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When Trade Compresses: The Impact of Liberalization on Wage Inequality

Victor Hernandez Martinez† Nicholas Kozeniauskas‡ Roman Merga⋆

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Abstract

We study the effects of trade liberalization on the full wage distribution, exploiting Spain's 1993 entry into the European Single Market. Using employer-employee data, we identify the causal effects of trade across the entire wage distribution, using a novel shift-share instrument embedded in an unconditional quantile regression. We find that the liberalization reduced wage inequality, leading to wage compression through earnings gains at the bottom of the distribution and wage losses at the top. We trace this compression to two asymmetric channels: import competition disproportionately harmed high earners, while export opportunities benefited low earners. The key mechanism is an import-driven "skill-downgrading." A multi-region multi-sector model shows that the key insight for understanding these empirical results is that trade's distributional effects depend on the skill intensity of a country's tradable sector, and Spain's was relatively low-skill intensive back then.

Keywords: Trade Liberalization, Inequality, ESM

JEL Codes: F15, F16, J24, J31.

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† Federal Reserve Bank of Cleveland, email: victor.hernandezmartinez@clev.frb.org.

‡ Bank of Portugal and Universidade Católica Portuguesa, Católica-Lisbon School of Business and Economics, email: nicjkoz@gmail.com.

⋆ International Monetary Fund, email: merga.roman@gmail.com

1 Introduction

The link between international trade and rising income inequality is one of the most critical economic questions of our time. The proposition that trade harms lower-income workers has fueled intense political shifts and shaped policy agendas worldwide. Understanding the causal effects of trade across the entire income distribution is therefore essential. This paper offers new evidence and a new perspective on this topic.

Specifically, we investigate the causal effect of international trade on the full wage distribution. We study Spain's 1993 entry into the European Single Market (ESM), a major trade liberalization episode. To isolate the causal effect, we develop a novel shift-share IV strategy that exploits the sequential entry of later ESM members—the Czech Republic, Hungary, and Poland—using their post-2004 trade outcomes to instrument for Spain's post-1993 experience. To move beyond the mean and estimate the causal effect across the entire distribution, we integrate this IV strategy into an unconditional quantile regression framework. Using comprehensive Spanish employer-employee data, we find that increased trade openness significantly reduced wage inequality, driving a wage compression with gains for workers at the bottom of the distribution and losses for workers at the top.

Estimating the causal effect of trade openness is challenging, as OLS estimates are usually biased by confounding shocks and potential reverse causality. Our novel shift-share IV strategy, which addresses these issues, exploits the sequential timing of ESM accession, using the common policy shock of ESM entry experienced by different countries at different times. We instrument Spain's industry-level trade (post-1993) using the trade changes of later entrants—the Czech Republic, Hungary, and Poland—after their own 2004 accession. The construction of the IV implies that our estimates capture the relative effects of trade, as is common in the literature. That is, it captures the differential effect of trade on more-exposed provinces relative to less-exposed ones. The identifying assumption is that these shocks are correlated through the common policy but uncorrelated with Spain's idiosyncratic local shocks a decade earlier. While similar to Autor et al. (2013), our exclusion restriction, which we thoroughly test, directly addresses key critiques of their approach. First, the 11-year time lag makes our IV robust to contemporaneous global shocks (Jaeger et al. 2018). Second, the structural differences between the countries' economies make a common unobserved trend highly unlikely.

However, a causal estimate of the *average* effect of trade is insufficient to determine the winners and losers of trade, a central aspect of the inequality debate. To capture the total distributional impact of trade, our paper's second methodological contribution is to integrate our IV strategy into the recentered influence function (RIF) regression framework of Firpo et al. (2009). This step, which we validate via simulation, is crucial because the standard alternative, conditional quantile regression (CQR), only captures how trade affects earnings within groups of similar workers but fails to capture how trade reallocates workers across the distribution. To our knowledge, we provide the first estimates of the total causal effect of trade over the unconditional earnings and wage distributions.

The wage compression from increased trade exposure is the net result of the asymmetric effects of imports and exports in the labor market. We find that the import channel drove the wage losses, and these were concentrated on high-earners: increased import openness significantly reduced wages and earnings for workers above the median but had little effect on those at the bottom. Conversely, the export channel drove the gains at the bottom: increased export openness significantly raised earnings for low-income workers, but had little effect for top earners.

We connect these asymmetric effects with a key labor market mechanism: an import-driven shift in labor composition toward low-skill jobs. This "skill-downgrading" explains how high earners were harmed (as import competition pushed them into lower-skill roles) and helps explain the relative gains for low earners (increased demand for their labor services). We also rule out other common channels from the trade literature, finding no evidence that the trade shock operated through unemployment risk or aggregate labor market churning.

This set of findings is in sharp contrast to the established literature. Prominent studies find that import competition harms low-skill workers,[1] while exporting benefits high-skill workers—both factors that exacerbate inequality.[2] We find the opposite: imports harmed high-earners and exports benefited low-earners. Furthermore, the "skill-downgrading" mechanism we uncover contrasts with many modern heterogeneous firm frameworks that predict that liberalization triggers a reallocation toward more skill-intensive firms, raising the skill premium.[3]

[1] See, for example, Autor et al. (2013), Amiti and Cameron (2012), and Topalova (2010).

[2] For the effect of trade on high-skill workers, see Helpman et al. (2017), Bernard and Bradford Jensen (1999), and Verhoogen (2008).

[3] See, for example, Egger and Kreickemeier (2009), Egger and Kreickemeier (2012), Harrigan and Reshef (2015), Helpman et al. (2010), and Helpman et al. (2017). Burstein and Vogel (2017) also have this prediction within sectors, although reallocation due to comparative advantage can offset this effect in the aggregate.

These apparent paradoxes are resolved by one key insight: the distributional effects of trade depend critically on the skill intensity of a country's tradable sector. Much of the literature finds that trade exacerbates inequality because it studies settings in which tradables are relatively skill-intensive. In Spain, at the time of its ESM integration, the opposite is true. We formalize this insight in a multi-region, multi-sector model with two distinct labor skill types. This structure provides a unified theoretical foundation for our results, analytically linking the relative skill intensity of tradables to the observed skill downgrading and wage compression. We also show that Spain was relatively low-skill-abundant compared to its ESM trading partners, making the patterns consistent with Spain specializing in tradable goods per the Heckscher-Ohlin theory.

This paper makes three major contributions to the literature. First, our primary contribution is to the literature on trade and wage inequality. Our central finding is that Spain's 1993 entry into the European Single Market (ESM) caused significant wage compression, benefiting low earners while harming high earners. The result provides an important, causally identified counter-narrative to studies of North-South trade. For example, the "China shock" literature (Autor et al. 2013; Autor et al. 2016) and work on NAFTA (Hakobyan and McLaren 2016) found that import competition increased inequality by harming low-skill workers. We show that the distributional consequences of trade are not universal but depend on the economic context of the integration.

Second, we contribute to the literature on heterogeneous labor market adjustments by simultaneously estimating the causal effects of both import and export channels within a single framework. Doing this avoids the omitted-variable bias that arises from focusing on a single channel, and allows us to identify their asymmetric effects: imports caused wage losses among high earners, while exports created earnings gains for low-income workers. We show that this compression is explained by an import-driven "skill-downgrading." This indicates that the "skill-upgrading" mechanism that is prominent in the literature (Burstein and Vogel 2017; Verhoogen 2008) is context-specific, and the effect can actually go in the opposite direction.

Our findings on these asymmetric channels also extend the heterogeneous firms literature. Compared to Amiti and Cameron (2012), our analysis shifts from firm-level averages to the entire unconditional distribution of individual worker outcomes, documenting a different pattern in which import competition specifically harms high earners. Our results also indicate that reallocation between tradable and non-tradable sectors is a quantitatively important margin for the overall effects of trade on inequality, even if within sectors exporters tend to pay higher wages (Bernard and Bradford Jensen 1999; Helpman et al. 2017).

Third, we contribute to the empirical trade literature by implementing a rigorous causal inference strategy to overcome the key challenges in estimating trade's average and distributional effects. To address the endogeneity of trade flows, we construct a novel shift-share instrument that builds on prior applications in the trade literature (Autor et al. 2013), addressing critiques regarding unobserved global shocks (Jaeger et al. 2018). Furthermore, beyond conceptually defending its validity, we test our approach using the latest recommendations from the shift-share econometrics literature (Borusyak et al. 2022; Borusyak et al. 2025). To estimate causal effects across the entire distribution, we integrate our IV strategy with the unconditional quantile regression framework of Firpo et al. (2009). Our distributional approach is, to the best of our knowledge, a first in the trade literature. It allows us to capture the total causal effect of trade by including the "between-group" compositional effects that are missed by commonly used conditional quantile regressions.

The rest of the paper is organized as follows. Section 2 sets the historical context for the ESM, and describes its key features. Section 3 describes the employer-employee and trade data. Section 4 presents the empirical strategy, detailing both the shift-share IV and the RIF-IV methodologies. Section 5 presents the main findings on average and distributional effects and our investigation of mechanisms. Section 6 covers robustness exercises and IV validity tests. Section 7 develops the theoretical model that rationalizes our findings. Section 8 concludes.

2 The ESM: A Push to Remove Non-Tariff Barriers in the EU

The European Single Market originated from a 1985 European Commission white paper aiming to finalize the creation of an economic area without internal frontiers for goods, people, services, and capital. It is important to distinguish the ESM from earlier integration phases. The ESM did not primarily focus on tariffs between EU members; the removal of tariffs and quantitative restrictions stemmed from the 1968 Treaty of Rome. The ESM aimed to remove non-tariff barriers (NTBs) and other frictions hindering deeper integration. As noted by Head and Mayer (2021), by the early 1980s it was clear that eliminating formal tariffs alone had not created a fully integrated market, primarily due to border checks and divergent national regulations acting as NTBs.[4] The economic weight of these barriers was considerable. The IMF (2024) estimates that, still in 2020, the remaining NTBs within the EU were equivalent to an ad-valorem tariff of approximately 44

[4]For instance, Italy required all pasta to contain 100 percent durum semolina, while Germany only allowed four ingredients in beer, based on the 1815 Bavarian Purity Law.

percent for goods and 110 percent for services.

To dismantle these regulatory barriers, the ESM employed two main mechanisms. First, legislative harmonization replaced varied national rules with common EU regulations in areas such as product safety and environmental protection, allowing European firms to produce a single version of a product for the entire European market. Second, the principle of mutual recognition established that a product lawfully marketed in one member state must generally be allowed in others, shifting the burden of proof to importing authorities and limiting protectionist uses of national rules.

These changes significantly reduced intra-EU trade costs. According to Head and Mayer (2021), intra-EU trade costs had fallen 15 to 18 percent from the mid-1960s until the early 1990s, but progress had stalled.[5] The ESM reignited this decline, leading to a 25 percent total reduction by 2004 relative to the mid-1960s. This reduction in trade frictions was transformative for key sectors of the Spanish economy, enabling firms to integrate into pan-European supply chains and gain new market access (Broberg 2007; CaixaBank Research 2021; Gil et al. 2015).

This paper, therefore, interprets Spain's 1993 entry into the ESM as a major trade liberalization shock, one primarily defined by the removal of non-tariff barriers to trade in goods. While this integration was multifaceted—including the liberalization of capital and labor flows and the expansion of EU funds, as detailed in Appendix B—our empirical analysis abstracts from these other channels to isolate the causal effect of the resulting trade exposure on the Spanish labor market.[6]

3 Data

Our primary data source is the Spanish Social Security Registry (MCVL) [7]. The MCVL contains longitudinal labor histories for a random 4 percent sample of individuals who worked or received social security benefits between 2006 and 2018. A key advantage is its retrospective nature: sampling an individual provides their complete social security record back to their entry into the labor market, allowing us to construct a worker panel from 1980 to 2004.

The data offer daily information on employment spells, including job characteristics (contract

[5]Head and Mayer (2021) estimate that in 1980 goods' trade costs had already declined by around 12 percent, while in 1993 the decline was only 5 or 6 additional percentage points.

[6]In addition, Appendix B provides a richer picture of Spain's economic conditions during its accession to the EU and the ESM.

[7]Dirección General de Ordenación de la Seguridad Social

type, skill group, hours, location), individual attributes (age, gender), and firm details (ID, industry). Monthly wages (top-coded) or benefits are available for employment, unemployment, and retirement records, but not for self-employment spells.

We create a yearly panel with the data, focusing on each individual's primary job each year (the job with the most hours worked). Total annual income and hourly wages are calculated using all jobs held during the year. We exclude observations where the main activity is self-employment, agriculture, or a public administration position with a highly structured career and wage path.[8] We also discard all observations where no location or industry code is available. We retain unemployment spells but exclude UI benefits from income and wage calculations. Income and wages are converted to 2006 euros using the national CPI.

For trade data, we use input-output (IO) tables from two sources to build an annual dataset of Spain's imports and exports at the industry level. For 1995–2016, we use OECD tables covering over 30 industry groups in Spain; for 1987–1994, we use INE tables. Since industry codes, classifications, and currencies differ across sources, we manually match industries based on naming conventions to create consistent annual series for imports, exports, and output from 1987 to 2004.[9]

To address the potential confounding effects of EU funding, which increased alongside trade openness post-ESM in Spain, we use data on EU grants and assisted expenditures from Fuente and Boscà (2010) and Fuente and Boscà (2013). These data provide annual totals received by each autonomous community between 1993 and 2004, including breakdowns by expenditure purpose (e.g., infrastructure, aid to private firms, or human resources). This allows us to control for the geographic distribution of these funds in our estimations.

Constructing our 1987–2004 worker sample from the post-2006 MCVL, an approach also followed by Arellano-Bover (2024), raises concerns about sample selection. The main issue is mortality bias. Individuals working during our period of interest who died before 2006 are not observed in the sample.[10] We address this concern in two ways. First, we restrict our sample to individuals aged

[8] Agriculture is excluded due to imprecise wage data. Public administration officials ("Funcionarios") are excluded because their rigid, predetermined wage paths and job security make them unexposed to typical labor market shocks. Other public-sector workers without these specific contracts remain in the sample.

[9] The structure of the OECD's and INE's IO tables follows standard conventions. Exports are attributed to the exporting industry, regardless of whether the good is final or intermediate. Imports are assigned to the industry that would produce the good domestically, irrespective of the actual importer. For example, imported wood is assigned to the logging industry regardless of whether a furniture maker or a utility company imports it. Our final industry import measure sums imports used as intermediates by other sectors and imports for final demand.

[10] A secondary concern is whether the degree of job informality changed over time, which could affect the representativeness of the sample over time.

TABLE I: SUMMARY STATISTICS

	1987		1993		1998		2004	
	Data	Pop	Data	Pop	Data	Pop	Data	Pop
N (000's)	246	8,408	343	9,542	441	11,311	603	15,088
Pop in Data	0.029		0.036		0.039		0.040	
Female	0.295	0.306	0.348	0.346	0.377	0.368	0.420	0.413
20-29	0.406	0.351	0.376	0.323	0.369	0.315	0.329	0.294
30-39	0.359	0.367	0.363	0.381	0.364	0.382	0.377	0.390
40-49	0.232	0.283	0.257	0.295	0.263	0.303	0.290	0.316
Manufacturing	0.290	0.286	0.233	0.237	0.206	0.222	0.168	0.186
Construction	0.108	0.102	0.114	0.105	0.116	0.108	0.137	0.131
Service	0.604	0.612	0.653	0.658	0.678	0.670	0.695	0.683
Large City	0.325	0.299	0.321	0.282	0.308	0.284	0.300	0.289
Medium City	0.273	0.296	0.269	0.295	0.275	0.291	0.286	0.294
Small City	0.402	0.405	0.409	0.423	0.417	0.425	0.414	0.417
Average Earnings	15,346	16,045	17,957	18,068	16,820	18,260	17,082	17,043
Median Earnings	14,252		16,494		15,219		15,454	
Average H Wages	8.04		9.45		9.21		9.30	

Note: Table I compares summary statistics between our primary sample derived from the Spanish Social Security Registry (MCVL) ("Data" columns) and aggregate population data from the Spanish National Institute of Statistics (INE) ("Pop" columns) for selected years. The INE data are restricted to individuals aged 20-54 and excludes those employed in agriculture to enhance comparability with our MCVL sample, which is restricted to ages 20-55 and excludes agriculture and structured public administration careers. "Pop in Data" shows the ratio of our sample size to the comparable INE population. Age groups and sectoral shares are calculated based on employment. "Large City" refers to the provinces of Madrid and Barcelona; "Medium City" and "Small City" categorize the remaining provinces based on population thresholds. Average and Median Earnings and Average Hourly Wages are expressed in constant 2006 euros.

from 20 to 55, to ensure that no individual is older than 74 by 2006. This reduces the extent of selection due to mortality. Second, in Table I, we assess the representativeness of our sample by comparing it to a relevant comparison population, constructed from aggregate INE data.[11]

The comparison shows very similar levels and trends for most variables. The sample-to-population ratio declines further back in time, from 4.0 percent in 2004 (consistent with the MCVL design) to 2.9 percent in 1987. However, this attrition does not appear to be driven by selection based on observable characteristics. Gender and sectoral employment shares closely track their population counterparts,[12] as does the earnings distribution.

There are two main differences. First, large cities are slightly overrepresented in our sample during the late 1980s and early 1990s (by 3.5 percentage points), possibly due to lower informality in

[11] The INE data are restricted to individuals aged 20 to 54 not employed in the agricultural sector.

[12] We find a 1.8 percentage point divergence in the manufacturing share for 2004, potentially due to industry coding harmonization across datasets.

major urban areas during that time.[13] Second, our sample is slightly younger than the population, particularly in the earlier years, reflecting the expected effect of mortality bias.

Overall, our MCVL sample provides a good representation of the Spanish labor market for our study period, especially from 1993 onward, which is our primary focus.

4 Empirical Strategy

Our empirical goal is to estimate the effects of international trade on individual workers' labor market outcomes. We measure average effects across all workers, as effects across the full distribution. In this section, we outline the methodology for both exercises.

4.1 Baseline Specification for Average Effects

The first thing we need is a measure of a worker's exposure to trade. We follow the literature (e.g., Autor et al. 2013) and proxy for this with the exposure of their employment location, measured by the *trade openness* (the sum of imports and exports, as a share of output) of the province where they work. We use a location-based measure because it aligns with workers' labor markets. In our sample, workers change industries relatively frequently (15 percent annually), while inter-province migration is much less common (around 3 percent annually).[14] We use provinces as the unit for location for several reasons: Spain's 50 provinces provide substantial cross-sectional variation; provinces closely align with local labor markets,[15] as evidenced by low inter-province commuting rates (below 3 percent according to the Spanish Survey of the Labor Force);[16] low inter-province migration suggests limited labor supply adjustments across provinces; and provinces are the smallest geographic unit consistently and reliably measured in our data, avoiding sample loss associated with finer geographic units.

Following the China shock literature that constructs local exposure measures from industry-level trade data (Autor et al. 2013; Autor et al. 2016; Dauth et al. 2014; Jakubik and Stolzenburg 2021),

[13] The structural transformation of the Spanish economy, particularly the decline of agriculture where informality is prevalent, likely contributed to the homogenization of the informal sector over time and space.

[14] The annual cross-province migration rate ranges from 3 to 4 percent during our sample period. This rate is consistent with estimates from the Spanish Labor Force Survey (EPA). In addition, Autor et al. (2014) and Autor et al. (2016) show that import shocks have a relatively small impact on workers' migration probability in the USA.

[15] Most provinces in Spain contain one or two major cities and a surrounding area whose labor market activity is heavily determined by these cities.

[16] Intra-province commuting, particularly to larger cities, is much more common.

we compute province-level trade openness as:

$$TO_{p,t} = \sum_k z_{p,k,t} TO_{k,t}, \tag{1}$$

where $TO_{p,t}$ is province p's trade openness in year t, $TO_{k,t}$ is industry k's trade openness in the same year, and $z_{p,k,t}$ is the share of province p's employment in industry k at time t.[17]

Our baseline specification relates individual labor market outcomes, such as earnings or wages, to province-level trade openness:

$$Y_{i,p,k,t} = +\beta_1 \ln TO_{p,t} + \beta X_{i,p,k,t} + \alpha_i + \epsilon_{i,p,k,t}, \tag{2}$$

where $Y_{i,p,k,t}$ is a labor market outcome of individual i, $X_{i,p,k,t}$ contains control variables detailed below, α_i is the individual fixed effect, and $\epsilon_{i,p,k,t}$ is the residual.

Because this shift-share design combines industry-level shocks with pre-existing local industry shares, identification is not driven by aggregate time-series changes (which are absorbed by year fixed effects). Instead, our coefficient of interest is identified by comparing the differential outcomes across provinces that are more exposed to these shocks (due to their industrial structure) against those that are less exposed. Our estimates, therefore, capture the *relative effects* of trade, measuring the impact on more-exposed provinces relative to less-exposed ones.

While trade openness captures the total impact of ESM entry, its effects may combine opposing influences from imports and exports (Feenstra et al. 2019). The literature has typically focused on the effects of these two channels separately, but we seek to disentangle them. Given that these trade flows are often correlated, this is important. To do this, we define import and export openness as imports and exports as shares of output, respectively, and construct province-level measures analogously to trade openness. We run specifications in which we replace the trade openness term in equation (2) with terms for the logs of import openness and export openness *simultaneously*. Variation in changes to our import and export measures across provinces provides the basis for identification.

A limitation of specification (2) is that it does not provide a causal estimate of the effect of trade openness on labor market outcomes. Unobserved variables might simultaneously affect trade

[17] The shares add up to one, by definition: $\sum_k z_{p,k,t} = 1$.

openness and labor outcomes. For instance, shifts in local labor supply or the targeted allocation of EU funds could correlate with both. While we control for EU funds, it is not possible to account for all potential omitted variables. Second, there may be reverse causality. Provinces with higher or lower wage growth, for example, might have been more likely to engage in more international trade. To address these issues, we employ a shift-share instrumental variable (IV) strategy.

