t+1}'^{i,j} \tag{B.20}$$

$$X_{t+1}'^{n,j} = \sum_{k=1}^{J} \gamma^{n,kj} \sum_{i=1}^{N} \pi_{t+1}'^{in,k} X_{t+1}'^{i,k} + \alpha^{j} \left(\sum_{k=1}^{J} \hat{w}_{t+1}^{n,k} \hat{L}_{t+1}^{n,k} w_t'^{n,k} L_t'^{n,k} \dot{w}_{t+1}^{n,k} \dot{L}_{t+1}^{n,k} + \iota^{n} \sum_{i=1}^{N} \sum_{k=1}^{J} \frac{\xi^{i}}{1-\xi^{i}} \hat{w}_{t+1}^{i,k} \hat{L}_{t+1}^{i,k} w_t'^{i,k} L_t'^{i,k} \dot{w}_{t+1}^{i,k} \dot{L}_{t+1}^{i,k} \right) \tag{B.21}$$

Equations (B.14)-(B.21) form a non-linear system that can be used to solved for the impacts on the paths labor prices $\{\hat{w}_t^{n,j}\}_{n=1,j=1,t=0}^{N,J,\infty}$, sectoral reallocation shares $\{\hat{\mu}_t^{n,jk}\}_{n=1,j=1,k=1,t=0}^{N,J,J,\infty}$, lifetime utilities $\{\hat{u}_t^n\}_{n=1,t=0}^{N,\infty}$ and labor $\left\{\hat{L}_t^n\right\}_{n=1,t=0}^{N,\infty}$. The system is solved using the numerical algorithm proposed by CDP.

C Additional Tables

Table C.1 – Routes with Available Information on Freight Rates

Original route name	Source	Assigned Origin Region Code*	Assigned Destination Region Code*
Los Angeles to Shanghai	Drewry	15	7
New York to Rotterdam	Drewry	14	3
Rotterdam to New York	Drewry	3	14
Rotterdam to Shanghai	Drewry	3	7
Shanghai to Genoa	Drewry	7	1
Shanghai to Los Angeles	Drewry	7	15
Shanghai to New York	Drewry	7	14
Shanghai to Rotterdam	Drewry	7	3
China to Mediterranean	Freightos/Baltic	7	1
China to US East Coast	Freightos/Baltic	7	14
China to US West Coast	Freightos/Baltic	7	15
China to Europe	Freightos/Baltic	7	2
Europe to US East Coast	Freightos/Baltic	2	14
Europe to China	Freightos/Baltic	2	7
Europe to South America Atlantic	Freightos/Baltic	2	12
Europe to South America Pacific	Freightos/Baltic	2	13
Mediterranean to China	Freightos/Baltic	1	7
US East Coast to China	Freightos/Baltic	14	7
US East Coast to Europe	Freightos/Baltic	14	2
US West Coast to China	Freightos/Baltic	15	7
Ningbo to Australia/New Zealand	Ningbo	7	16
Ningbo to Black Sea	Ningbo	7	4
Ningbo to East US	Ningbo	7	14
Ningbo to Japan	Ningbo	7	11
Ningbo to East Mediterranean	Ningbo	7	9
Ningbo to East South America	Ningbo	7	12
Ningbo to Europe	Ningbo	7	2
Ningbo to India/Pakistan	Ningbo	7	8
Ningbo to North Africa	Ningbo	7	17
Ningbo to Philippines	Ningbo	7	5
Ningbo to South Africa	Ningbo	7	18
Ningbo to Singapore/Malaysia	Ningbo	7	10
Ningbo to Thailand/Vietnam	Ningbo	7	6
Ningbo to West US	Ningbo	7	15
Ningbo to West Mediterranean	Ningbo	7	1
Ningbo to West South America	Ningbo	7	13

* The corresponding 18 regions for the displayed codes are available in Table C.2

Table C.2 – List of Regions

Region Code	Region Name	Countries* (ISO3) in Region
1	West Mediterranean	ESP, ITA, POR,
2	North Europe	DNK, DEU, POL, RUS, SWE
3	Central Europe & UK	BEL, FRA, NLD, CHE, GBR
4	Black Sea	HUN, ROU, SVK
5	Philippines	PHL
6	Thailand & Vietnam	THA, VNM
7	China	CHN, HKG
8	India	IND
9	East Mediterranean	ISR, TUR
10	Singapore & Malaysia	SGP, MYS
11	Japan & Korea	JPN, KOR
12	East South America	ARG, BRA
13	West South America	CHL, COL, PER
14	East North America	CAN1, MEX1,USA1
15	West North America	CAN2, MEX2, USA2
16	Australia	AUS
17	North Africa	MAR
18	South Africa	ZAF

* The corresponding names of the countries are displayed in Table A.1

Table C.3 – PPML Results for Reduced Forms

	IV	PPML
Dependent variable	ln(Trade)	Trade
Instrument	0.014**	0.017***
	(0.007)	(0.006)
Importer x Industry x Time FE	Yes	Yes
Exporter x Industry x Time FE	Yes	Yes
Exporter x Importer x Industry FE	Yes	Yes
Observations	81,200	80,980

Notes: Results correspond to the reduced forms of the specification with $\Upsilon^{ni,j}$ as an exporter-importer-industry FE. Both regressions control for tariffs. PPML regression drops singleton observations or those separated by a FE. Heteroskedasticity robust errors in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table C.4 – Results for Linear Probability Model (LPM)

	Second stages		Reduced forms	
	IV	LPM	IV	LPM
Dependent variable	ln(Trade)	Binary trade	ln(Trade)	Binary trade
ln(Freight)	-1.035**	-0.005		
	(0.508)	(0.026)		
Instrument			0.014**	0.000
			(0.007)	(0.000)
Importer x Industry x Time FE	Yes	Yes	Yes	Yes
Exporter x Industry x Time FE	Yes	Yes	Yes	Yes
Exporter x Importer x Industry FE	Yes	Yes	Yes	Yes
Observations	81,200	81,200	81,200	81,200
F first stage (Kleibergen-Paap)	101.0	101.0		

Notes: All regressions control for tariffs. Results correspond to the reduced forms of the specification with $\Upsilon^{ni,j}$ as an exporter-importer-industry FE. Heteroskedasticity robust errors in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table C.5 – IV Results with Clustered Errors

	(1)	(2)	(3)
	ln(Trade)	ln(Trade)	ln(Trade)
ln(Freight)	-1.035**	-1.035*	-1.035**
	(0.508)	(0.550)	(0.497)
Importer x Industry x Time FE	Yes	Yes	Yes
Exporter x Industry x Time FE	Yes	Yes	Yes
Exporter x Importer x Industry FE	Yes	Yes	Yes
Observations	81,200	81,200	81,200
F first stage (Kleibergen-Paap)	101.0	54.1	81.0

Notes: All regressions control for tariffs. (1) Corresponds to the baseline results.
(2) Clustered standard errors at the exporter-importer-industry level in parentheses
(3) Clustered standard errors at the exporter's region-importer's region-industry level in parentheses. * p<0.1, ** p<0.05, *** p<0.01

Table C.6 – Trade Elasticities θ^j from Fontagné, Guimbard and Orefice (2022)

No.	Sector	$1/\theta^j$
1	Agriculture, hunting, forestry, fishing and aquaculture	2.91
2	Food products, beverages and tobacco	4.17
3	Textiles, textile products, leather and footwear	4.71
4	Wood, products of wood and cork, paper products and printing	8.51
5	Coke and refined petroleum products	3.67
6	Chemical and chemical products	10.56
7	Pharmaceuticals, medicinal and chemical and botanical prod.	10.56
8	Rubber, plastics prod. and other non-methalic mineral prod.	5.77
9	Basic metals	7.39
10	Fabricated metal products	4.22
11	Computer, electronic and optical equipment	5.14
12	Electric equipment	4.11
13	Machinery and equipment, nec	5.00
14	Motor vehicles, trailers, and other transport equipment	8.95
15	Manufacturing nec; repair and installation of machinery equip.	4.06

D Additional Figures

Figure D.1 – Quality of Port Infrastructure in 2019 in Selected Countries ($PortQua^n_{2019}$)