4.2 Shift-Share Instrumental Variable

The construction of our shift-share IV follows the ideas of Autor et al. (2013). Since our measure of trade openness (or export and import openness) is constructed by combining location employment shares and industry openness, we modify both the shares and the shift component to build the instrument.

For the shares, we follow the recent literature (Borusyak et al. 2022; Borusyak et al. 2025) and use province-level industry employment shares lagged by three years ($z_{p,k,t-3}$) instead of contemporaneous shares ($z_{p,k,t}$). This mitigates potential bias arising from the endogeneity of current employment shares to ongoing trade dynamics.[18]

For the shift, our identification relies on exogenous variation in industry-level trade openness. We instrument Spain's industry-level trade openness using the average openness evolution in the same industry in the Czech Republic (CZ), Hungary (HU), and Poland (PL) after their later ESM accession.

The key to our identification is the timing of the accession to the ESM. The Czech Republic, Hungary, and Poland joined the ESM 11 years after Spain (2004 vs. 1993) and, like Spain at the time, did not immediately adopt the euro.[19] We define our shift instrumental variable as

$$\left(\frac{TO^{CZ}_{k,t+11} + TO^{HU}_{k,t+11} + TO^{PL}_{k,t+11}}{3} \right),$$

where $TO^{c}_{k,t+11}$ is the trade openness of industry k in country c, 11 years after the year that we

[18] Lagging the shares helps ensure they are not mechanically affected by contemporaneous trade shocks, which could violate the exclusion restriction. This places our identification within the exogenous shifts framework described in Borusyak et al. (2025). We rely on this approach because the alternative—relying on exogenous shares— assumes local industry employment shares are uncorrelated with all unobserved shocks, an implausible assumption for "generic" shares like ours. While Borusyak et al. (2025) warn that even lagged shares may be biased if past shifts persist and influence current shares, we test for this directly and find no significant correlation between today's shares and the shifts from three years ago. This suggests our lag is sufficient to break the link between the persistent shock process and the share measure.

[19] The Czech Republic, Hungary, and Poland still use their own currencies. Spain adopted the euro in 2002.

use this instrument for. The lag is 11 years, so that we are always comparing the Czech Republic, Hungary, and Poland with Spain at a time when their tenure in the ESM was identical to Spain's in year t. For example, to instrument Spain's *first* year in the ESM ($t = 1993$), we use the average of the *first* year of ESM membership for the other countries ($t + 11 = 2004$). This aligns the shock we are studying—the immediate trade effects of joining the ESM—with our instruments and instrumented variables. Averaging across three countries, as in Autor et al. (2013), aims to isolate the common ESM variation by reducing the influence of idiosyncratic country-specific shocks (e.g., domestic policy in Poland).

Combining the lagged shares and the instrumental shift, we reach our shift-share IV:

$$TO^{IV}_{p,t} = \sum_k z_{k,p,t-3}(TO^{CZ}_{k,t+11} + TO^{HU}_{k,t+11} + TO^{PL}_{k,t+11})/3. \tag{3}$$

To use this instrument in the estimation, we implement the following first-stage specification:

$$\ln TO_{p,t} = \gamma_1 \ln TO^{IV}_{p,t} + \gamma X_{i,p,k,t} + \theta_i + e_{i,p,k,t}, \tag{4}$$

where θ_i is an individual fixed effect, and the second stage is:

$$Y_{i,p,k,t} = +\beta_1 \ln \widehat{TO}_{p,t} + \beta X_{i,p,k,t} + \alpha_i + \epsilon_{i,p,k,t}. \tag{5}$$

We include a number of controls in the $X_{i,p,k,t}$ vector: industry and province dummies to account for persistent differences in trade openness levels across these groups,[20] and year fixed effects to extract the common evolution of trade openness in Spain over our years of interest. Since all our specifications are at the individual level, we also control for persistent worker characteristics unaffected by the evolution of trade: age fixed effects interacted with gender and individual fixed effects. Finally, since our variation in trade openness is at the province-year level rather than the individual level, we cluster the standard errors at the province level.

The validity of our IV design requires it to satisfy the exclusion restriction. This necessitates that the shifts (i.e., industry-level changes in trade openness in the Czech Republic, Hungary, and Poland after 2004) must be uncorrelated with unobserved factors (i.e., the error term) that affected the Spanish labor market post-1993.

[20]For workers whose main/only activity in a year is non-employment, we create a separate industry dummy.

Our defense of the exclusion restriction rests on two pillars: the 11-year time gap between the ESM accession of Spain and the instrumenting countries, and the fundamental structural differences between Spain and these countries. These features underpin the plausibility of a *common component* in post-ESM trade dynamics—namely, that ESM entry triggered similar trade responses across countries. The time lag substantially mitigates concerns about persistent unobserved trends, a common issue in shift-share designs (Jaeger et al. 2018). Furthermore, in 1993, Spain's economy was very different from the post-communist transition economies of Central and Eastern Europe in 2004. The differences in industrial compositions, labor market institutions, and pre-ESM trade patterns (Eichengreen 2008) make it implausible that the same set of unobserved, industry-specific shocks would affect both Spain in the 1990s and this distinct group of nations 11 years later.

This assumption of a "common component" implies that ESM accession generated comparable directional trade shocks across countries, conditional on industry. Under this assumption, the average post-ESM trade response observed in the instrumenting countries serves as a valid counterfactual for Spain's industry-level exposure, isolating variation attributable to ESM entry from country-specific confounders.

Having said this, two concerns remain regarding the exclusion restriction. First, the instrument might capture general industry-development trends if Spain (in 1993) and the instrumenting countries (in 2004) were at similar economic-development stages, leading to parallel trade and labor-market evolutions unrelated to the effects of the ESM. Second, joining the ESM triggered other concurrent policies, in particular, the provision of EU Cohesion and Structural Funds targeted at specific regions and industries. These funds were large and have been shown to have had meaningful effects on local growth, employment, and investment (Becker et al. 2010). If these funds are correlated with our instrument (ESM-induced trade changes), and also directly affect Spanish labor markets, then the exclusion restriction would be violated. We address these threats empirically in Section 6: we test for parallel pre-ESM trade trends between Spain and the instrumenting countries and explicitly control for EU funding flows. We do not find evidence supporting either concern.

4.3 Measurement of the Distributional Impact of Trade

The average effects of changes in trade on workers may mask significant heterogeneity. For example, the Stolper-Samuelson theorem predicts different effects across production factors, and more recent work also predicts that there are winners and losers among workers (e.g., Helpman et al. 2010). Empirical work confirms that trade does not affect everyone equally. For instance, import competition can suppress wages for lower-skill workers (Amiti and Cameron 2012; Autor et al. 2013), while export opportunities can create wage premiums for high-skill workers.(Bernard and Bradford Jensen 1999; Verhoogen 2008).

In this section, we explain how we estimate the effects of trade openness over the entire earnings distribution using unconditional quantile regressions (UQR), and how we implement a novel integration of an IV approach within this framework. We first discuss the need and advantage of using UQR over more traditional methods, such as conditional quantile regressions. From there, we detail how we implement it in practice using recentered influence functions (RIFs). Finally, we explain how we integrate an instrumental variable approach within the RIF framework, discuss the assumptions underlying it, and establish its validity via simulations.

To estimate the distributional impact of international trade, we employ the unconditional quantile regression (UQR) methodology in Firpo et al. (2009). An unconditional approach is necessary because it estimates the total effect of trade on the overall wage distribution, capturing not only how trade affects earnings within groups of similar workers but also how trade shifts the composition of the workforce between groups.[21]

UQR employs the recentered influence function (RIF), which transforms the outcome variable (e.g., wages) so that the effect of a covariate on a specific unconditional quantile can be estimated via linear regression.[22] To implement the RIF-OLS, we compute the RIF for the τ^{th} quantile, q_τ, (we use 9 deciles in our estimation, from the 10th percentile to the 90th) for the variable of interest Y:

$$RIF(y; q_\tau) = q_\tau + \frac{\tau - \mathbf{1}\{y \leq q_\tau\}}{f_Y(q_\tau)}, \tag{6}$$

where $f_Y(q_\tau)$ is the density of Y evaluated at q_τ. We denote the estimated RIF by $\widehat{RIF}(y; q_\tau)$.

[21] Conditional quantile regression (CQR) cannot answer this question, since it estimates the impact of trade on quantiles conditional on covariates, capturing only the *within-group* effect (i.e., how trade alters wage dispersion among similar workers). As Firpo et al. (2009) show, this effect misses the crucial *between-group* effect: how trade may shift the entire wage distribution of one group relative to another, altering the composition of the unconditional quantiles. The UQR method is specifically designed to estimate the total impact by capturing both of these effects.

[22] The RIF-OLS method requires us to assume that the probability of a worker's income being above a given quantile τ is linear in our trade openness measure. For a deeper discussion of this method, see Firpo et al. (2009), Currie et al. (2020), and Fortin et al. (2011).

Second, we estimate the following equation (RIF-OLS regression) for each τ:

$$\widehat{RIF}(y; q_\tau) = \beta_1^\tau \ln TO_{p,t} + \beta X_{i,p,k,t} + \alpha_i + \epsilon_{i,p,k,t}, \tag{7}$$

where β_1^τ measures the effect of trade on the τ^{th} quantile of variable Y.

The linearity of the RIF-OLS regression allows for seamless integration of our shift-share IV. This is essential since the same endogeneity concerns present in the mean analysis remain here. Therefore, for our identification strategy, we apply a standard two-stage least squares (2SLS) procedure to Equation (7), using $\ln TO_{p,t}^{IV}$ to instrument for our endogenous trade openness measure $\ln TO_{p,t}$. While Firpo et al. (2009) do not develop an IV application for their method, the linearity of the RIF-OLS specification makes the extension to a 2SLS framework a natural one. To validate this approach, in Appendix C we conduct simulations to demonstrate that a 2SLS application to the RIF equation successfully corrects for endogeneity bias and recovers the true causal parameter at each quantile.[23]

4.4 First-Stage Results

Before presenting the main results, we discuss the first-stage results for the instrument. First, we present graphical evidence on the sources of its variation, and how the evolution of trade openness across different countries' industries follows a similar pattern after the countries access the ESM. After that, we focus on the instrument's relevance and power. We discuss the instrument's validity in Section 6.2.

Our first objective is to visualize the "common component" assumption behind our shift-share instrument. Figure A.1 shows the aggregate evolution of trade, export, and import openness for Spain and the average for the Czech Republic, Hungary, and Poland, with the time series aligned by their respective ESM entry years. All three panels show a consistent pattern: we find no clear relationship in openness before the ESM accession line, but after entry, the series trend upward together. This provides visual support for our identification strategy. Figure A.2 confirms that these conclusions hold when the data are disaggregated into manufacturing and services. Figures A.3, A.4, and A.5 then show the underlying industry-level shifts (g_k) that are the source of our

[23] Our simulation proceeds in three steps. First, in a clean setting with no endogeneity, we implement RIF-OLS and recover unbiased estimates. Second, we introduce endogeneity by omitting a key covariate, which leads RIF-OLS to produce biased estimates. Third, we apply RIF-IV with a valid instrument and confirm that it corrects the bias, yielding consistent estimates and validating our approach.

instrument's variation. Across many individual ISIC-4 industries, these plots are consistent with the aggregate findings: the evolution of openness appears to be unrelated before the ESM but exhibits similar trends after entering the ESM.

Figure A.6 plots the 1995–2004 change in trade, export, and import openness, highlighting the considerable heterogeneity of the ESM-related shock across industries. For instance, substantial increases occurred in sectors like motor vehicles (D29), other transport equipment (D30), and furniture (D31), while others, such as non-metallic mineral products (D23), saw slight decreases. As shown in Figure A.7, this heterogeneity in the industry-level shifts, when weighted by each province's unique, pre-existing industrial structure (our lagged shares), generates the differential cross-regional impact on trade exposure necessary for our identification.

Figure A.8 shows the pre-existing heterogeneity in employment shares by industry pre-ESM, which is the basis for our shares in the shift-share design. Manufacturing employment was highly concentrated in northern provinces and around Madrid. In contrast, service employment was more prevalent in southern and coastal regions. It is this interaction between the uneven industry-level shocks shown in Figure A.6 and these varied local employment structures shown in Figure A.8 that creates the cross-regional variation in our data.

While the graphical evidence is supportive of the instrument's relevance, Table II provides formal first-stage tests for the post-ESM period. Column (1) shows that a 1 percent increase in the instrument results in a significant 0.65 percent increase in trade openness, with a strong F-statistic of 33.9. Columns (2) and (3) show the results when instrumenting import and export openness simultaneously with their respective instruments. Both instruments are jointly relevant, with a KP F-statistic of 34.0.[24]

5 The Labor Market Consequences of International Trade

This section presents the main empirical findings in three parts. First, we estimate the average causal effects of trade on earnings, wages, and hours worked. Second, we move beyond mean effects to analyze the distributional consequences of trade, estimating the impact across the quan-

[24]Our first stage includes both import and export instruments simultaneously. While the export instrument does not predict imports, the import instrument significantly predicts exports. However, identification with multiple endogenous variables requires only joint relevance (as confirmed by the KP F-statistic) and a full-rank first-stage matrix, not a one-to-one mapping between instruments and endogenous variables. Furthermore, this cross-effect is also economically plausible: export growth in the instrumenting countries could increase their demand for imports, potentially including goods produced in Spain (e.g., vehicles from plants established post-ESM as a result of the accession).

TABLE II: FIRST STAGE RESULTS. POST-ESM ACCESSION

	$\ln TO_{p,t}$	$\ln EO_{p,t}$	$\ln IO_{p,t}$
$\ln TO_{p,t}^{IV}$	0.653***		
	[0.112]		
$\ln IO_{p,t}^{IV}$		0.345***	-0.075
		[0.082]	[0.045]
$\ln EO_{p,t}^{IV}$		0.904***	0.939***
		[0.244]	[0.163]
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Male×Age FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
N	4,419,529	4,419,529	4,419,529
KP F-Stat	33.88	33.98	

Note: Table II displays the first-stage IV regressions for the post-ESM accession period (1993-2004). Column (1) shows the regression of log province-level trade openness on its corresponding instrument. Columns (2) and (3) show the regressions of log province-level export openness and log province-level import openness, respectively, on both the instrument for import openness and the instrument for export openness simultaneously. All specifications include year, industry, province, gender-specific age, and individual fixed effects. The KP F-statistic in between columns (2) and (3) refers to the test for the joint significance of both instruments. Province-level clustered standard errors are shown in brackets. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

tiles of earnings and wages. Finally, we investigate driving mechanisms, documenting the importance of trade's impact on skill composition while finding the labor market churning channel to be irrelevant. Throughout these steps, we systematically disentangle the distinct roles of imports and exports in the overall effects of trade openness.

5.1 Average Effect of Trade Openness: Increased Exposure Reduces Earnings and Wages

Table III presents IV estimates of the average effect of total trade openness on key labor market outcomes. We find that a 1 percent increase in trade openness leads to a decrease in log individual earnings of approximately 0.1 percent, although this estimate is statistically insignificant (column 1). In contrast, the impact on log hourly wages is statistically significant: a 1 percent increase in trade openness causes an average decrease of 0.12 percent (column 2). Consistent with the lack of a strong earnings effect, we find no statistically significant impact of trade openness on log hours worked (column 3).

The negative wage elasticity aligns with Dix-Carneiro and Kovak (2017), who find that Brazilian regions more exposed to tariff reductions experienced persistent declines in formal earnings. However, our findings contrast with other results. For instance, they differ from those reported

TABLE III: EFFECTS OF TRADE OPENNESS ON EARNINGS, WAGES, AND HOURS

	ln Earnings	ln Hourly Wages	ln Hours Worked
ln $TO_{p,t}$	-0.096	-0.117***	0.028
	[0.073]	[0.035]	[0.077]
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Male× Age FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
N	4,419,529	4,370,631	4,370,631
KP F-Stat	33.88	33.98	33.98

Note: Table III displays the second-stage IV regressions for the post-ESM accession period (1993-2004). The dependent variables are log earnings, log hourly wages, and log hours worked, as indicated in each column. The primary explanatory variable is log province-level trade openness, instrumented as described in the main text. All specifications include year, industry, province, gender-specific age, and individual fixed effects. KP F-statistics for the first-stage regressions are shown in the last row. Province-level clustered standard errors are shown in brackets. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

by Peluffo (2013) on Mercosur's creation in Uruguay, which found a positive effect on both hourly wages and monthly earnings. Furthermore, our null finding on hours worked is informative. It is consistent with the "margins of adjustment" framework of Dix-Carneiro and Kovak (2019), who document that quantity adjustments to trade shocks occur primarily on the extensive and formality margins (i.e., shifts to informal work or non-employment) rather than the intensive (hours) margin for incumbents. This null-hours effect also provides a direct counterpoint to the "leisure gains" hypothesis of Velasquez (2025), who argues that openness reduces labor supply by increasing real income. Our identified decrease in real hourly wages shows that the positive income effect necessary for that channel is absent.

5.2 Imports vs. Exports: Opposing Average Effects, Import Channel's Negative Effects Dominate

To disentangle the components of trade openness, Table IV presents IV estimates of import and export openness, estimated in a single joint specification.

Increased import openness results in a consistent negative effect across outcomes: a 1 percent increase significantly decreases earnings by 0.22 percent and hourly wages by 0.12 percent. Turning to export openness, the effects are generally positive but vary across outcomes: A 1 percent increase significantly increases earnings by 0.35 percent and hours worked by 0.28 percent, but has no effect on hourly wages.

TABLE IV: EFFECTS OF EXPORT AND IMPORT OPENNESS ON EARNINGS, WAGES, AND HOURS

	ln Earnings	ln Hourly Wages	ln Hours Worked
ln $IO_{p,t}$	-0.215***	-0.120**	-0.081
	[0.074]	[0.051]	[0.056]
ln $EO_{p,t}$	0.353***	0.052	0.278**
	[0.115]	[0.080]	[0.105]
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Male× Age FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
N	4,419,529	4,370,631	4,370,631
KP F-Stat	34.02	33.87	33.87

Note: Table IV displays the second-stage IV regressions for the post-ESM accession period (1993-2004). The dependent variables are log earnings, log hourly wages, and log hours worked, as indicated in each column. The primary explanatory variables are log province-level import and export openness, instrumented as described in the main text. All specifications include year, industry, province, gender-specific age, and individual fixed effects. KP F-statistics for the first-stage regressions are shown in the last row. Province-level clustered standard errors are shown in brackets. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

These opposing coefficient signs help interpret the net negative effect of total trade openness found in Table III. Spain's ESM accession period was marked not only by increased trade but also by rising trade deficits, indicating that import growth outpaced export growth. This implies that rising imports accounted for a greater share of the increase in aggregate trade openness. Given the negative coefficients on import openness and the generally positive ones on export openness, the significant negative average wage effect of total trade openness reflects the dominance of the import channel in the aggregate result. Thus, the average trade effects largely capture the downward wage pressure from increased import competition.

Our findings of opposing effects —imports reducing wages and exports boosting earnings— align with the literature. While much of this work focuses on employment instead of earnings, Autor et al. (2013) also find negative wage effects from import competition in the US. Similarly, Costa et al. (2016), studying Brazilian trade with China, document opposing impacts from imports and exports.

5.3 The Effects of Trade Openness Do Not Arise Through Labor Market Churning

Previous work suggests that increased trade exposure can intensify labor market churning, potentially increasing inequality (e.g., Egger and Kreickemeier 2009 and Davis and Harrigan 2011). To test if this mechanism applies during Spain's ESM accession, we examine the causal effect of trade openness on unemployment propensity, a proxy for labor market churning.

TABLE V: EFFECTS OF TRADE OPENNESS ON UNEMPLOYMENT

	Panel (a): Trade Openness			
	$U_{i,t}$	Months $U_{i,t}$	$U_{i,t+1}$	Prov. UR
ln $TO_{p,t}$	-0.004	-0.161	-0.051	0.020
	[0.021]	[0.127]	[0.033]	[0.056]
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	No
Province FE	Yes	Yes	Yes	Yes
Male×Age	Yes	Yes	Yes	No
Individual FE	Yes	Yes	Yes	No
N	4,419,529	4,419,529	3,689,052	600
KP F-Stat	33.88	33.88	25.47	27.57

	Panel (b): Import and Export Openness			
	$U_{i,t}$	Months $U_{i,t}$	$U_{i,t+1}$	Prov. UR
ln $IO_{p,t}$	-0.009	-0.143	-0.062	0.047
	[0.019]	[0.109]	[0.050]	[0.061]
ln $EO_{p,t}$	0.020	0.042	0.036	-0.089
	[0.021]	[0.168]	[0.062]	[0.085]
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	No
Province FE	Yes	Yes	Yes	Yes
Male×Age	Yes	Yes	Yes	No
Individual FE	Yes	Yes	Yes	No
N	4,419,529	4,419,529	3,689,052	600
KP F-Stat	34.02	34.02	23.49	43.98

Note: Table V displays the second-stage IV regressions for the post-ESM accession period (1993-2004). The primary explanatory variable in Panel (a) is log province-level trade openness, instrumented as described in the main text. The primary explanatory variables in Panel (b) are log province-level import and export openness, instrumented as described in the main text. The dependent variables are a dummy for whether the worker is unemployed in that year (column 1), the number of months the worker is unemployed that year (column 2), a dummy for whether the worker is unemployed in the following year (column 3), and the province-level unemployment rate. All specifications in columns 1 to 3 include year, industry, province, gender-specific age, and individual fixed effects. In column 4, the sample is province-year, and the specifications include only province and year fixed effects. KP F-statistics for the first-stage regressions are shown in the last row. Province-level clustered standard errors are shown in brackets. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

We construct two individual-level measures based on social security records: a dummy indicating whether the worker spends the majority of the year collecting unemployment insurance (UI) benefits, and the total number of months the worker collects UI. To address the limitations inherent in social security records (such as eligibility requirements, benefit exhaustion, and non-claiming),[25] we supplement this individual-level analysis by also using the official unemployment rate at the province-year level from the INE. This allows us to circumvent the limitations of our constructed individual-level unemployment measures.

Table V presents the IV estimates. Panel (a) shows that total trade openness has no statistically

[25] Our unemployment measure comes from social security records showing whether individuals received UI benefits. This introduces limitations: workers with less than a year of prior employment are excluded; individuals disappear once benefits expire, even if they are still jobless; and some eligible workers may choose not to claim benefits.

significant impact on any of the unemployment measures analyzed. The point estimates are consistently small and statistically indistinguishable from zero, aligning with our earlier null finding for average hours worked. Panel (b) confirms this null result when decomposing trade into import and export openness. Neither channel significantly affects any unemployment measure. This implies that the previously documented average wage and earnings effects do not operate through changes in unemployment risk or duration in this context.

These findings contrast with predictions that trade might increase displacement (Egger and Kreickemeier 2009; Davis and Harrigan 2011). For Spain during this period, trade exposure did not significantly alter unemployment outcomes, suggesting that labor market churning is unlikely to be the primary mechanism driving the effects on wages and earnings documented earlier.

The Distributional Consequences of International Trade

We now move beyond average effects to estimate the causal impact of trade openness across the entire unconditional distribution of earnings and wages. A rich literature documents complex links between trade and inequality. Some studies, like Helpman et al. (2017) for Brazil, find exporting benefits workers in larger, more productive firms, potentially exacerbating inequality.[26] Others, like Burstein and Vogel (2017) and Harrigan and Reshef (2015), find that liberalization often triggers reallocation to more skill-intensive firms and sectors, driving up the skill premium.[27] Conversely, other work finds negative wage pressure concentrated on specific worker groups (Acemoglu et al. 2016; Amiti and Cameron 2012; Autor et al. 2013; Topalova 2010). While this literature offers crucial insights, establishing the causal effect across the full distribution while addressing endogeneity remains challenging. Our RIF-IV strategy is designed to provide this more comprehensive causal assessment, capturing total effects, including the between-group shifts missed by conditional quantile methods.

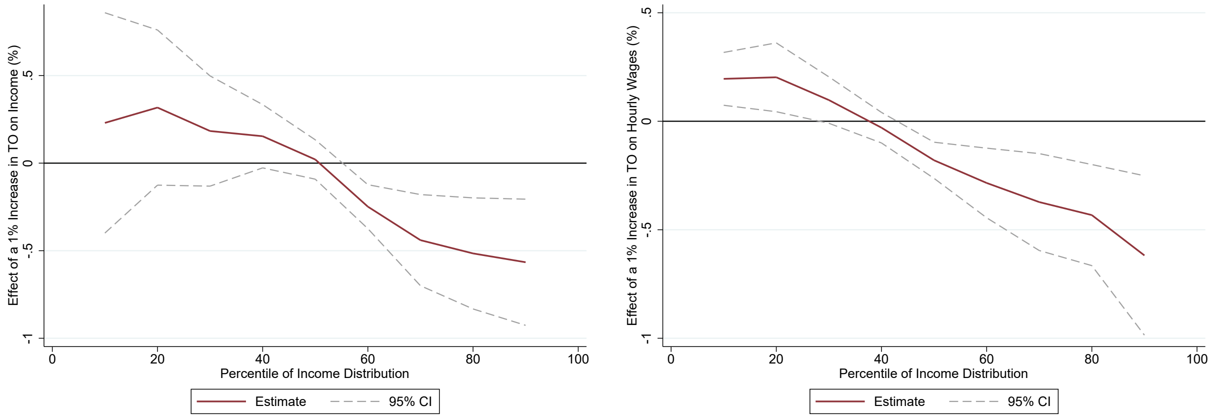
5.4 Trade Openness: Gains at the Bottom and Losses at the Top of the Distribution

Figure I presents our RIF-IV estimation results, showing the causal effect of a 1 percent increase in trade openness across the unconditional distributions of total earnings and hourly wages. The

[26] The model in Helpman et al. (2017) could also predict lower wage inequality if most workers are employed in exporting firms.

[27] Theoretically, Burstein and Vogel (2017) offer a more nuanced view, arguing that lower trade costs shift factors toward comparative-advantage sectors, raising skill premia in skill-intensive economies. Yet their quantitative results show that liberalization generally increases skill premia as resources shift within sectors toward skill-intensive firms.

quantiles for each distribution are calculated by pooling all observations from 1993 to 2004.[28]



(a) Total Earnings

(b) Hourly Wages

Notes: Figure I plots the estimated causal effect of a 1 percent increase in log province-level trade openness on log earnings (Panel a) and log hourly wages (Panel b) across the unconditional distributions of log total earnings (Panel a) and log hourly wages (Panel b). Effects are estimated using the RIF-IV methodology described in the main text for the post-ESM period (1993-2004). The x-axis represents the percentile of the respective distribution (total earnings in Panel a, hourly wages in Panel b), calculated by pooling all observations across years. The y-axis shows the estimated percent effect. The solid line represents the point estimate at each percentile, and the dashed lines indicate the 95 percent confidence interval, based on province-level clustered standard errors. All specifications include year, industry, province, gender-specific age, and individual fixed effects.

FIGURE I: DISTRIBUTIONAL EFFECTS. TRADE OPENNESS

For total earnings in Panel (a), we find statistically insignificant but positive effects of trade openness for workers below the median earnings distribution. For the top half of the distribution, however, increased trade openness leads to a statistically significant negative impact on earnings. This negative effect becomes more pronounced at higher percentiles; for instance, at the 60th percentile, a 1 percent increase in trade openness decreases earnings by approximately 0.25 percent, while at the 80th percentile, the decrease exceeds 0.5 percent.

For hourly wages in Panel (b), the pattern is broadly similar but differs at the lower end of the distribution. We find increased trade openness leads to a statistically significant positive effect on hourly wages for workers in roughly the bottom 30 percentiles. For instance, workers at the 20th percentile see wages increase by approximately 0.2 percent from a 1 percent increase in trade openness. The effect crosses zero around the 40th percentile and becomes statistically significant and negative above this point. As with earnings, the negative impact on hourly wages intensifies

[28]Calculating quantiles year-by-year yields very similar results, as shown in Figures A.9 and A.10 (b). While the RIF literature primarily considers cross-sectional data (Firpo et al. 2009; Fortin et al. 2011) or panels with stable units (Currie et al. 2020), applying it to panels with worker entry and exit raises questions about how to define a stable underlying distribution. If the workforce composition changes significantly, the meaning of a specific pooled quantile could shift. Calculating quantiles relative to each year's distribution anchors the interpretation to the contemporaneous workforce, potentially offering a more robust approach. In this sense, the robustness of our results across both methods is reassuring.

at higher percentiles, reaching a decrease of approximately 0.45 percent at the 80th percentile.

Finally, Figure A.10 (a) considers the effects on hours worked. Because we are interested in the effect of trade openness on hours worked over the earnings distribution, not the hours distribution itself, the RIF-IV methodology cannot be applied. Instead, we estimate CQR where the outcome is hours worked at each decile of the earnings distribution.[29] We find no significant effect of trade openness on hours worked across the earnings distribution.

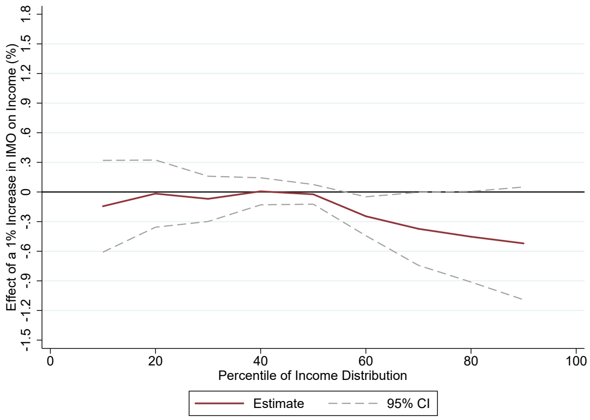
5.5 Asymmetric Trade Effects: Export Gains at the Bottom, Import Losses at the Top

Figure II presents the distributional effects, disentangling the impact of import and export openness on total earnings and hourly wages. The figures show the distinct channels driving the overall effects on trade openness.

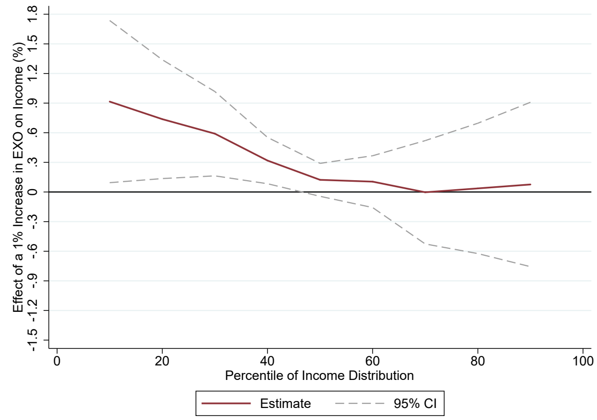
Panels (a) and (c) show that import openness primarily harms workers in the upper half of the distributions. For total earnings in Panel (a), the effect is statistically insignificant below the median but becomes significantly negative above it, reaching approximately -0.5 percent for a 1 percent increase in import openness at the 80th percentile. The impact on hourly wages in Panel (c) follows a similar pattern: insignificant effects at the bottom turn significantly negative around the 40th percentile, with the negative impact intensifying to -0.4 percent at the 80th percentile. These findings contrast with Autor et al. (2013) and Amiti and Cameron (2012), who emphasize negative wage pressure from import competition on lower-skill workers. Our results show that, in Spain, the top of the distribution experienced the most significant negative consequences from import exposure.

Conversely, Panels (b) and (d) show export openness tends to benefit workers, particularly at the lower end of the earnings distribution. For total earnings in Panel (b), a 1 percent increase in export openness significantly raises earnings by nearly 0.8 percent at the 20th percentile; this positive effect diminishes and becomes statistically insignificant around the median. This suggests that export opportunities provided the most significant earnings gains for low earners. Consistent with Table IV, these effects appear to result from increased hours worked. Panel (d) shows that the impact on hourly wages is much weaker; point estimates are close to zero and statistically insignificant across the entire distribution. The finding that export earnings benefits concentrate at the bottom contrasts with the literature, such as Helpman et al. (2017), that suggests that export

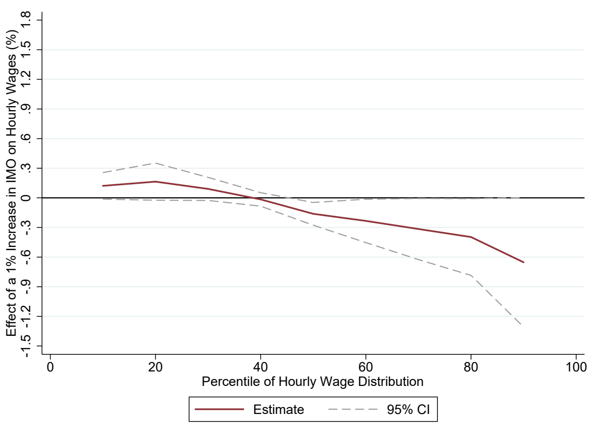
[29] The explanatory variable is still trade openness, instrumented using the same IV strategy as that used throughout the paper.



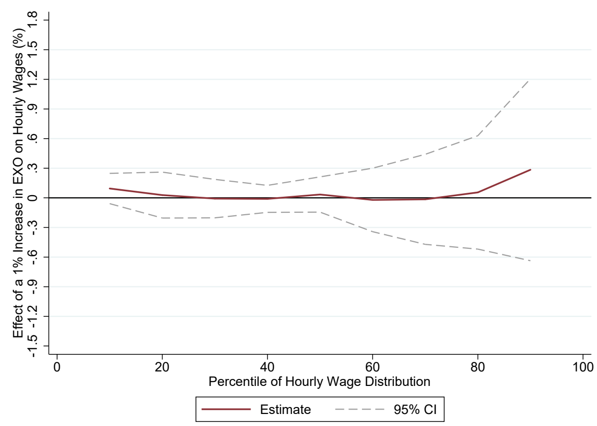
(a) Total Earnings. Imports



(b) Total Earnings. Exports



(c) Hourly Wages. Imports



(d) Hourly Wages. Exports

Notes: Figure II plots the estimated causal effect of a 1 percent increase in log province-level import (Panels a and c) and export (Panels b and d) openness on log earnings (Panels a and b) and log hourly wages (Panels c and d) across the unconditional distributions of log total earnings (Panels a and b) and log hourly wages (Panels c and d). Effects are estimated using the RIF-IV methodology described in the main text for the post-ESM period (1993-2004). The x-axis represents the percentile of the respective distribution (total earnings in Panels a and b, hourly wages in Panels c and d), calculated by pooling all observations across years. The y-axis shows the estimated percent effect. The solid line represents the point estimate at each percentile, and the dashed lines indicate the 95 percent confidence interval, based on province-level clustered standard errors. All specifications include year, industry, province, gender-specific age, and individual fixed effects.

FIGURE II: DISTRIBUTIONAL EFFECTS. IMPORTS VS. EXPORTS

gains often favor higher-paid workers in larger firms. The lack of a significant wage effect also differs from previous findings of meaningful export wage premiums (Bernard and Bradford Jensen 1999).

Our estimates show clear asymmetric effects of the two trade channels, explaining the overall pattern for total trade openness in Figure I. The significant negative impact of trade openness on workers above the median is almost entirely driven by imports, whose adverse effects are concentrated in the upper halves of the earnings and wage distributions. Exports provided little

TABLE VI: EFFECTS OF TRADE OPENNESS ON SKILL LEVEL OF THE JOB

	$Low\ Skill_{i,t}$	$Low\ Skill_{i,t}$
$\ln TO_{p,t}$	0.060**	
	[0.030]	
$\ln IO_{p,t}$		0.042*
		[0.024]
$\ln EO_{p,t}$		0.023
		[0.058]
Year FE	Yes	Yes
Industry FE	Yes	Yes
Province FE	Yes	Yes
Male× Age FE	Yes	Yes
Individual FE	Yes	Yes
N	4,419,529	4,419,529
KP F-Stat	33.88	34.02

Note: Table VI displays the second-stage IV regressions for the post-ESM accession period (1993-2004). The dependent variable is a dummy for whether the worker works in a low-skill job. The primary explanatory variable in column (1) is log province-level trade openness, instrumented as described in the main text. The primary explanatory variables in column (2) are log province-level import and export openness, instrumented as described in the main text. All specifications include year, industry, province, gender-specific age, and individual fixed effects. KP F-statistics for the first-stage regressions are shown in the last row. Province-level clustered standard errors are shown in brackets. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

offset for workers at the top. Conversely, the positive wage and earnings effects of trade openness at the bottom result from exports boosting earnings for low earners, as import competition has negligible effects in this part of the distribution.

This decomposition indicates that during Spain's ESM integration, the import channel was the dominant force shaping the average wage response and driving the negative wage effect in Table III. The asymmetric forces from imports and exports resulted in the compression of the earnings and wage distributions shown in Figure I. This inequality-reducing outcome, driven by non-linear distributional effects—specifically import-induced losses at the top and export-related earnings gains at the bottom—suggests a distinct labor market adjustment process during Spain's ESM accession, compared to those documented by previous work.

5.6 Trade and Skill Composition: An Import-Driven Shift to Low-Skill Jobs

To explore a mechanism driving the observed wage compression, we examine how trade exposure affects employment skill composition. Changes in relative demand for skill groups are a central prediction of trade models and could explain the distributional patterns we document. Specifically, if liberalization pushes workers toward lower-skill roles, this could contribute to wage declines at the upper end of the distribution and explain the (earnings) gains at the lower end.

We estimate the causal impact of trade exposure on the probability of an individual working in a low-skill job, defined by a dummy variable for a low-skill occupation. Column (1) of Table VI presents the trade openness results. We find that a 1 percent increase in trade openness leads to a statistically significant increase of approximately 0.06 percentage points in the probability of holding a low-skill job.

Column (2) decomposes the trade effect into imports and exports. We find a significant positive coefficient for import openness (0.042 pp), similar in magnitude to column (1). In contrast, the export openness coefficient is statistically insignificant and close to zero. This suggests that increased import competition pushes workers toward lower-skill positions, while export opportunities do not significantly affect skill composition. This aligns with our finding that imports negatively impact higher earners, suggesting that these workers relocate into lower-paying, lower-skill roles. These results also help reconcile the positive export earnings effect for low earners with the lack of an average export wage premium, suggesting that exports may have increased demand within the low-skill segment rather than inducing average skill upgrading.

Increased trade exposure, driven primarily by imports, pushing workers toward lower-skill jobs, appears to be inconsistent with Heckscher-Ohlin predictions for a developed, skill-abundant country. Liberalization would typically suggest that Spain should specialize in skill-intensive activities, reducing demand for low-skill labor. This prediction, however, overlooks Spain's relative position within the ESM in 1993. As shown in Figure A.11, compared with core EU members (e.g., Germany, France, Italy, and the UK), Spain was less skill- and capital-abundant. Therefore, within the ESM, Spain might have held a comparative advantage in relatively less skill-intensive goods than its richer partners.

Our findings, therefore, support an intra-bloc specialization pattern in Spain. The observed skill-downgrading, driven by the import channel, aligns with Spain facing increased competition in skill-intensive sectors from ESM partners, pushing domestic resources toward less skill-intensive activities. This interpretation is supported by the literature showing that intense import competition can lead to occupational downgrading, irrespective of simple factor endowment predictions (Autor et al. 2013 on employment structure; Ashournia et al. (2014) on downward wage adjustments). The skill composition shift may thus reflect Spain's specific ESM integration dynamics.

In summary, our results indicate that increased trade exposure following Spain's ESM accession reduced wage inequality through wage compression. The import channel, which dominated this liberalization episode, led to a negative average wage effect, affecting earnings and wages most harshly above the median of their respective distributions. Conversely, export openness boosted earnings primarily below the median. A key mechanism appears to be skill-downgrading driven by imports, which forced workers into lower-skill jobs. On the other hand, the unemployment and churning channels appear to be irrelevant. This pattern, not common in other liberalization episodes, suggests that import pressure disproportionately affected high earners, while export gains were concentrated among low earners in Spain. In Section 7, we analyze how these results align with a standard multi-region sector model of international trade and differentiated labor skills.

6 Robustness and IV Validity

6.1 Robustness

This section assesses the robustness of our central findings—that increased trade exposure reduced wage inequality via wage compression—by addressing two concerns. First, Spain's ESM accession coincided with a substantial increase in potentially confounding EU subsidies and grants, which were often targeted regionally and sectorally. We therefore explicitly account for these contemporaneous funding flows. Second, we test the sensitivity of our findings to our baseline log-log specification, which assumes a constant elasticity. Because the proportional impact might vary with integration and alternative functional forms are common, we re-estimate our results using log-level specifications.

To ensure that trade effects are not confounded by contemporaneous EU funding, we incorporate controls for assisted expenditures and grants received by Spain's autonomous communities between 1993 and 2004, using data from Fuente and Boscà (2010) and Fuente and Boscà (2013). These funds are a potential source of bias if their regional distribution is correlated with our instrumented trade exposure. We add the log of real funding as additional covariates to our main IV specifications.[30]

Table A.1 confirms that our average estimates (shown in Tables III and IV) are robust to controlling for total assisted expenditures (Panel b) and grants (Panel a). All coefficients for trade, import, and export openness remain unchanged. The EU funding controls themselves show a small, statistically significant association with hourly wages, implying a cumulative wage impact of 0.3-0.4

[30]We convert their nominal data to real Euros using appropriate GDP deflators and apply a log transformation.

percent over the period.[31] Our distributional findings are equally robust. Figures A.12 and A.13 reveal patterns virtually identical to those in our baseline results (Figures I and II). The key features —the downward slope for trade openness, negative import effects at the top, and positive export earnings at the bottom— are preserved. This stability provides strong evidence that our findings are not driven by contemporaneous EU subsidies and confirms that these funding flows are largely uncorrelated with our instrumented trade measures.

Our baseline results rely on a log-log specification, relating log earnings/wages to log trade openness. This estimates a constant elasticity, implying that a 1 percent relative increase in trade openness has the same percentage wage impact regardless of the initial openness level. While log transformations are common, applying them to a ratio variable makes specific assumptions about relative versus absolute changes.[32] Because specifications relating log outcomes to level variables are also common in previous work (e.g., Autor et al. 2013), we assess the sensitivity of our results to a log-level functional form.[33]

The findings for total trade openness, shown in Table A.2, confirm our baseline results: the instrument is strong (F-statistics above 50), and we estimate a statistically significant negative effect on earnings and hourly wages and an insignificant impact on hours worked. To compare economic magnitudes, the observed 5 percentage point increase in aggregate trade openness between 1995 and 2004 implies a 2.3 percent wage decrease in this log-level model,[34] which is very similar to the 2.6 percent decrease implied by our baseline log-log elasticity.[35] The robustness of our results to this alternative functional form extends to the distributional findings (in Figure A.14), which mirror our baseline results, showing wage compression driven by significant negative effects above the median.

When decomposing the channels between imports and exports, however, the joint log-level model suffers from a weak identification problem. As shown in Table A.4, the KP F-statistic for joint instrument relevance is very low (0.26), driven by the level-instrument's failure to predict export openness. This renders the joint estimates, shown in Table A.3, and particularly the distributional

[31] The cumulative wage impact is calculated using the average increase in total real grants (280 percent) and assisted expenditures (370 percent) across autonomous communities between 1993 and the average of 1994-2004.