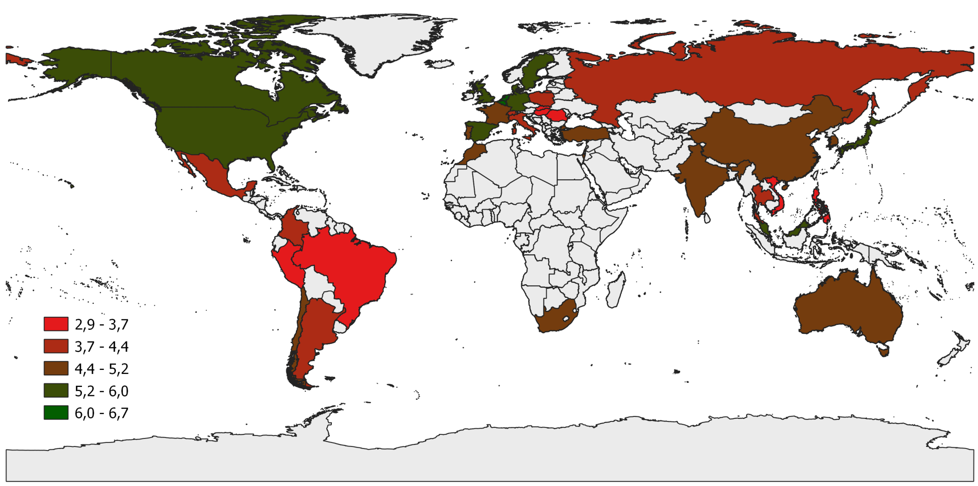


Figure D.2 – Timing of Covid-19 Lockdowns in Selected Countries

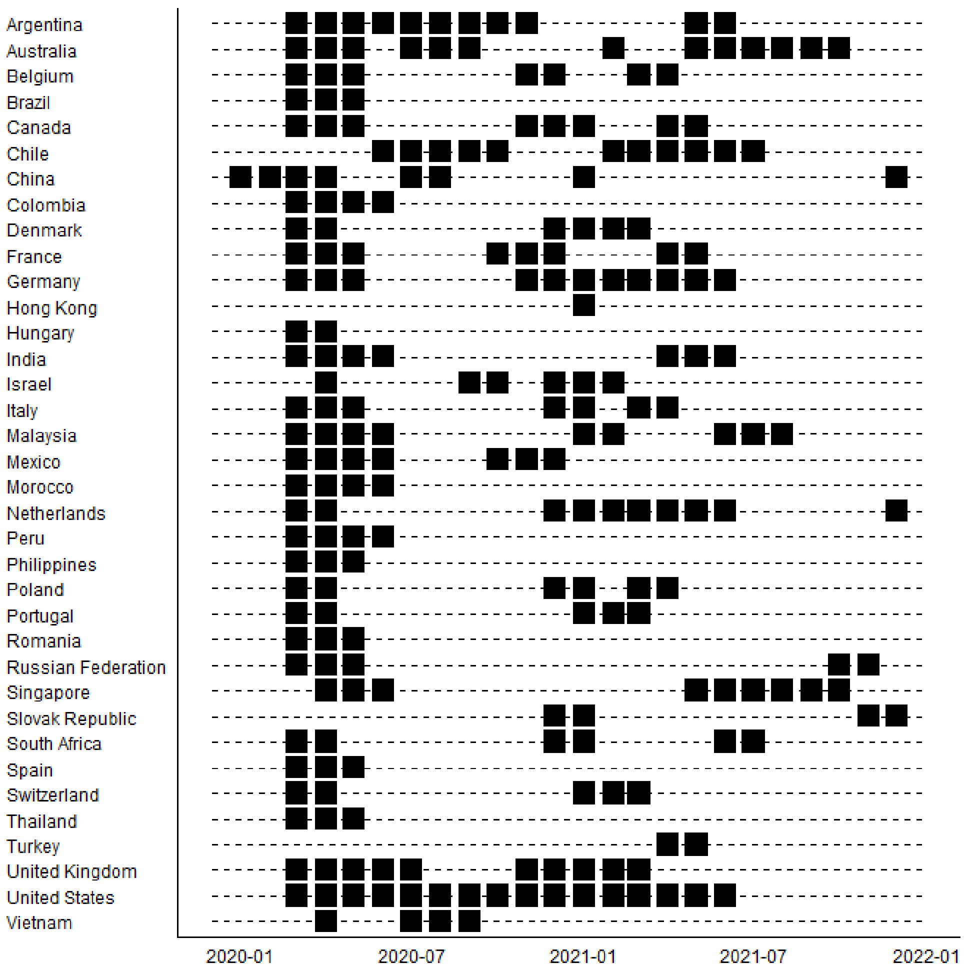


Figure D.3 – Fit of the Estimated Equation (11)