[32] For example, a 1 percentage point increase in openness (e.g., from 10 percent to 11 percent) is a much larger relative change than going from 100 percent to 101 percent.

[33] We use a level version of the independent variables and of the same instrument introduced in Section 4.

[34] $-0.456 \times 0.05 \times 100.1$

[35] The log-level model estimate for earnings implies a 4.6 percent decrease in average earnings, compared to the 2.2 percent implied by the (insignificant) point estimate from our baseline log-log specification.

results for the export channel, in Figure A.15, imprecise and uninformative.

To reliably assess the import channel, we therefore estimate a separate log-level specification that includes and instruments only for import openness. This import-only model is strongly identified (KP F-Stat > 86 from Table A.5). The results, shown in Table A.5, confirm our baseline finding: import openness has significant negative effects on earnings and wages. The magnitudes are also consistent with those from our baseline specification. The observed 3.2 percentage point increase in import openness from 1995 to 2004 implies decreases of 4.7 percent (earnings) and 1.9 percent (wages) in the log-level specification, comparable to the declines of 4.8 percent (earnings) and 2.7 percent (wages) implied by our main log-log specification. Furthermore, the distributional results for this import-only, strongly identified model (shown in Figure A.16) confirm the robustness of the import channel's impact, showing a consistent pattern of negative effects concentrated above the median. Thus, our central finding—that import competition drives wage compression—is robust to this alternative functional form.

Beyond the empirical identification challenges of the log-level specification, our baseline log-log model offers compelling conceptual advantages. The log-log specification's focus on relative changes is relevant given the context. Spain in 1993 and the instrumenting countries in 2004 had different levels of initial trade integration and economic development. Assuming that the ESM entry induces a similar proportional increase in trade openness (our "common component" assumption) is more plausible than assuming a similar absolute percentage-point increase, which would represent vastly different relative shocks depending on the different countries' starting points. Elasticities naturally account for these baseline differences, providing a scale-invariant measure of impact that is more comparable across heterogeneous units and consistent with how economic growth is modeled (Wooldridge 2010). For these reasons, we maintain the log-log specification as our primary approach.

While our robustness checks address confounding from EU funding and sensitivity to functional form, some methodological and data limitations remain in our analysis. First, our use of a national price index due to data constraints could bias real-wage-level estimates if prices varied differentially across provinces, although within-province distributional effects are likely less affected. Second, our EU subsidy controls are measured at the broader autonomous community level, not at the province level, potentially limiting their effectiveness due to a mismatch in geographic aggregation. Finally, the ESM also liberalized capital flows (Head and Mayer 2021). If capital flows were correlated with changes in trade openness, our estimates might capture a combined effect. While we cannot directly control for capital flows, our results' robustness to controlling for other EU financial flows provides some reassurance that our identification captures the trade channel.

6.2 IV Validity

To assess the validity of our shift-share IV, we follow the guidance of Borusyak et al. (2025) for shift-share designs that rely on exogenous shifts. This framework is appropriate given our use of "generic" employment shares. We conduct several validity exercises. First, we test whether our instrument captures a general industry trend by examining its predictive power for trade openness in the pre-ESM period. Second, we conduct falsification tests to check if future values of the instrument predict past Spanish labor market outcomes. Finally, we perform balance tests to ensure that the instrument is uncorrelated with predetermined province characteristics.

An important robustness component of the Borusyak et al.'s (2025) framework for shift-share designs is the "incomplete share" control. Borusyak et al. (2025) argue for its inclusion when shares do not sum to one. Our specifications omit this control because our exposure shares are defined as the share of total province employment in an industry. By construction, these shares mechanically sum to one across all industries for each province, rendering the control unnecessary.

Our first validity test assesses if the instrument predicts trade openness in the pre-ESM period (1987-1992), addressing the concern that it might capture general economic development trends. The validity of our "common component" assumption requires that the instrument lacks predictive power prior to countries' accession to the ESM. Table VII presents the pre-ESM first-stage estimates. Column (1), which focuses on trade openness, yields a small, insignificant estimate, contrasting the strong positive coefficient found post-ESM (Table II). Columns (2) and (3) corroborate this for export and import openness. The consistent lack of predictive power supports our identification, suggesting that the instrument isolates the variation specific to ESM integration rather than pre-existing trends.

Our second set of exercises tests whether future instrument values correlate with pre-ESM province outcomes. We provide an overview of these validity exercises below, and relegate the methodological details and specifications for these falsification tests to Appendix D. The first of these exercises examines whether our instrument, designed to capture trade dynamics specifically related to ESM entry from 1993 onward, correlates with Spanish labor market outcomes in the years before this in-

TABLE VII: FIRST-STAGE RESULTS FOR PRE-ESM ACCESSION

	$\ln TO_{p,t}$	$\ln EO_{p,t}$	$\ln IO_{p,t}$
$\ln TO^{IV}_{p,t}$	-0.025		
	[0.025]		
$\ln IO^{IV}_{p,t}$		-0.045*	-0.017
		[0.024]	[0.014]
$\ln EO^{IV}_{p,t}$		0.013	-0.006
		[0.180]	[0.066]
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Male×Age	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
N	1,401,702	1,401,702	1,401,702
KP F-Stat	0.95	0.01	

Note: Table VII displays the first-stage IV regressions for the pre-ESM accession period (1987-1992). Column (1) shows the regression of log province-level trade openness on its corresponding instrument. Columns (2) and (3) show the regressions of log province-level export openness and log province-level import openness, respectively, on both the instrument for import openness and the instrument for export openness simultaneously. All specifications include year, industry, province, gender-specific age, and individual fixed effects. The KP F-statistic in columns (2) and (3) refers to the test for the joint significance of both instruments. Province-level clustered standard errors are shown in brackets. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

tegration (1987-1992). Finding such a correlation would suggest that the instrument is picking up pre-existing trends, violating the exclusion restriction. Table VIII presents the results of the first test, regressing pre-ESM outcomes on future, post-ESM entry, instrument values. Panel (a) shows that the future, post-ESM values of the trade openness instrument do not significantly predict pre-ESM earnings, wages, hours worked, or unemployment status. Panel (b) confirms this lack of predictive power for the future import and export openness instruments. While the coefficient for the Low-Skill dummy in Panel (a) is statistically significant, its small magnitude, combined with the insignificant results across the other outcomes, reinforces the conclusion that significant pre-trends are absent. Figures A.17 and A.18 extend this analysis to our distributional results using the RIF-IV methodology. The figures show insignificant coefficients across all quantiles, providing further evidence against pre-existing confounding trends and reinforcing our confidence in the exclusion restriction being satisfied.

Our final validity exercise conducts a joint test of pre-existing trends, assessing whether the evolution of various covariates before the ESM accession predicts future variation in our instrument. This approach directly tests the exclusion restriction by checking if factors potentially correlated with the error term (pre-period outcomes) are also correlated with the instrument. Table IX presents the results of the joint test, regressing the future instrument on past values of our pri-

TABLE VIII: CORRELATION BETWEEN FUTURE VALUES OF THE INSTRUMENT AND OUTCOMES IN THE PRE-ESM PERIOD

	Panel a: Trade Openness				
	ln Earnings	ln Hourly Wages	ln Hours Worked	Low-Skill	$U_{i,t}$
ln $TO_{p,t+\{6to12\}}$	0.005	-0.004	0.009	0.005**	0.003
	[0.010]	[0.006]	[0.010]	[0.003]	[0.004]
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Male× Age FE	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
N	1,410,129	1,388,217	1,388,217	1,674,911	1,674,911
KP F-Stat	107.79	107.60	107.60	109.22	109.22
	Panel b: Imports and Exports Openness				
	ln Earnings	ln Hourly Wages	ln Hours Worked	Low-Skill	$U_{i,t}$
ln $IO_{p,t+\{6to12\}}$	-0.010	-0.001	-0.015	0.002	0.002
	[0.054]	[0.030]	[0.038]	[0.008]	[0.013]
ln $EO_{p,t+\{6to12\}}$	0.021	-0.006	0.037	0.004	0.001
	[0.084]	[0.047]	[0.060]	[0.015]	[0.018]
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Male× Age FE	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
N	1,410,129	1,388,217	1,388,217	1,674,911	1,674,911
KP F-Stat	13.84	13.86	13.86	14.61	14.61

Note: Table VIII displays the results of a pre-trend falsification test, regressing individual labor market outcomes from the pre-ESM period (1987-1992) on future values of the instrumental variables. The dependent variables are log earnings, log hourly wages, log hours worked, a dummy for low skill, and a dummy for unemployment, as indicated in the column headers. Panel (a) uses the future log trade openness instrument as the explanatory variable, constructed by stacking instrument values lagged forward by 6 to 12 years. Panel (b) uses the future log import and log export instruments simultaneously, also stacked across lags 6 to 12. All specifications include year, industry, province, gender-specific age, and individual fixed effects. The estimations use a random sample drawn from the stacked dataset equal in size to the original estimation sample. The KP F-stat corresponds to the first stage of the IV specifications. Province-level clustered standard errors are shown in brackets. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

mary outcome variables. Across all three specifications, the F-statistic is low (2.16 for trade openness and 2.06 for imports and exports) —being insignificant for imports and exports and only marginally significant for trade openness— indicating that pre-period outcomes have very weak joint predictive power for the future instrument. Past earnings, wages, and unemployment are never significantly correlated with future instrument values. While a small, significant coefficient exists for the pre-period Low-Skill dummy, the overall lack of joint predictive power supports our instrument's validity.

Overall, the results in this section support the robustness of our findings and the validity of our IV. Our effects are robust to controlling for confounding EU subsidies and hold under an alternative log-level functional form. The validity tests confirm that our instrument lacks predictive power

TABLE IX: CORRELATION BETWEEN FUTURE VALUES OF THE INSTRUMENT AND PRE-ESM OUTCOMES

	$\ln TO_{p,t+\{6to12\}}$	$\ln IO_{p,t+\{6to12\}}$	$\ln EO_{p,t+\{6to12\}}$
ln Earnings	-0.0000	-0.0001	0.0001
	[0.0001]	[0.0002]	[0.0002]
ln Hourly Wages	-0.0003	-0.0002	-0.0008
	[0.0012]	[0.0014]	[0.0011]
Low-Skill	0.0013***	0.0013**	0.0013**
	[0.0005]	[0.0005]	[0.0006]
Ui, t	-0.0001	-0.0003	0.0001
	[0.0004]	[0.0005]	[0.0004]
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Male$\times$ Age FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
N	1,389,309	1,389,309	1,389,309
F-Stat	2.16*	2.06	2.06

Note: Table IX presents the results of a joint pre-trend test, assessing the correlation between future instrument values and pre-ESM outcomes. The dependent variables are the future log trade openness instrument, the future log import openness instrument, and the future log export openness instrument, constructed by stacking instrument values lagged forward by 6 to 12 years. The explanatory variables are individual labor market outcomes from the pre-ESM period (1987-1992): log earnings, log hourly wages, a dummy for low skill, and a dummy for unemployment. All specifications include year, industry, province, gender-specific age, and individual fixed effects. The estimation uses a random sample drawn from the stacked dataset equal in size to the original estimation sample. The F-stat tests the joint significance of the coefficients on the four pre-period explanatory variables. Province-level clustered standard errors are shown in brackets. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

before ESM entry and that future instrument values do not predict past labor market outcomes. These results confirm that our strategy isolates the causal impact of post-ESM trade changes, rather than merely reflecting pre-existing trends or confounding alternative channels.

7 Model

This section presents a stylized theory that's consistent with the data on multiple important dimensions to rationalize the empirical results. We aim to replicate the patterns in the data for the effects of trade across the income distribution, and for the shift toward low-skill work. We focus on a relatively parsimonious environment with the main ingredients necessary to speak to the data: two regions, two types of workers, and two industries so that trade can shift production between them.

7.1 Environment

There is a single period and two regions indexed by $r \in \{1, 2\}$. Each region has a representative household that supplies fixed amounts of low- and high-skill labor, $\bar{L}_r$ and $\bar{H}_r$, respectively. A household owns all firms in its region and, in principle, collects their profits. In equilibrium, these will be zero, so that total income is determined by labor income. A household gets utility from consuming a non-tradable good produced in its region and a bundle of three tradable goods. These are tradable goods from the two regions and a third tradable good imported from abroad. The preferences of the household in region r are

$$U_r = (C_r^{TB})^{\beta}(C_r^{N})^{1-\beta},$$

where $\beta \in (0,1)$ and

$$C_r^{TB} = \left[\theta_1 (C_r^{Tr})^{\frac{\sigma-1}{\sigma}} + \theta_2 (C_r^{Tr'})^{\frac{\sigma-1}{\sigma}} + \theta_M (C_r^{M})^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}.$$

The parameter values satisfy $\theta_1, \theta_2, \theta_M > 0$, $\theta_1 + \theta_2 + \theta_M = 1$, and $\sigma \in (1, \infty)$, and r' denotes the other region. C_r^N is the consumption of non-tradables and C_r^{TB} is the consumption of a bundle of the tradable goods. This bundle is composed of the consumption of the tradables from the home region, the other region, and those imported from overseas, denoted by C_r^{Tr}, $C_r^{Tr'}$ and C_r^M, respectively.

We assume that Spain is a small open economy, so that it can buy as much of the imported good as it likes, at a constant price. There is an international price for this good, p^M, and trade is subject to an iceberg cost $\tau_r^M > 1$. Thus, the household in region r pays $\tau_r^M p^M$. The household chooses how much of the four goods to consume to maximize utility, taking prices and income as given.

On the production side, each region has two sectors. One produces a non-tradable good and the other produces a tradable good. We index these by $j \in \{N, T\}$. Within a region, each sector has a representative firm that produces with the technology

$$Y_r^j = A_r^j (L_r^j)^{\alpha_r^j} (H_r^j)^{1-\alpha_r^j},$$

where $A_r^j > 0$ is productivity, L_r^j and H_r^j are the low- and high-skill labor inputs, respectively, and $\alpha_r^j \in (0,1)$. The firm sets its price competitively and we denote the region r price of the sector j good by p_r^j.

The tradable good produced in region r can be sold in three markets: region r, region r', and overseas. There are no trade costs domestically, so the price of this good in region r' is also p_r^T.

Exporting overseas incurs an iceberg cost, $\tau_r^X > 1$. For the competitive representative firm to sell overseas, it must receive the price $\tau_r^X p_r^T$. At this price, the demand from overseas is

$$X_r = B_r(\tau_r^X p_r^T)^{-\eta},$$

with $B_r, \eta > 1$.

7.2 Optimization Problems and Equilibrium

Since the firms have constant returns to scale and price competitively, they choose their labor inputs to minimize costs for a given level of output, and set their prices to equal marginal cost. For total demand of Y_r^j, the labor demands and prices are

$$\begin{aligned}
L_r^j &= \frac{Y_r^j}{A_r^j}\left(\frac{\alpha_r^j w_r^H}{(1-\alpha_r^j)w_r^L}\right)^{1-\alpha_r^j}, \\
H_r^j &= \frac{Y_r^j}{A_r^j}\left(\frac{(1-\alpha_r^j)w_r^L}{\alpha_r^j w_r^H}\right)^{\alpha_r^j}, \\
p_r^j &= \frac{1}{A_r^j}\left(\frac{w_r^L}{\alpha_r^j}\right)^{\alpha_r^j}\left(\frac{w_r^H}{1-\alpha_r^j}\right)^{1-\alpha_r^j}.
\end{aligned}$$

The problem for the household in region r is

$$\begin{aligned}
\max_{C_r^N, C_r^{Tr}, C_r^{Tr'}, C_r^M} \quad & (C_r^{TB})^\beta (C_r^N)^{1-\beta} \\
\text{s.t.} \quad & C_r^{TB} = \left[\theta_1 (C_r^{Tr})^{\frac{\sigma-1}{\sigma}} + \theta_2 (C_r^{Tr'})^{\frac{\sigma-1}{\sigma}} + \theta_M (C_r^M)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \\
& E_r \geq C_r^N p_r^N + C_r^{Tr} p_r^T + C_r^{Tr'} p_{r'}^T + \tau_r^M p^M, \\
& E_r = w_r^L \bar{L}_r + w_r^H \bar{H}_r. \qquad (8)
\end{aligned}$$

where E_r denotes the total earnings of the household. This problem yields the following demand functions for the four goods available to the household:

$$\begin{aligned}
C_r^N &= \frac{(1-\beta)E_r}{p_r^N}, \\
C_r^{Tr} &= \left(\frac{\theta_1 P_r^{TB}}{p_r^T}\right)^{\sigma} \frac{\beta E_r}{P_r^{TB}}, \\
C_r^{Tr'} &= \left(\frac{\theta_2 P_r^{TB}}{p_{r'}^T}\right)^{\sigma} \frac{\beta E_r}{P_r^{TB}}, \\
C_r^{M} &= \left(\frac{\theta_M P_r^{TB}}{p^M \tau_r^M}\right)^{\sigma} \frac{\beta E_r}{P_r^{TB}},
\end{aligned}$$

where P_r^{TB} is the price index for the tradable bundle,

$$P_r^{TB} = \left[\theta_1^{\sigma}(p_r^T)^{1-\sigma} + \theta_2^{\sigma}(p_{r'}^T)^{1-\sigma} + (\tau_r^M p^M)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}. \tag{9}$$

There are eight markets that need to clear in equilibrium. Each region has two labor markets, and markets for the tradable and non-tradable goods. The market-clearing conditions for region r are

$$\bar{L}_r = L_r^N + L_r^T, \tag{10}$$

$$\bar{H}_r = H_r^N + H_r^T, \tag{11}$$

$$Y_r^N = C_r^N, \tag{12}$$

$$Y_r^T = C_r^{Tr} + C_{r'}^{Tr} + \tau_r^X X_r. \tag{13}$$

The definition of the equilibrium is as follows.

Equilibrium *The competitive equilibrium consists of, for both regions $r \in \{1,2\}$: a pricing policy, p_r^j, and labor demand functions, L_r^j and H_r^j, for sectors $j \in \{N, T\}$; demand functions C_r^N, C_r^{Tr}, $C_r^{Tr'}$, and C_{rM}, and the level of earnings, E_r, for the household; and a price index for the bundle of tradables P_r^{TB}; such that (i) the decisions of the firms and the households solve their optimization problems, (ii) the earnings of the household satisfy equation* (8), *(iii) the price index for the bundle of tradable goods satisfies equation* (9), *and (iv) the market clearing conditions in equations* (10)–(13) *hold.*

To solve the model, we reduce it to a set of three equations, log-linearize, and then solve. One feature of the equilibrium to note is the nature of trade balances. The economy's resource constraints imply that the country always has balanced trade: when the two regions are combined, total exports equal total imports. However, trade between the regions can be unbalanced, and individual regions can have trade deficits with the rest of the world. A region's trade deficit (surplus) with the rest of the world must equal its trade surplus (deficit) with the other region.

7.3 Parameterization

Since the effects of changes in trade costs depend on the parameter values of the model, as explained below, we parameterize the model with guidance from the data. To simplify the exercise and focus attention on the effects of changes in trade costs, the baseline parameterization is for the case of two symmetric regions. While the regions are symmetric in the initial equilibrium, we allow their changes in trade costs to differ, so they are not the same after these shocks.

Given the nature of the model solution, it is not necessary to specify all model parameters. For some of them, there are sufficient statistics from the data that pin them down jointly. The parameters that need individual values are the price elasticity (σ), the intensity of low-skill labor in the two sectors ($\alpha^j\ for\ j \in \{T, N\}$), and the expenditure share on tradable goods (β). The effects of the remaining parameters can be captured through specifying values for the following moments of the model: the low- and high-skill employment shares in tradables; the labor income shares for each skill; the own-region's, other-region's, and exports' shares of total demand for the tradable goods; and the expenditure shares of own-region tradables, other-region tradables, and imports. The values of these parameters and moments are summarized in Table X, and the mathematical details of the relationships between these moments and the model parameters are provided in Appendix E. Manufacturing is taken as the tradables sector in the data, and non-tradables are all services.[36] The values are guided by the data and the literature.

The main features of the parameterization are the values of α^j for the two sectors. This parameter determines the weight on low-skill labor in the production function. At the time of joining the ESM, Spain's manufacturing sector was more intensive in low-skill labor than its service sector, so $\alpha^T > \alpha^N$.

7.4 Effects of Trade Liberalization

Our analysis focuses on evaluating the effects of a 10 percent reduction in export and import costs in region one. We study these changes separately to distinguish the effects of increased imports

[36] The share of trade belonging to the service sector during our time period of interest was very small, so this assumption approximates the data well.

TABLE X: BASELINE PARAMETERIZATION

Parameter	*Value*	*Description*
σ	3.0	CES elasticity of substitution
α^T	0.75	Low-skill labor share in tradables
α^N	0.6	Low-skill labor share in non-tradables
β	0.6	Expenditure share on tradables
Value	*Moment*	
0.82	Low-skill employment share in tradables	
0.24	High-skill employment share in tradables	
0.6	Low-skill labor income share	
0.4	High-skill labor income share	
0.5	Share of own-region demand	
0.35	Share of other-region demand	
0.15	Share of exports	
0.45	Expenditure share on own-region tradables	
0.3	Expenditure share on other-region tradables	
0.25	Expenditure share on imports	

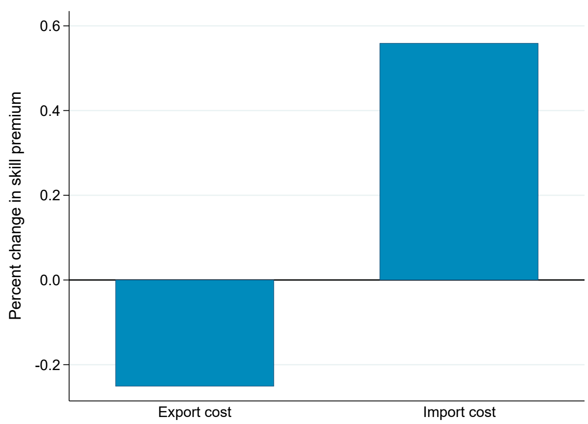
Note: The upper panel provides the parameter values for parameters that are directly given a value. The lower panel provides the values of moments that are used to determine the values of functions of multiple parameters..

and exports, following our previous empirical analysis.

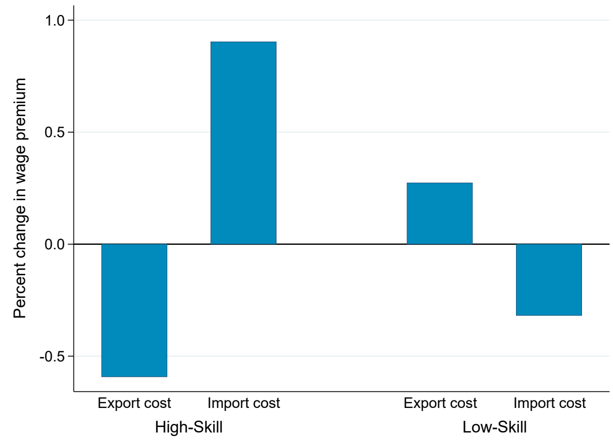
The analysis focuses on the effects of trade on the wage distribution. To speak directly to the empirical results, we are interested in how relative wages across regions, conditional on skill, change when exports or imports increase. To help with this, we define the *regional wage premium* as the ratio of the region one to the region two wage, conditional on a skill level (i.e., w_1^L/w_2^L and w_1^H/w_2^H). We also consider the effects on the *skill premium* within a region, refined as the ratio of the high-skill to the low-skill wage (i.e., w_r^H/w_r^L).

Skill premium. First, consider the effects of changes in trade costs on the skill premium in region one. A reduction in export costs increases export efficiency and shifts production in region one towards the tradables sector. Under the model's parameterization, this sector is relatively intensive in low-skill labor, so this shift pushes labor demand toward low-skill workers. The result is a decrease in the skill premium. In contrast, when import costs decrease, local consumers shift their demand from the local tradable good toward the imported one. This results in the domestic tradables sector shrinking in favor of the non-tradables sector, shifting labor demand toward high-skill workers and increasing the skill premium. Panel (a) of Figure III quantifies these effects.

To highlight the importance of the relative low-skill intensity of the two sectors, Figure IV plots the impact of the trade cost reductions on the skill premium as a function of the low-skill intensity of the tradables sector (a^T). The key message from this figure is that when low-skill intensity is higher in the tradables sector, a reduction in export costs decreases the skill premium, whereas a reduction in import costs increases it. If the opposite is true, then the results reverse.



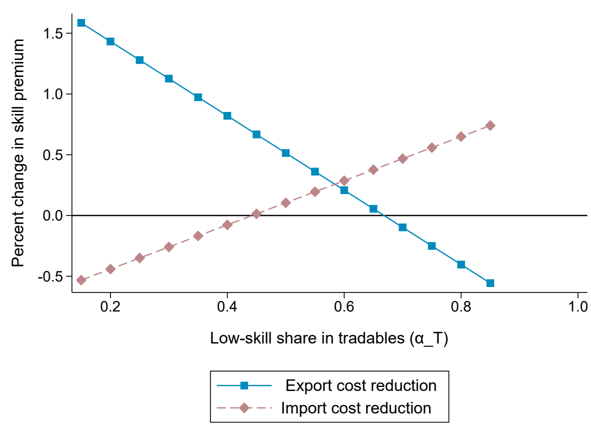
(a) Region One skill premium



(b) Regional wage premium by skill type

Notes: Panel (a) presents results for the effects of a 10 percent decrease in export and import costs on the skill premium in region one. Panel (b) presents the effects of the same cost changes on the regional wage premium for low- and high-skill workers.

FIGURE III: WAGE EFFECTS OF TRADE LIBERALIZATION



Notes: This figure plots the region one skill premium response to a reduction of 10 percent in region one export or import costs for different values in the low-skill labor share parameter (α^T).

FIGURE IV: REGION ONE SKILL PREMIUM

Regional wage premium. We now focus on how relative wages across regions change, conditional on skill. The overall quantitative results are presented in panel (b) of Figure III. When export costs decrease, region one's low-skill wages increase relative to region two's. A reduction in import costs has the opposite effect.

For the same reasons we just discussed regarding the skill premium, when export costs decrease in region one, the tradables sector expands, relative demand for low-skill labor increases, and the low-skill wage in region one therefore rises. This raises the regional wage premium for low-skill workers. The direct effects of a reduction in export costs on region one also affect the demand for goods in region two, ultimately leading to changes in wages in that region as well. Therefore, the effect of a change in region one's export costs on the regional wage premium ultimately depends on how this change affects region one relative to region two.

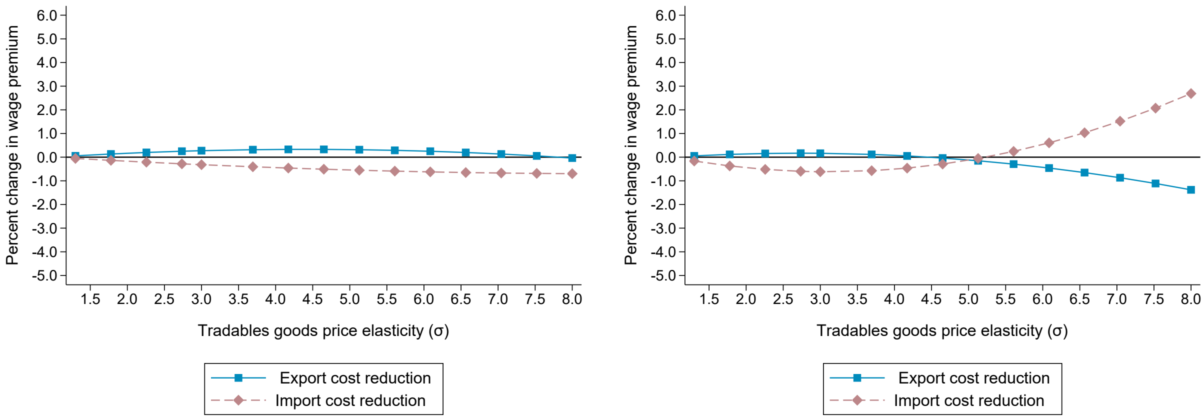
Figure V presents the quantitative evidence for this relative effect, illustrating how the low-skill wage premium changes as we adjust the price elasticity of demand (σ). Panel (a), shown with blue squares, plots this relationship for the baseline calibration. The results show that under this baseline, the regional low-skill wage premium increases when export costs are reduced for most levels of the price elasticity; however, for high values of σ, the premium can be reduced.

Panel (b) then shows how this relationship changes in a counterfactual economy with a high expenditure share on imports ($\lambda^M = 0.8$) and low shares on domestic tradables (0.1 each). This alternative calibration changes the relationship. In this case, a reduction in export costs can decrease the regional low-skill wage premium if price elasticity is sufficiently high.

A similar intuition applies to the effects of changes in import costs. Import cost reductions reduce the demand for tradable goods in both regions. Depending on the magnitude of the effect on each region, the regional wage premium can either increase or decrease. Looking at this change from the perspective of region one, import cost reductions shift region one's domestic demand away from both domestically produced goods and from goods produced in region two toward imports. When the first dominates the second, the regional wage premium increases, and vice versa.

Figure V shows the quantitative results of this mechanism. Panel (a) shows our baseline calibration, while panel (b) shows the counterfactual economy described above. The diamonds in panel (a) show how different price elasticity parameters affect the regional low-skill premium's response to reductions in import costs. As import costs decline, the regional wage premium generally decreases for most values of this elasticity. In panel (b), however, the regional low-skill wage premium can increase as import costs decrease if the price elasticity of demand is sufficiently high.

The effects of the regional wage premium for high-skill workers are the opposite. These workers experience a reduction in wages relative to their counterparts when export costs decline, but an increase in wages relative to their neighbors when import costs decline.



(a) Regional low-skill wage premium (baseline)

(b) Regional low-skill wage premium (low domestic expenditure share)

Notes: This figure plots the response of the regional low-skill wage premium to a reduction of 10 percent in region one export or import costs for different values of price elasticity (σ). Panel (a) uses the baseline calibration. Panel (b) utilizes the baseline calibration, but with adjustments to the expenditure shares. It assumes that the tradable expenditure share in imports is equal to 0.8, and the expenditure share on own-region tradables is 0.1.

FIGURE V: REGIONAL LOW-SKILL WAGE PREMIUM RESPONSE TO TRADE COSTS

8 Conclusion

This paper provides a causal counter-narrative to the trade and inequality literature, showing that trade liberalization can reduce inequality. We investigate the causal effect of international trade on the full wage distribution, exploiting Spain's 1993 entry into the European Single Market as a large-scale trade liberalization. We identify causal effects using a novel, non-contemporaneous shift-share instrument based on the sequential ESM accessions of the Czech Republic, Hungary, and Poland. We integrate this IV strategy with an unconditional quantile regression framework to estimate the causal effect over the entire wage and earnings distributions. We find that this liberalization episode significantly reduced wage inequality, driving a wage compression characterized by earnings gains at the bottom of the distribution and wage losses at the top.

We trace this wage compression to two asymmetric forces: import competition disproportionately harmed high earners, while export opportunities primarily benefited low earners. The key mechanism is an import-led "skill-downgrading," a shift in labor composition toward low-skill jobs. We show that this entire set of outcomes is the consistent result of Spain's integration context. Our quantitative model demonstrates that the distributional effects of trade depend critically on the skill intensity of a country's tradable sector. While many analyses focus on relatively skill-intensive tradables, we show that Spain's tradable sector was relatively low-skill-intensive. In summary, we highlight that the distributional consequences of trade are not universal but depend critically on the integration context.

Finally, our findings suggest promising avenues for future research. One is to quantify the firm-level mechanisms we identify. A richer analysis could disentangle the role of firms in the aggregate wage compression and the mechanisms behind their responses. Another promising area is to investigate whether the macro-level drop in TFP that Spain experienced post-ESM accession can be explained by this trade-induced reallocation toward a low-skill, low-productivity equilibrium. Lastly, our model's predictions for Spain's trading partners provide a testable hypothesis for future cross-country work.

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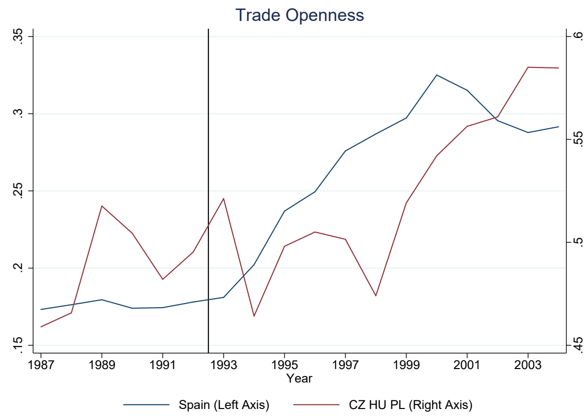
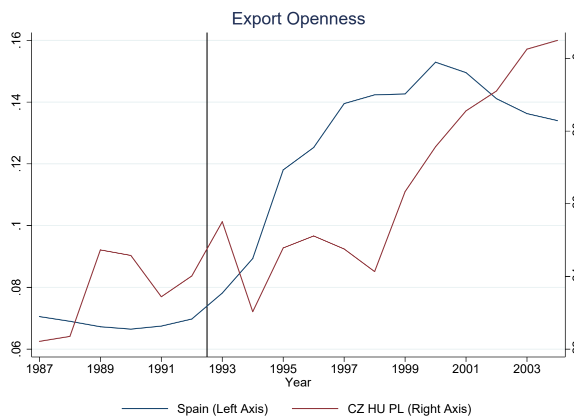
Appendix For Online Publication

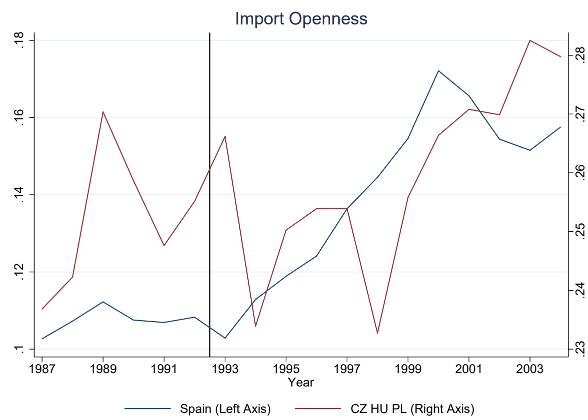
A Additional Figures



(a) Trade Openness



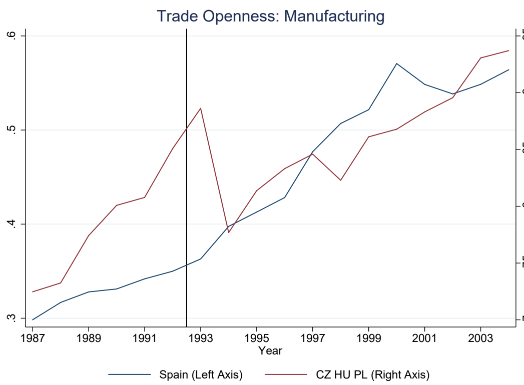
(b) Export Openness



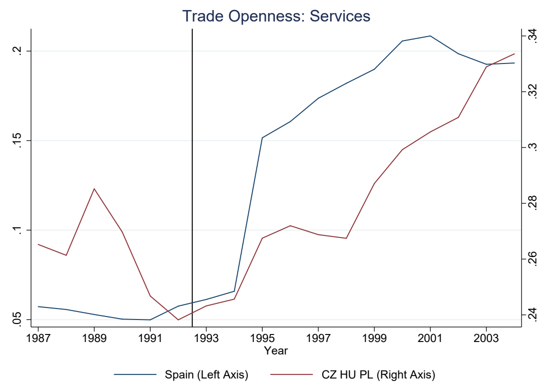
(c) Import Openness

Note: Figure A.1 plots the evolution of aggregate trade openness (Panel a), export openness (Panel b), and import openness (Panel c) for Spain (blue line, left axis) against the average of the Czech Republic, Hungary, and Poland (red line, right axis) at the aggregate level (all sectors). The x-axis represents calendar years for Spain. The series for CZ, HU, and PL is time-shifted such that their ESM entry year (2004) aligns conceptually with Spain's entry year (1993), marked by the vertical line. Data sources are OECD and INE input-output tables.

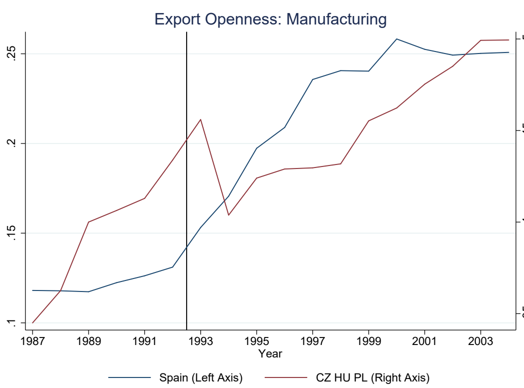
FIGURE A.1: OPENNESS AND THE ESM: SPAIN VS. CZ, HU, AND PO. AGGREGATE



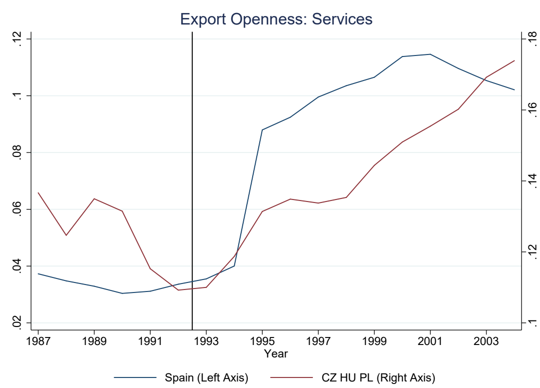
(a) Trade Openness. Manufacturing



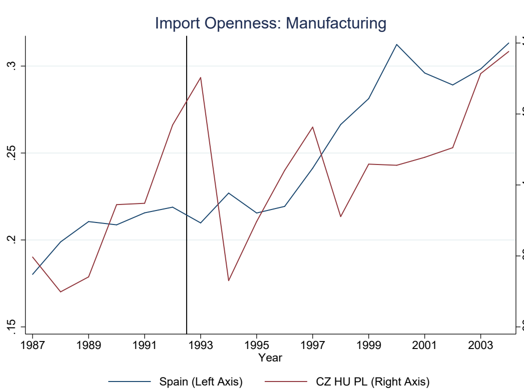
(b) Trade Openness. Services



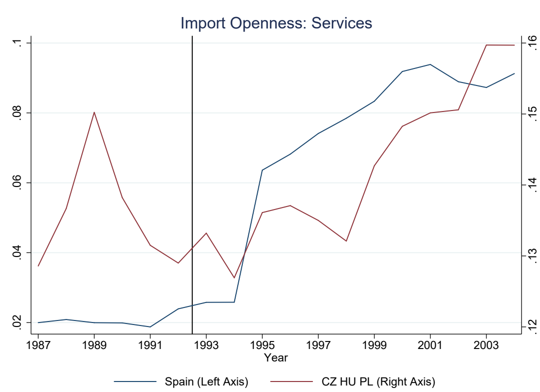
(c) Export Openness. Manufacturing



(d) Export Openness. Services



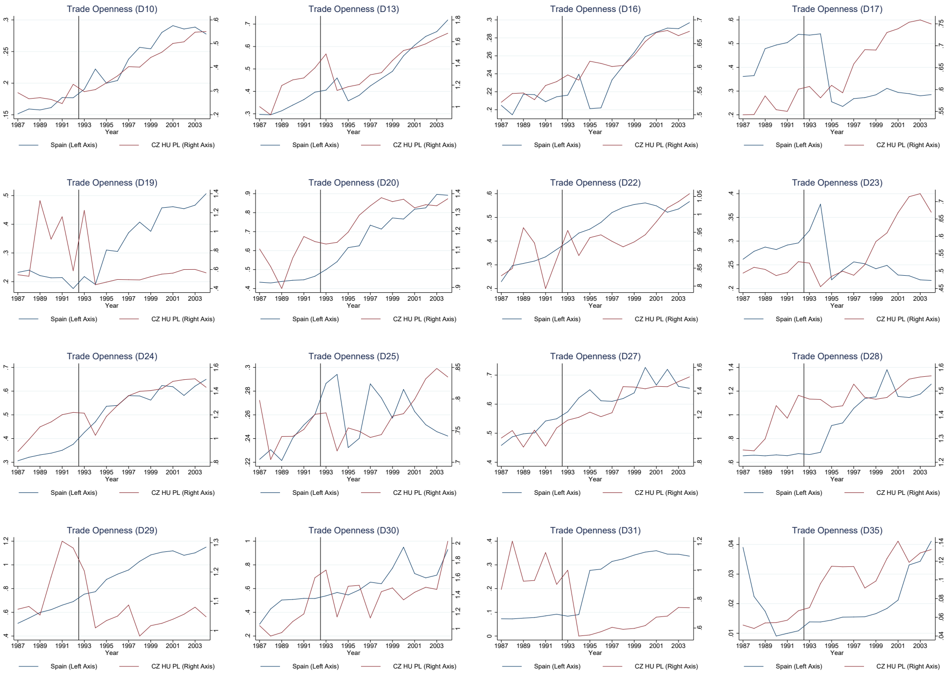
(e) Import Openness. Manufacturing



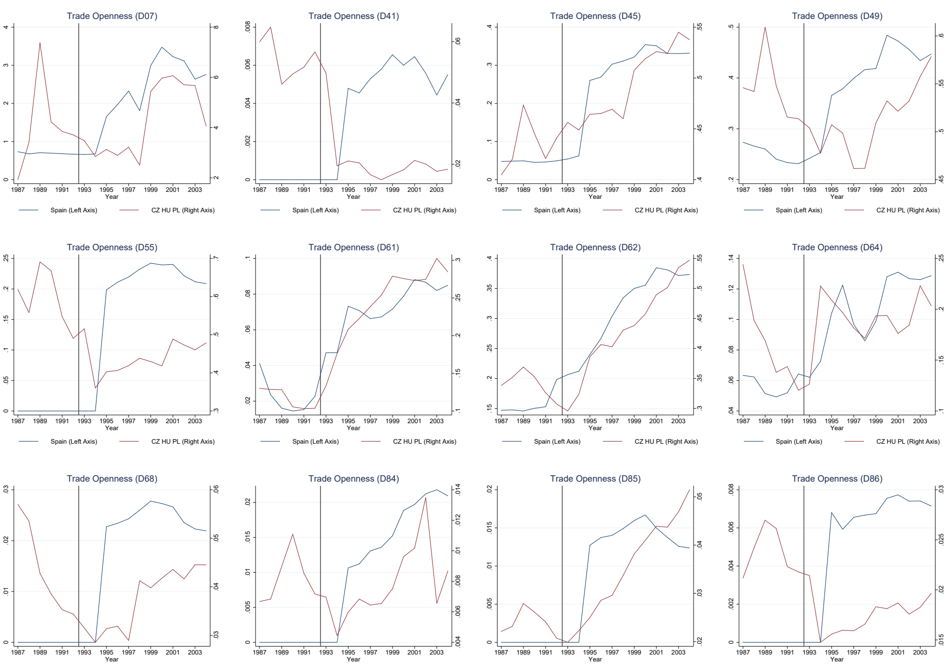
(f) Import Openness. Services

Note: Figure A.2 plots the evolution of trade openness (Panels a, b), export openness (Panels c, d), and import openness (Panels e, f) separately for the manufacturing sector (left column) and the services sector (right column). Each panel compares Spain (blue line, left axis) against the average of the Czech Republic, Hungary, and Poland (red line, right axis). The x-axis represents calendar years for Spain. The series for CZ, HU, and PL is time-shifted such that their ESM entry year (2004) aligns conceptually with Spain's entry year (1993), marked by the vertical line. Data sources are OECD and INE input-output tables.