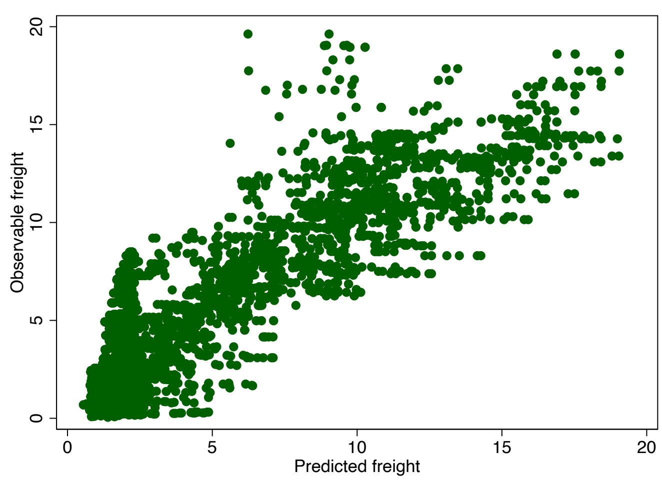
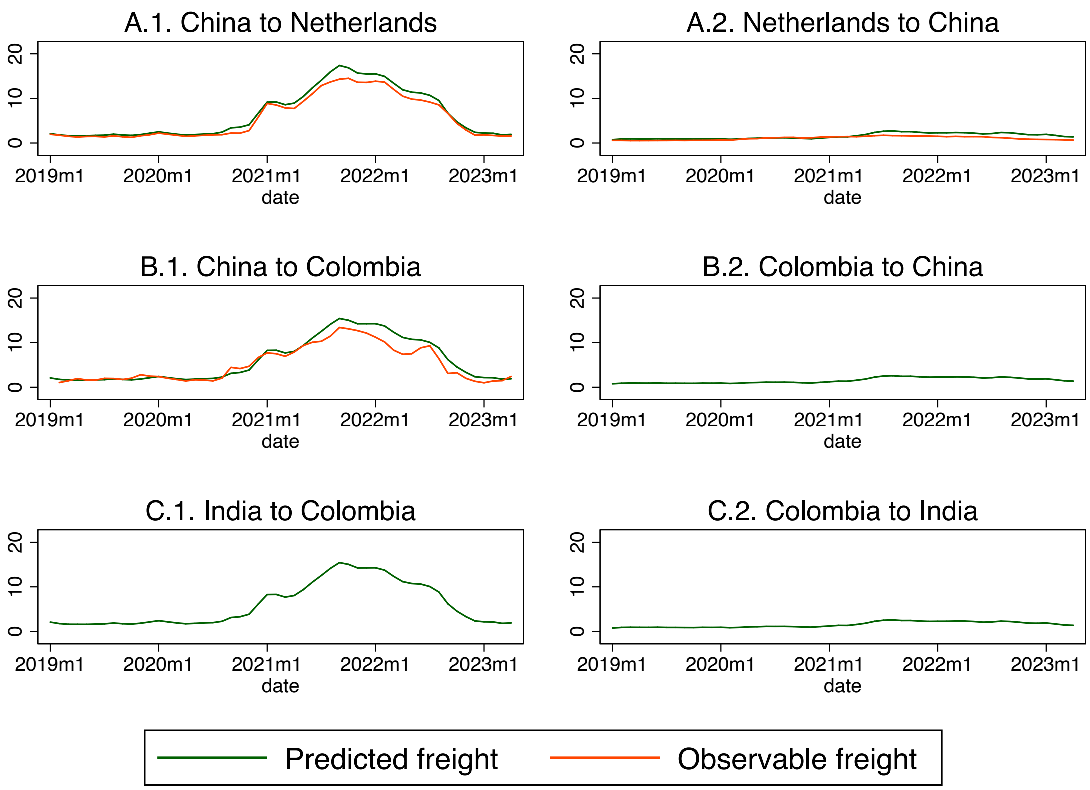
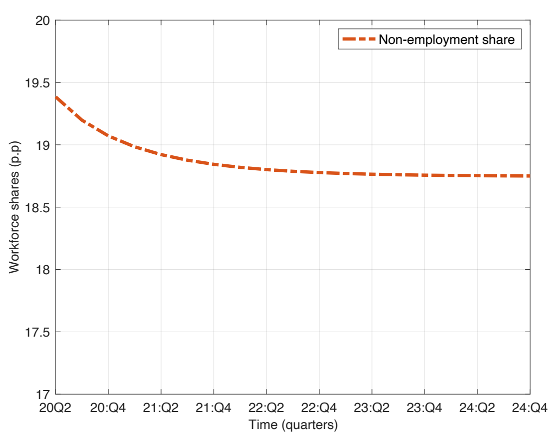