FIGURE A.2: OPENNESS AND THE ESM: SPAIN VS. CZ, HU, AND PO. MANUFACTURING VS. SERVICES



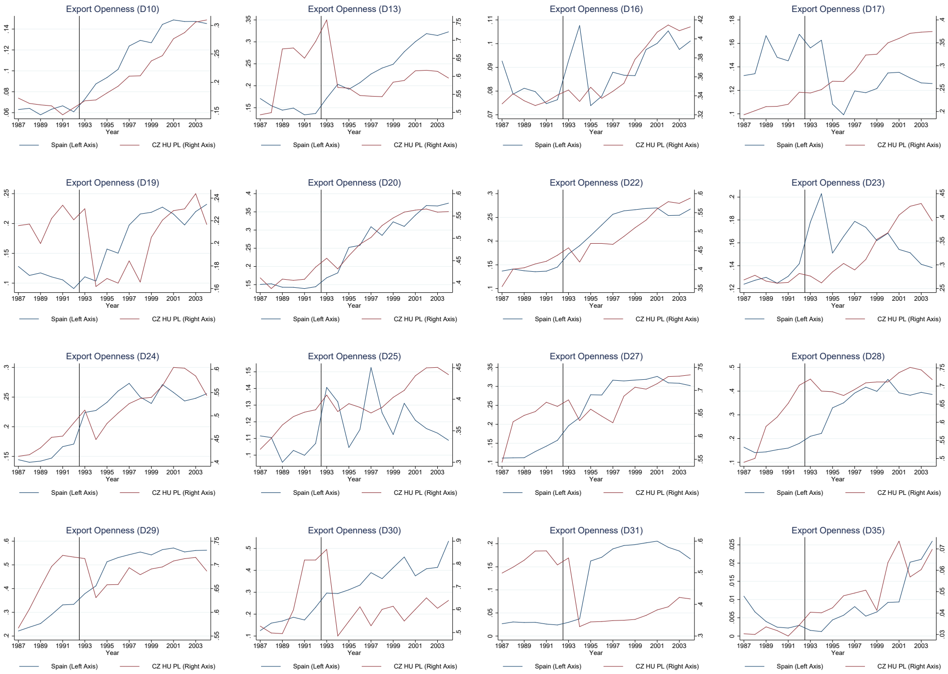
(a) Manufacturing Industries



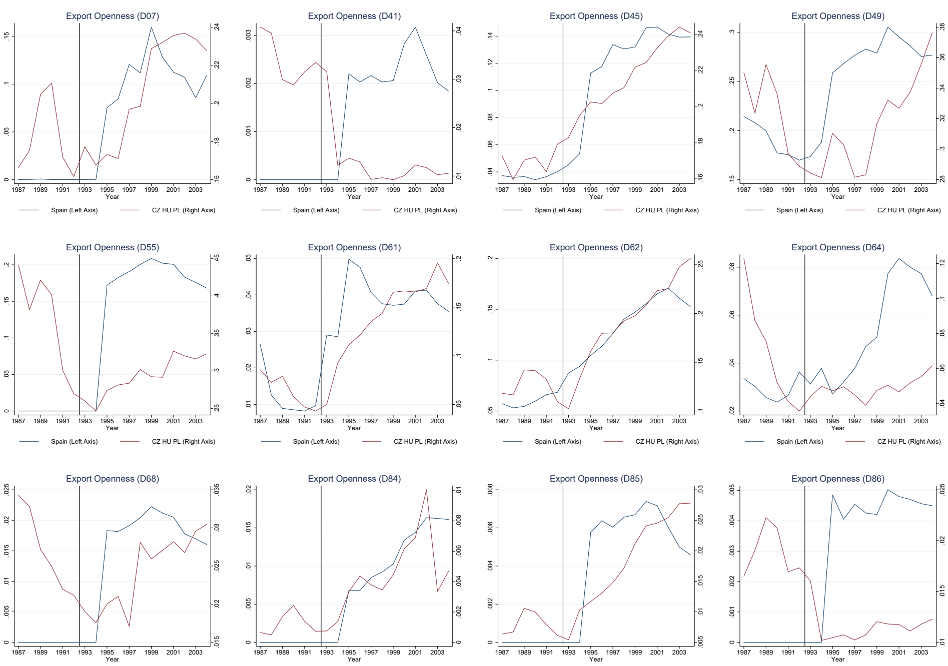
(b) Service Industries

Note: Figure A.3 plots the evolution of trade openness for individual ISIC-4 industries, separated into Manufacturing (Panel a) and Services (Panel b). Each panel compares the industry's evolution in Spain (blue line, left axis) against the average evolution in the Czech Republic, Hungary, and Poland (red line, right axis). The x-axis represents calendar years for Spain. The series for CZ, HU, and PL is time-shifted such that their ESM entry year (2004) aligns conceptually with Spain's entry year (1993), marked by the vertical line. Data sources are OECD and INE input-output tables.

FIGURE A.3: TRADE OPENNESS AND THE ESM: SPAIN VS. CZ, HU, AND PO. BY ISIC-4



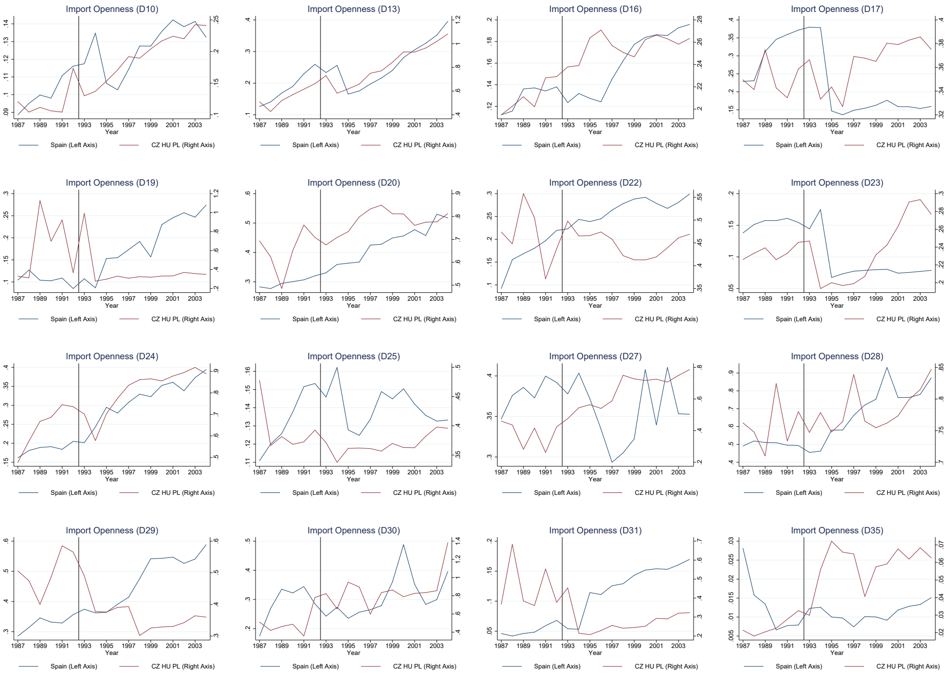
(a) Manufacturing Industries



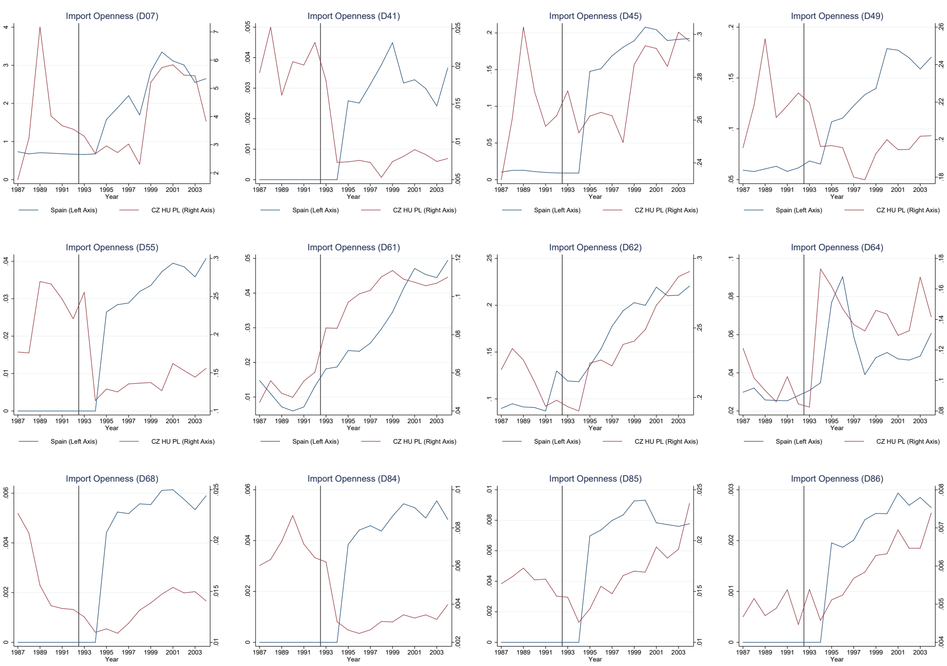
(b) Service Industries

Note: Figure A.4 plots the evolution of export openness for individual ISIC-4 industries, separated into Manufacturing (Panel a) and Services (Panel b). Each panel compares the industry's evolution in Spain (blue line, left axis) against the average evolution in the Czech Republic, Hungary, and Poland (red line, right axis). The x-axis represents calendar years for Spain. The series for CZ, HU, and PL is time-shifted such that their ESM entry year (2004) aligns conceptually with Spain's entry year (1993), marked by the vertical line. Data sources are OECD and INE input-output tables.

FIGURE A.4: EXPORT OPENNESS AND THE ESM: SPAIN VS. CZ, HU, AND PO. BY ISIC-4



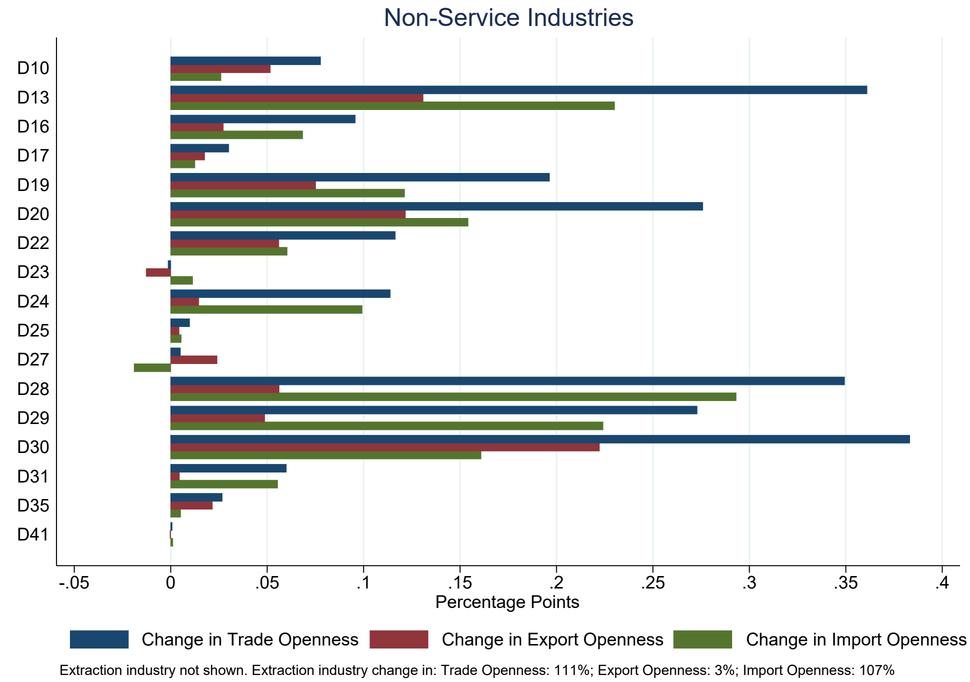
(a) Manufacturing Industries



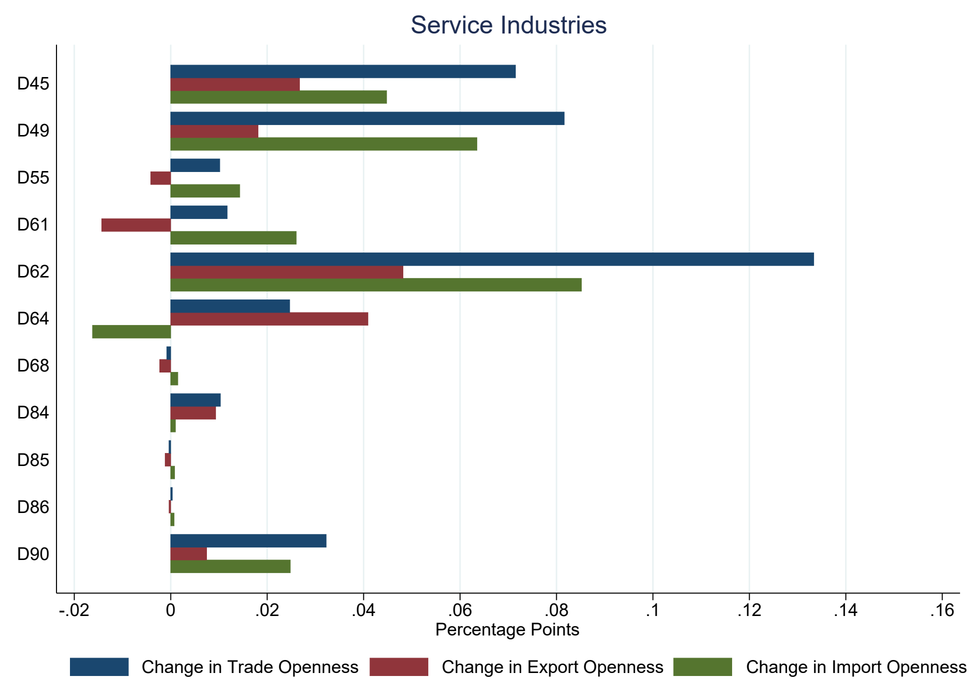
(b) Service Industries

Note: Figure A.5 plots the evolution of import openness for individual ISIC-4 industries, separated into Manufacturing (Panel a) and Services (Panel b). Each panel compares the industry's evolution in Spain (blue line, left axis) against the average evolution in the Czech Republic, Hungary, and Poland (red line, right axis). The x-axis represents calendar years for Spain. The series for CZ, HU, and PL is time-shifted such that their ESM entry year (2004) aligns conceptually with Spain's entry year (1993), marked by the vertical line. Data sources are OECD and INE input-output tables.

FIGURE A.5: IMPORT OPENNESS AND THE ESM: SPAIN VS. CZ, HU, AND PO. BY ISIC-4



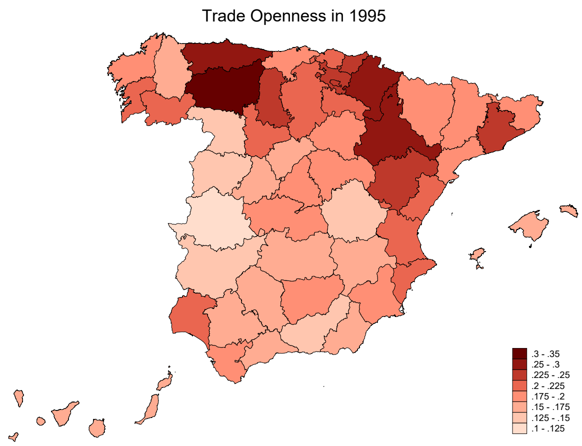
(a) Manufacturing Industries



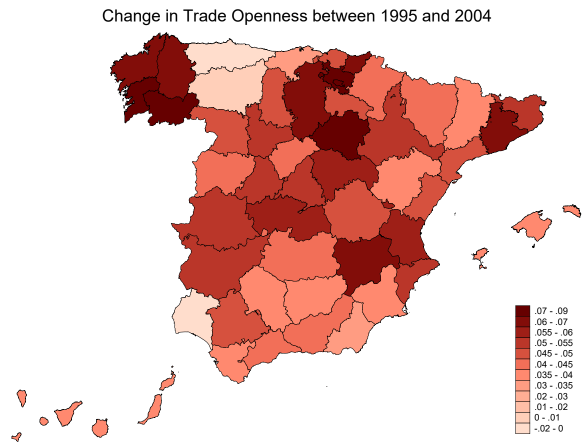
(b) Service Industries

Note: Figure A.6 plots the absolute change in openness measures (in percentage points) between 1995 and 2004 for individual ISIC-4 industries in Spain. Panel (a) shows manufacturing industries, and Panel (b) shows service industries. Within each industry, the blue bar represents the change in total trade openness, the red bar represents the change in export openness, and the green bar represents the change in import openness. The x-axis shows the change in percentage points. Data sources are OECD and INE input-output tables.

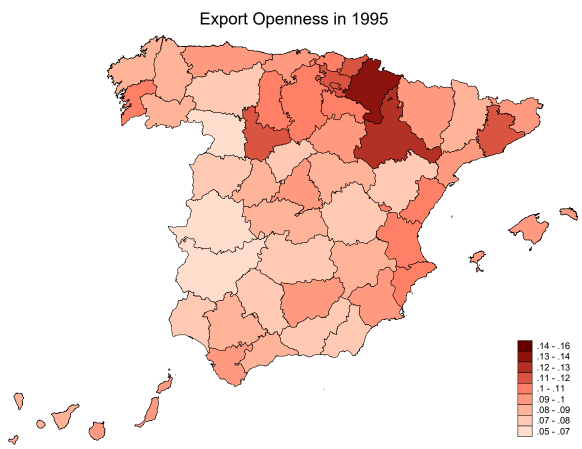
FIGURE A.6: CHANGE IN OPENNESS BY ISIC-4. 1995 TO 2004



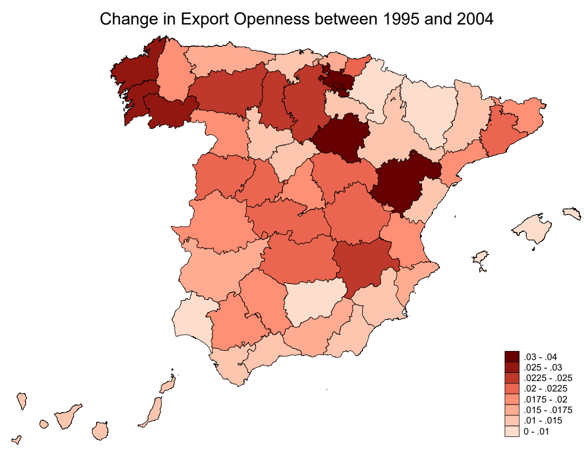
(a) Trade Openness. 1995



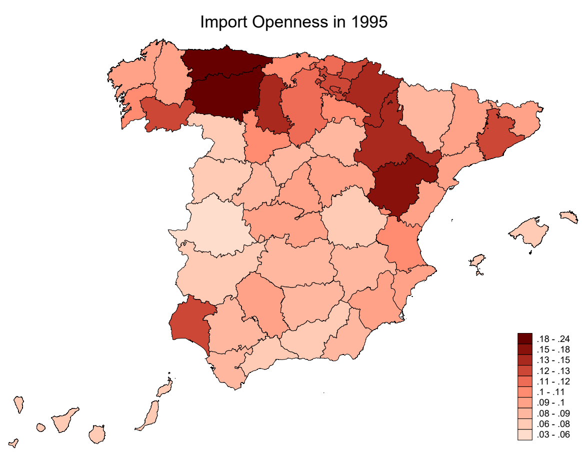
(b) Change in Trade Openness. 1995-2004



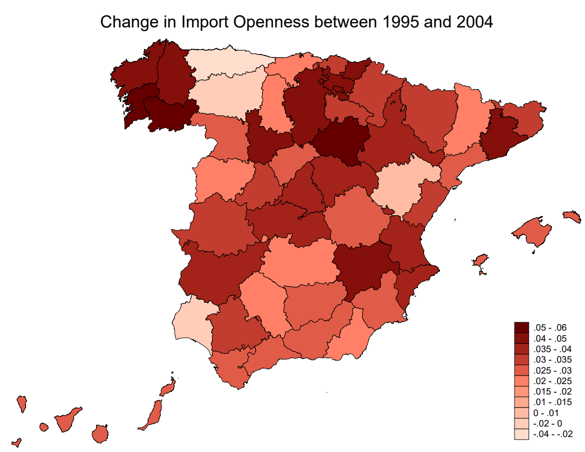
(c) Export Openness. 1995



(d) Change in Export Openness. 1995-2004



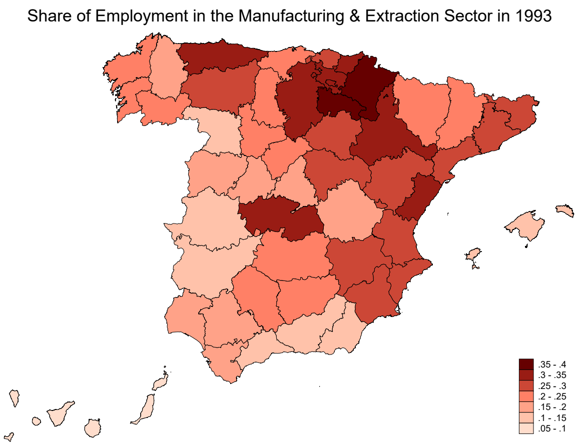
(e) Import Openness. 1995



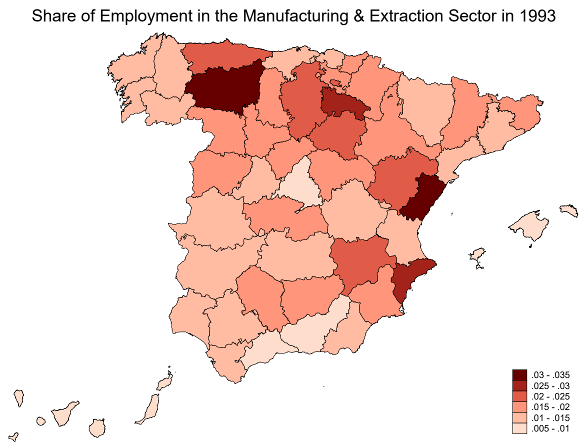
(f) Change in Import Openness. 1995-2004

Note: Figure A.7 displays the geographic distribution of trade exposure across Spanish provinces. Panels (a), (c), and (e) show the level of province-level trade openness, export openness, and import openness, respectively, in 1995. Panels (b), (d), and (f) show the absolute change (in percentage points) in these respective openness measures between 1995 and 2004. Province-level openness measures are constructed as weighted averages of industry-level openness, using provincial employment shares as weights. Darker shades indicate higher initial levels or larger positive changes. Data sources are OECD and INE input-output tables for trade data and MCVL for employment shares.

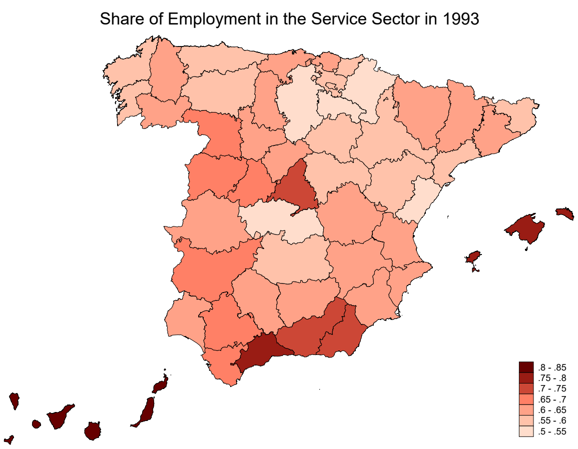
FIGURE A.7: STARTING OPENNESS AND CHANGE IN OPENNESS BY PROVINCE. 1995 TO 2004



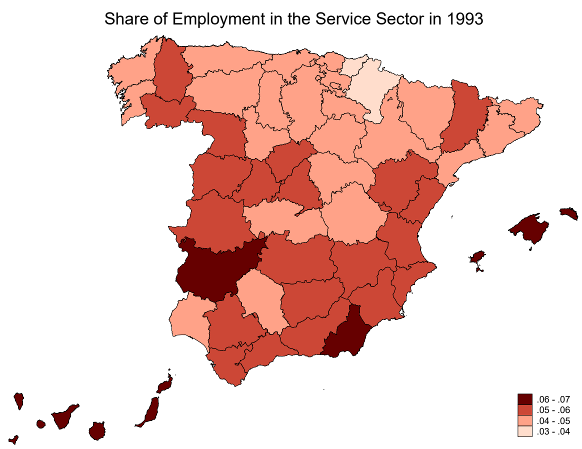
(a) Manufacturing's Share of Employment (Mean)



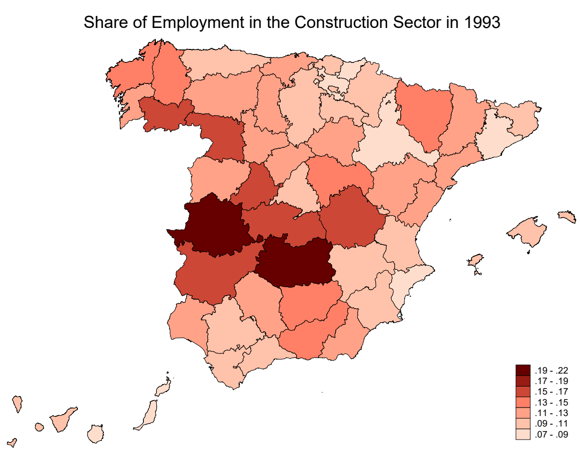
(b) Manufacturing's Share of Employment (Variance)



(c) Services' Share of Employment (Mean)



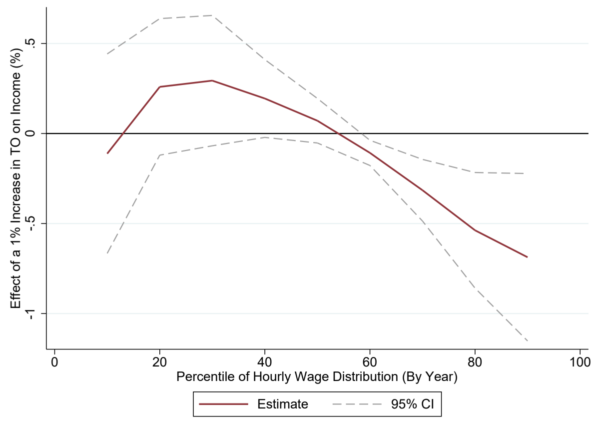
(d) Services' Share of Employment (Variance)



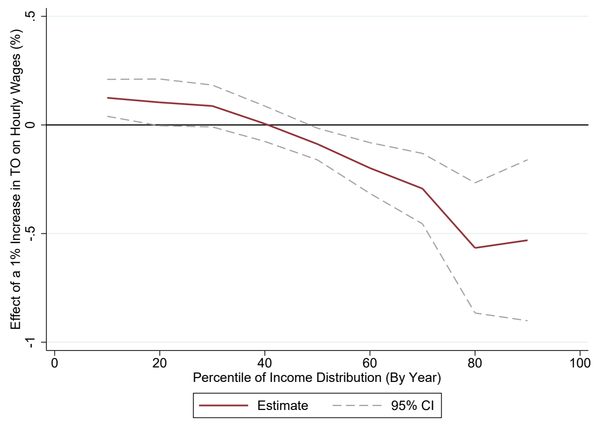
(e) Construction's Share of Employment (Mean)

Note: Figure A.8 displays the geographic distribution of employment structure across Spanish provinces in 1993. Panels (a), (c), and (e) show the mean provincial employment share (across all workers in the province) in the manufacturing and extraction sector, the service sector, and the construction sector, respectively. Panels (b) and (d) show the variance of ISIC-4 industry employment shares within the manufacturing and extraction sector and the service sector for each province. Darker shades indicate higher values. Data are derived from the MCVL. The construction industry comprises only one ISIC-4 code in our data; thus, the within-sector variance is zero for all provinces and is not displayed.

FIGURE A.8: SHARE (AND VARIANCE IN SHARE) OF EMPLOYMENT BY SECTOR AND PROVINCE. 1993



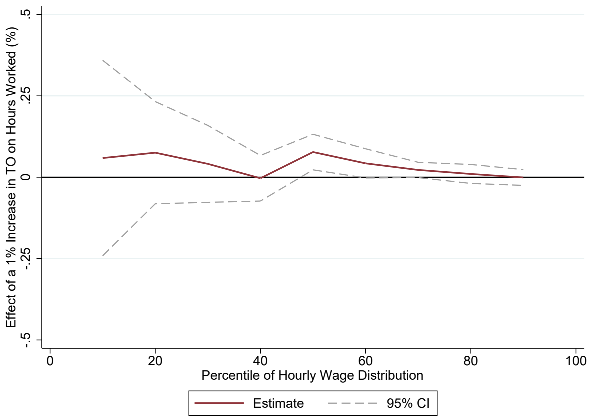
(a) Total Earnings, Yearly



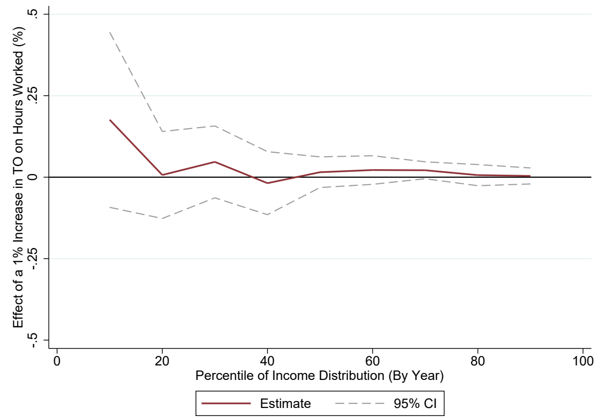
(b) Hourly Wages, Yearly

Notes: Figure A.9 plots the estimated causal effect of a 1 percent increase in log province-level trade openness on log earnings (Panel a) and hourly wages (Panel b) across the unconditional distributions of log total earnings (Panel a) and log hourly wages (Panel b). Effects are estimated using the RIF-IV methodology described in the main text for the post-ESM period (1993-2004). The x-axis represents the percentile of the respective distribution (total earnings in Panel a, hourly wages in Panel b), calculated by determining the place in the distribution of an observation by year. The y-axis shows the estimated percent effect. The solid line represents the point estimate at each percentile, and the dashed lines indicate the 95 percent confidence interval, based on province-level clustered standard errors. All specifications include year, industry, province, gender-specific age, and individual fixed effects.

FIGURE A.9: DISTRIBUTIONAL EFFECTS. DISTRIBUTION BY YEAR



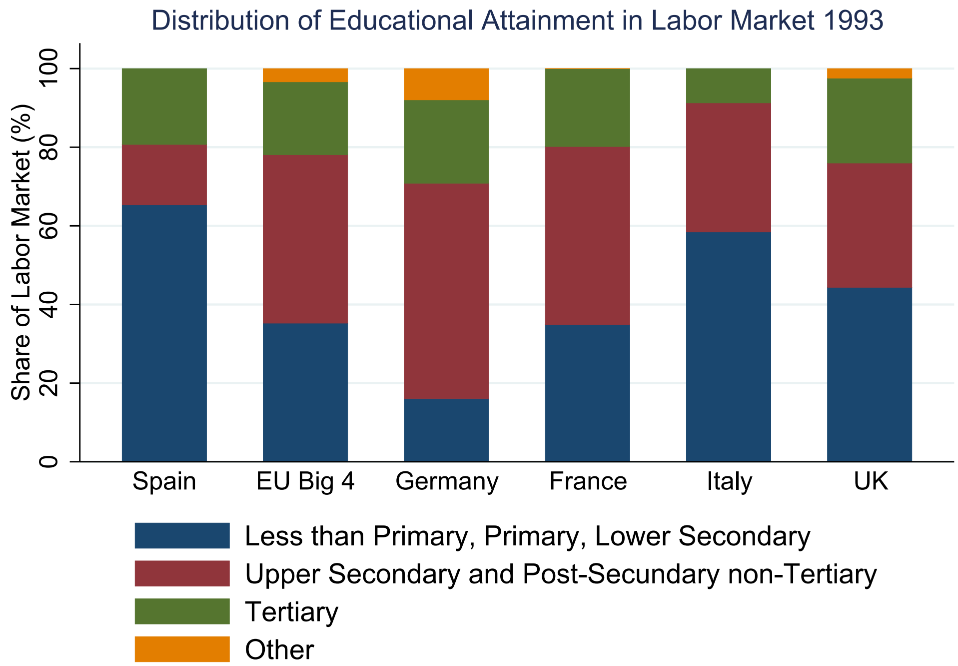
(a) Hours Worked



(b) Hours Worked, Yearly

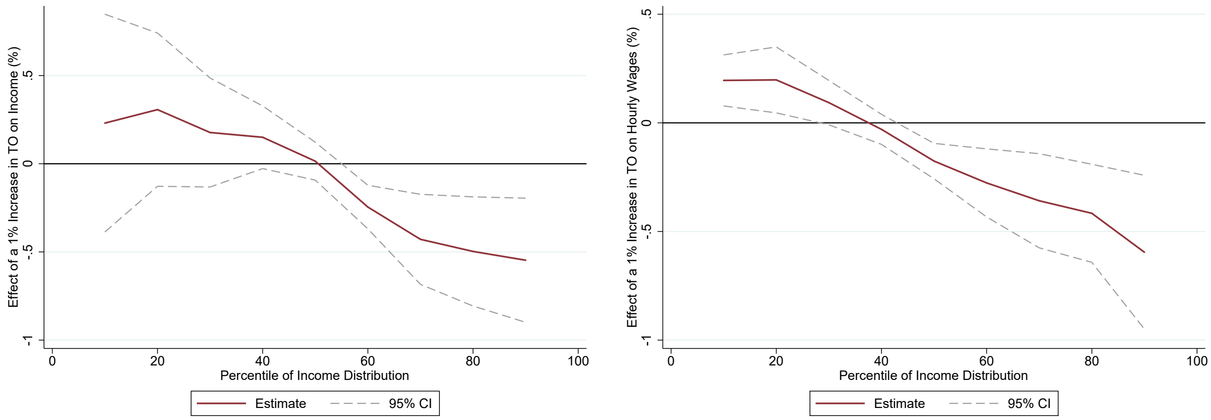
Notes: Figure A.10 plots the estimated causal effect of a 1 percent increase in log province-level trade openness on hours worked across the unconditional distribution of log total earnings. Effects are estimated using conditional quantile regressions for the post-ESM period (1993-2004). The x-axis represents the percentile of the respective distribution of earnings, calculated, in Panel a, by pooling all observations across years and, in Panel b, by calculating the place in the distribution by year. The y-axis shows the estimated percent effect. The solid line represents the point estimate at each percentile, and the dashed lines indicate the 95 percent confidence interval, based on province-level clustered standard errors. All specifications include year, industry, province, gender-specific age, and individual fixed effects.

FIGURE A.10: DISTRIBUTIONAL EFFECTS



Note: Figure A.11 displays a stacked bar chart illustrating the distribution of education in the labor market across educational categories of the four major European countries and Spain. The vertical axis represents the "Share of Labor Market (%)" from 0 to 100, and each bar corresponds to a specific country or region: Spain, EU Big 4, Germany, France, Italy, and the UK. The stacked segments show the share of the labor market for four distinct educational categories: "Less than Primary, Primary, Lower Secondary" (Blue), "Upper Secondary and Post-Secondary non-Tertiary" (Red), "Tertiary" (Green), and "Other" (Orange). Source: Eurostat (2025).

FIGURE A.11: DISTRIBUTION OF EDUCATIONAL ATTAINMENT IN THE LABOR MARKET. 1993

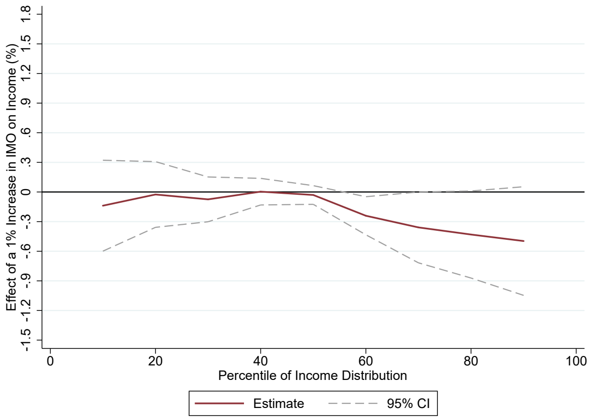


(a) Total Earnings

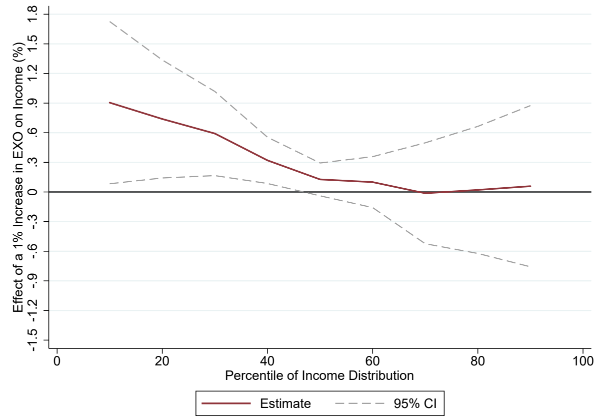
(b) Hourly Wages

Notes: Figure A.12 plots the estimated causal effect of a 1 percent increase in log province-level trade openness on log earnings (Panel a) and log hourly wages (Panel b) across the unconditional distributions of log total earnings (Panel a) and log hourly wages (Panel b). Effects are estimated using the RIF-IV methodology described in the main text for the post-ESM period (1993-2004), controlling for assisted expenditures and grants. The x-axis represents the percentile of the respective distribution (total earnings in Panel a, hourly wages in Panel b), calculated by pooling all observations across years. The y-axis shows the estimated percent effect. The solid line represents the point estimate at each percentile, and the dashed lines indicate the 95 percent confidence interval, based on province-level clustered standard errors. All specifications include year, industry, province, gender-specific age, and individual fixed effects.

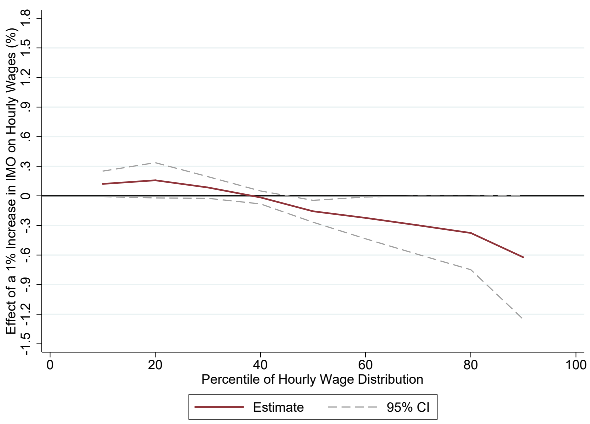
FIGURE A.12: DISTRIBUTIONAL EFFECTS. TRADE OPENNESS. CONTROLS FOR ASSISTED EXPENDITURES AND GRANTS.



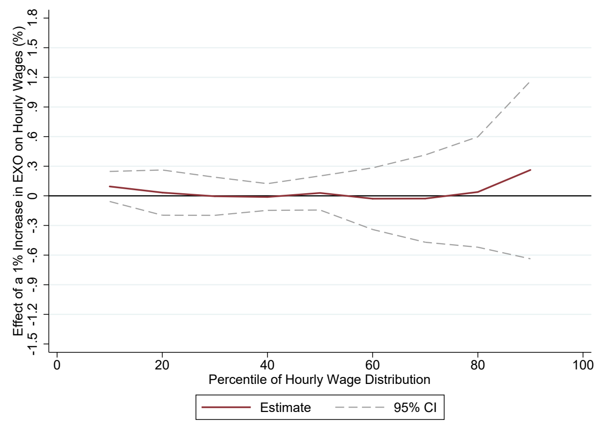
(a) Total Earnings. Imports



(b) Total Earnings. Exports



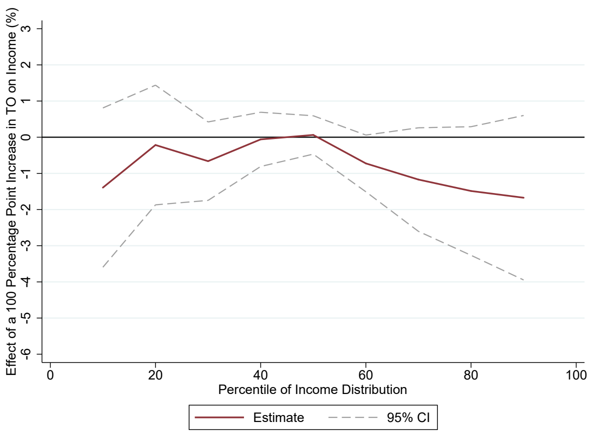
(c) Hourly Wages. Imports



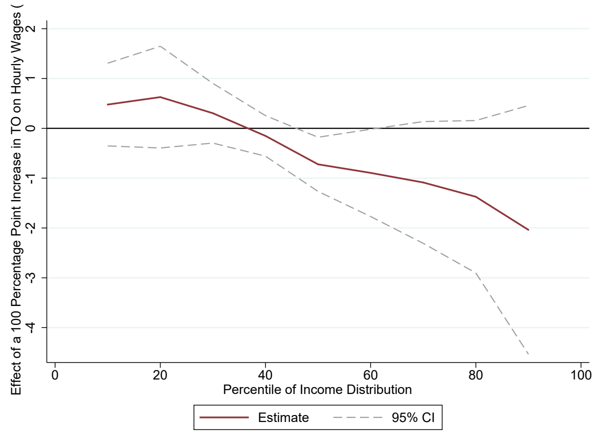
(d) Hourly Wages. Exports

Notes: Figure A.13 plots the estimated causal effect of a 1 percent increase in log province-level import (Panels a and c) and export (Panels b and d) openness on log earnings (Panels a an b) and log hourly wages (Panels c and d) across the unconditional distributions of log total earnings (Panels a and b) and log hourly wages (Panels c and d). Effects are estimated using the RIF-IV methodology described in the main text for the post-ESM period (1993-2004), controlling for assisted expenditures and grants. The x-axis represents the percentile of the respective distribution (total earnings in Panels a and b, hourly wages in Panels c and d), calculated by pooling all observations across years. The y-axis shows the estimated percent effect. The solid line represents the point estimate at each percentile, and the dashed lines indicate the 95 percent confidence interval, based on province-level clustered standard errors. All specifications include year, industry, province, gender-specific age, and individual fixed effects.

FIGURE A.13: DISTRIBUTIONAL EFFECTS. IMPORTS VS. EXPORTS. CONTROLS FOR ASSISTED EXPENDITURES AND GRANTS.