Figure D.4 – Examples of Forecasts for Three Country-Pairs*

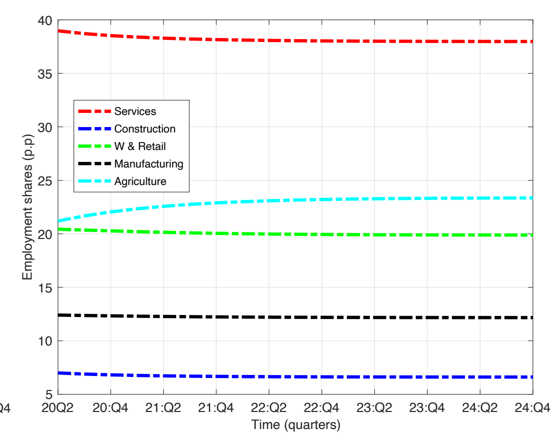


*Note: Panel A (first row) includes a country-pair with information of freight for both directions; Panel B (second row) includes a country-pair with information of freight in only one-direction; Panel C (third row) includes a country-pair with no freight information.

Figure D.5 – Labor Reallocation in the Baseline Economy

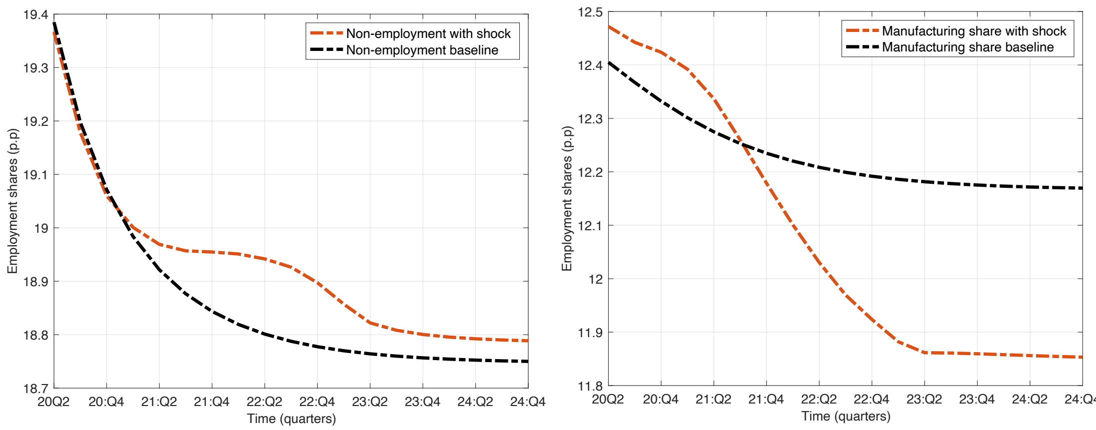


(a) Non-employment (as % of total employment)



(b) All main sectors (as % of total employment)

Figure D.6 – Labor Reallocation in the Baseline Economy and the Economy with Transportation Shocks: Some Examples



(a) Non-employment (as % of the workforce)

(b) Manufacturing (most affected sector) (as % of total employment)