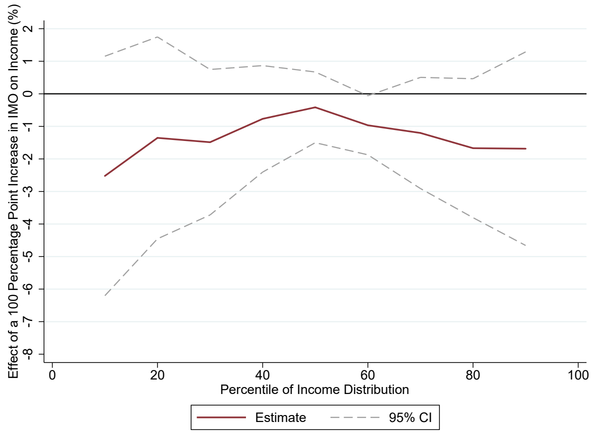
(a) Total Earnings



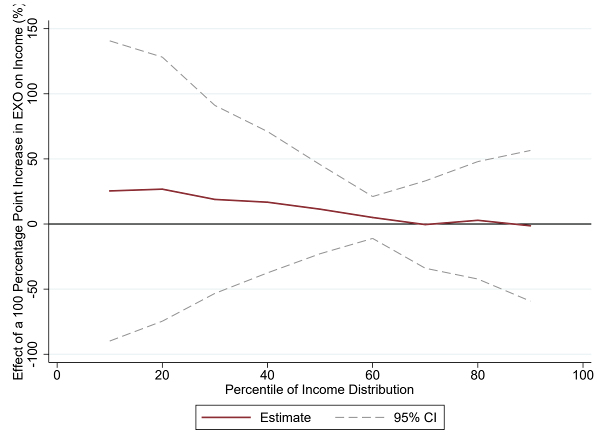
(b) Hourly Wages

Notes: Figure A.14 plots the estimated causal effect of a 100 percentage point increase in province-level trade openness (in levels) on log earnings (Panel a) and log hourly wages (Panel b) across the unconditional distributions of log total earnings (Panel a) and log hourly wages (Panel b). Effects are estimated using the RIF-IV methodology described in the main text for the post-ESM period (1993-2004). The x-axis represents the percentile of the respective distribution (total earnings in Panel a, hourly wages in Panel b), calculated by pooling all observations across years. The y-axis shows the estimated effect. The solid line represents the point estimate at each percentile, and the dashed lines indicate the 95 percent confidence interval, based on province-level clustered standard errors. All specifications include year, industry, province, gender-specific age, and individual fixed effects.

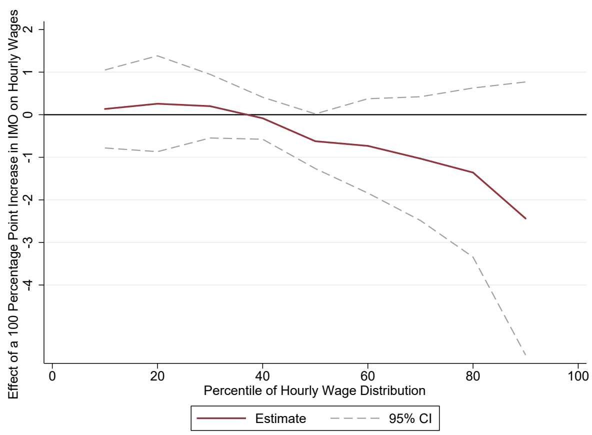
FIGURE A.14: DISTRIBUTIONAL EFFECTS. TRADE OPENNESS. SEMI-ELASTICITY.



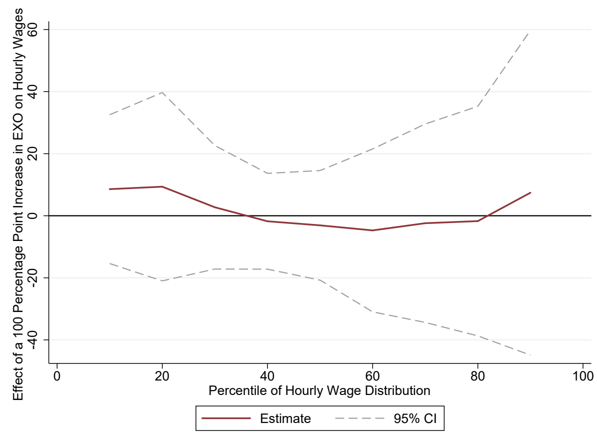
(a) Total Earnings. Imports



(b) Total Earnings. Exports



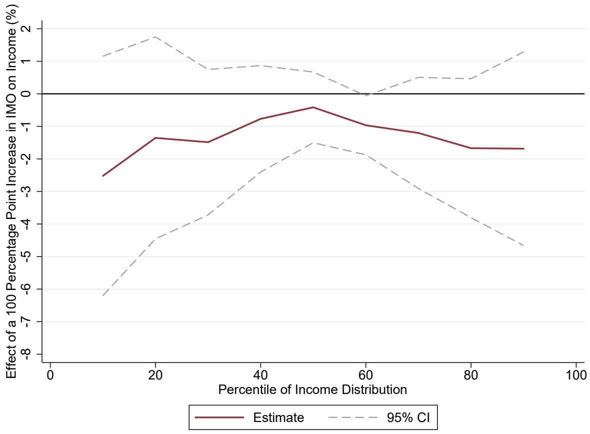
(c) Hourly Wages. Imports



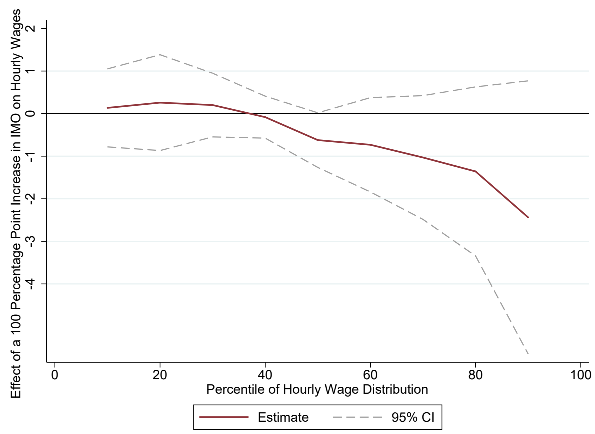
(d) Hourly Wages. Exports

Notes: Figure A.15 plots the estimated causal effect of a 100 percentage point increase in province-level import (Panels a and c) and export (Panels b and d) openness (in levels) on log earnings (Panels a an b) and log hourly wages (Panels c and d) across the unconditional distributions of log total earnings (Panels a and b) and log hourly wages (Panels c and d). Effects are estimated using the RIF-IV methodology described in the main text for the post-ESM period (1993-2004). The x-axis represents the percentile of the respective distribution (total earnings in Panels a and b, hourly wages in Panels c and d), calculated by pooling all observations across years. The y-axis shows the estimated effect. The solid line represents the point estimate at each percentile, and the dashed lines indicate the 95 percent confidence interval, based on province-level clustered standard errors. All specifications include year, industry, province, gender-specific age, and individual fixed effects.

FIGURE A.15: DISTRIBUTIONAL EFFECTS. IMPORTS VS. EXPORTS. SEMI-ELASTICITY.



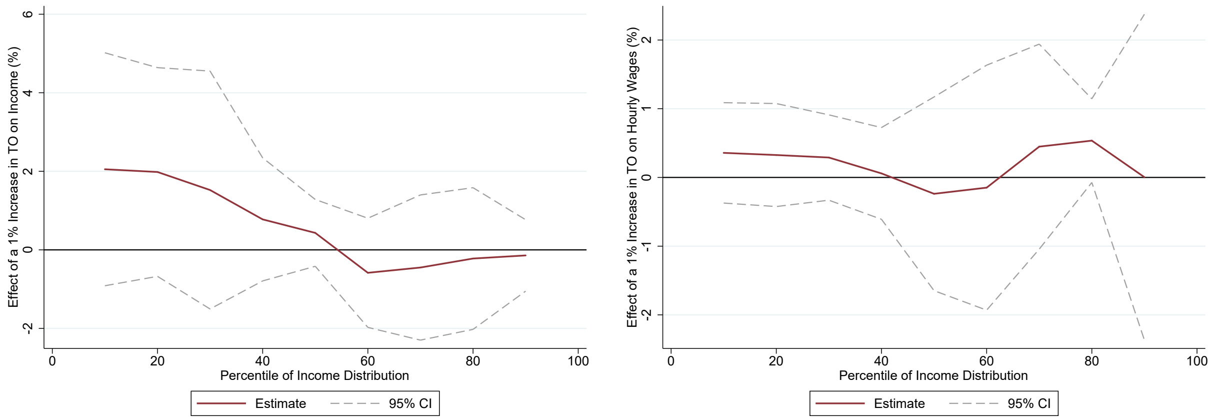
(a) Total Earnings. Imports



(b) Hourly Wages. Imports

Notes: Figure A.16 plots the estimated causal effect of a 100 percentage point increase in province-level import openness (in levels) on log earnings (Panel a) and log hourly wages (Panel b) across the unconditional distributions of log total earnings (Panel a) and log hourly wages (Panel b). Effects are estimated using the RIF-IV methodology described in the main text for the post-ESM period (1993-2004). The x-axis represents the percentile of the respective distribution (total earnings in Panels a and b, hourly wages in Panels c and d), calculated by pooling all observations across years. The y-axis shows the estimated effect. The solid line represents the point estimate at each percentile, and the dashed lines indicate the 95 percent confidence interval, based on province-level clustered standard errors. All specifications include year, industry, province, gender-specific age, and individual fixed effects.

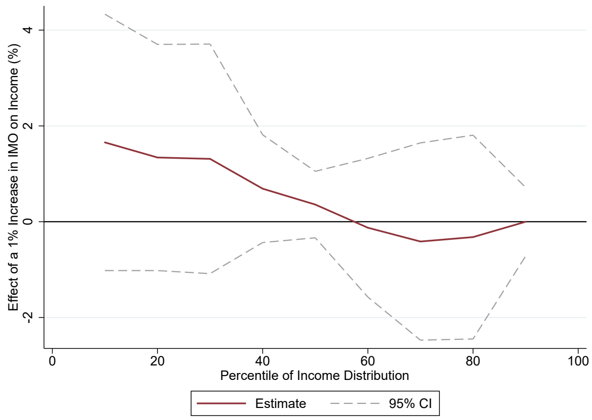
FIGURE A.16: DISTRIBUTIONAL EFFECTS. IMPORTS ONLY. SEMI-ELASTICITY.



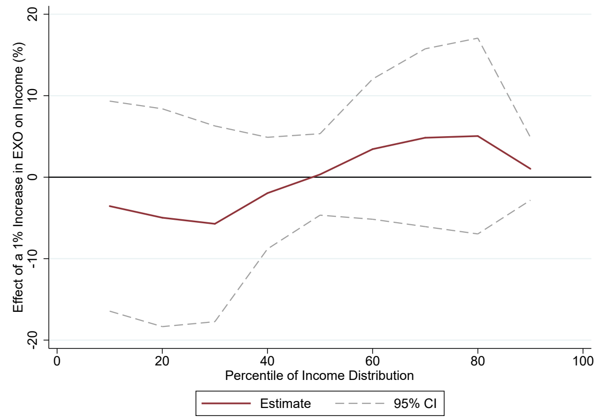
(a) Total Earnings (b) Hourly Wages

Notes: Figure A.17 plots the results of the falsification test described in Appendix D across the unconditional distributions of log total earnings (Panel a) and log hourly wages (Panel b). Effects are estimated using the RIF-IV methodology described in the main text for the post-ESM period (1993-2004). The x-axis represents the percentile of the respective distribution (total earnings in Panel a, hourly wages in Panel b), calculated by pooling all observations across years. The y-axis shows the estimated percent effect. The solid line represents the point estimate at each percentile, and the dashed lines indicate the 95 percent confidence interval, based on province-level clustered standard errors. All specifications include year, industry, province, gender-specific age, and individual fixed effects.

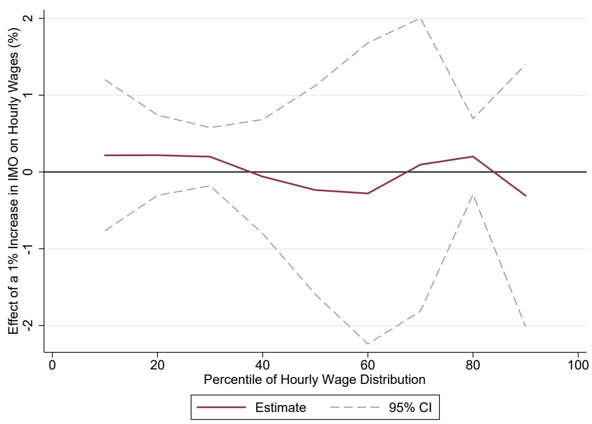
FIGURE A.17: FALSIFICATION TEST. TRADE OPENNESS



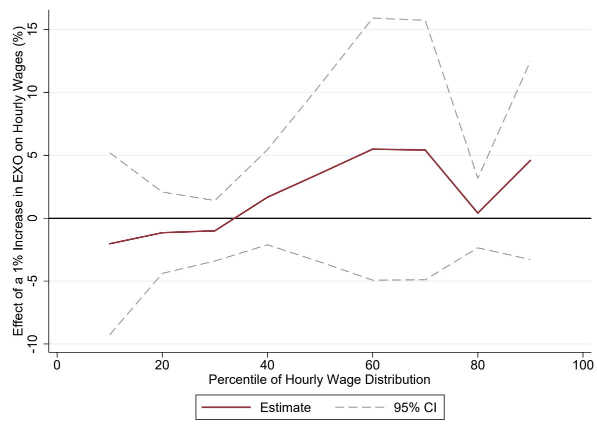
(a) Total Earnings. Imports



(b) Total Earnings. Exports



(c) Hourly Wages. Imports



(d) Hourly Wages. Exports

Notes: Figure A.18 plots the results of the falsification test described in Appendix D across the unconditional distributions of log total earnings (Panels a and b) and log hourly wages (Panels c and d). Effects are estimated using the RIF-IV methodology described in the main text for the post-ESM period (1993-2004). The x-axis represents the percentile of the respective distribution (total earnings in Panels a and b, hourly wages in Panels c and d), calculated by pooling all observations across years. The y-axis shows the estimated percent effect. The solid line represents the point estimate at each percentile, and the dashed lines indicate the 95 percent confidence interval, based on province-level clustered standard errors. All specifications include year, industry, province, gender-specific age, and individual fixed effects.

FIGURE A.18: FALSIFICATION TEST. IMPORTS VS. EXPORTS

Additional Tables

TABLE A.1: AGGREGATE EFFECTS. CONTROLS FOR ASSISTED EXPENDITURES AND GRANTS

	Panel (a): Grants					
	ln Earnings	ln Hourly Wages	ln Hours Worked	ln Earnings	ln Hourly Wages	ln Hours Worked
ln $TO_{p,t}$	-0.091	-0.113***	0.028			
	[0.071]	[0.034]	[0.076]			
ln $EO_{p,t}$				0.347***	0.047	0.278**
				[0.114]	[0.077]	[0.106]
ln $IO_{p,t}$				-0.208***	-0.114**	-0.081
				[0.073]	[0.049]	[0.056]
ln Total Grants	0.001	0.001*	-0.000	0.001	0.001**	0.000
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Male× Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,419,529	4,370,631	4,370,631	4,419,529	4,370,631	4,370,631
KP F-Stat	33.65	33.74	33.74	34.71	34.57	34.57
	Panel (b): Assisted Expenditures					
	ln Earnings	ln Hourly Wages	ln Hours Worked	ln Earnings	ln Hourly Wages	ln Hours Worked
ln $TO_{p,t}$	-0.092	-0.114***	0.029			
	[0.071]	[0.034]	[0.077]			
ln $EO_{p,t}$				0.347***	0.047	0.277**
				[0.114]	[0.078]	[0.105]
ln $IO_{p,t}$				-0.208***	-0.115**	-0.081
				[0.073]	[0.049]	[0.056]
ln Total AE	0.001	0.001*	0.000	0.001	0.001**	0.000
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Male× Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,419,529	4,370,631	4,370,631	4,419,529	4,370,631	4,370,631
KP F-Stat	33.88	33.97	33.97	34.65	34.51	34.51

Note: Table A.1 displays the second-stage IV regressions for the post-ESM accession period (1993-2004) after controlling for the autonomous community level of assisted expenditures (in Panel (b)), and grants (Panel (a)). The dependent variables are log earnings, log hourly wages, and log hours worked, as indicated in each column. The primary explanatory variable is log province-level trade openness, instrumented as described in the main text. All specifications include year, industry, province, gender-specific age, and individual fixed effects. KP F-statistics for the first-stage regressions are shown in the last row. Province-level clustered standard errors are shown in brackets. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

TABLE A.2: EFFECTS OF TRADE OPENNESS ON EARNINGS, WAGES, AND HOURS. SEMI-ELASTICITY

	ln Earnings	ln Hourly Wages	ln Hours Worked
$TO_{p,t}$	-0.916**	-0.456**	-0.385
	[0.365]	[0.204]	[0.298]
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Male× Age FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
N	4,419,529	4,370,631	4,370,631
KP F-Stat	54.93	55.66	55.66

Note: Table A.2 displays the second-stage IV regressions for the post-ESM accession period (1993-2004). The dependent variables are log earnings, log hourly wages, and log hours worked, as indicated in each column. The primary explanatory variable is province-level trade openness (in levels), instrumented (in levels) as described in the main text. All specifications include year, industry, province, gender-specific age, and individual fixed effects. KP F-statistics for the first-stage regressions are shown in the last row. Province-level clustered standard errors are shown in brackets. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

TABLE A.3: EFFECTS OF EXPORT AND IMPORT OPENNESS ON EARNINGS, WAGES, AND HOURS. SEMI-ELASTICITY

	ln Earnings	ln Hourly Wages	ln Hours Worked
$IO_{p,t}$	-1.473**	-0.559***	-0.789
	[0.638]	[0.207]	[0.552]
$EO_{p,t}$	12.286	1.987	9.153
	[19.266]	[3.854]	[18.013]
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Male$\times$ Age FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
N	4,419,529	4,370,631	4,370,631
KP F-Stat	0.26	0.27	0.27

Note: Table A.3 displays the second-stage IV regressions for the post-ESM accession period (1993-2004). The dependent variables are log earnings, log hourly wages, and log hours worked, as indicated in each column. The primary explanatory variables are province-level import and export openness (in levels), instrumented (in levels) as described in the main text. All specifications include year, industry, province, gender-specific age, and individual fixed effects. KP F-statistics for the first-stage regressions are shown in the last row. Province-level clustered standard errors are shown in brackets. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

TABLE A.4: FIRST STAGE RESULTS. POST-ESM ACCESSION. SEMI-ELASTICITY

	$TO_{p,t}$	$IO_{p,t}$	$EO_{p,t}$
$TO^{IV}_{p,t}$	0.176***		
	[0.024]		
$IO^{IV}_{p,t}$		0.177***	0.003
		[0.019]	[0.005]
$EO^{IV}_{p,t}$		0.097	0.041
		[0.085]	[0.053]
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Male$\times$ Age FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
N	4,419,529	4,419,529	4,419,529
KP F-Stat	54.93	0.26	

Note: Table A.4 displays the first-stage IV regressions for the post-ESM accession period (1993-2004) using trade, import, and export openness in levels. Column (1) shows the regression of log province-level trade openness on its corresponding instrument. Columns (2) and (3) show the regressions of log province-level import openness and log province-level export openness, respectively, on both the instrument for import openness and the instrument for export openness simultaneously. All specifications include year, industry, province, gender-specific age, and individual fixed effects. The KP F-statistic in columns (2) and (3) refers to the test for the joint significance of both instruments. Province-level clustered standard errors are shown in brackets. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

TABLE A.5: EFFECTS OF IMPORT OPENNESS ON EARNINGS, WAGES, AND HOURS. SEMI-ELASTICITY

	ln Earnings	ln Hourly Wages	ln Hours Worked
$IO_{p,t}$	-1.126***	-0.503**	-0.530*
	[0.355]	[0.194]	[0.265]
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Male$\times$ Age FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
N	4,419,529	4,370,631	4,370,631
KP F-Stat	86.55	88.53	88.53

Note: Table A.5 displays the second-stage IV regressions for the post-ESM accession period (1993-2004). The dependent variables are log earnings, log hourly wages, and log hours worked, as indicated in each column. The primary explanatory variable is province-level import openness (in levels), instrumented (in levels) as described in the main text. All specifications include year, industry, province, gender-specific age, and individual fixed effects. KP F-statistics for the first-stage regressions are shown in the last row. Province-level clustered standard errors are shown in brackets. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

B Broader Historical Context: Spain's Entry in the EU and ESM

The European Single Market originated from a 1985 European Commission white paper aiming to finalize the creation of an economic area without internal frontiers for goods, people, services, and capital.[37] The 300 proposed measures were legislated via the Single European Act in 1986, targeting completion by the end of 1992. By January 1, 1993, approximately 90 percent of these measures were implemented across member states, with national adoption rates ranging from 80 to 95 percent.[38]

It is important to distinguish the ESM from earlier integration phases. The ESM did not primarily focus on tariffs between EU members; the removal of tariffs and quantitative restrictions stemmed from the 1968 Treaty of Rome. Countries joining after 1968, including Spain (which joined in 1986), phased out tariffs over a transitional period. For Spain, this meant eliminating tariffs on most industrial goods over seven years, concluding around 1993 (Royo and Manuel 2008). This initial 1986-1992 integration was a significant shock, exposing previously protected industries like steel and textiles to intense competition from more advanced European firms (González 2005). This led to industrial restructuring, substantial job losses, and unemployment exceeding 24 percent in the early 1990s, setting the stage for the ESM era (Coe 1995; Royo 2007).

The ESM's purpose differed from that of the Treaty of Rome: it aimed to remove non-tariff barriers (NTBs) and other frictions hindering deeper integration. As noted by Head and Mayer (2021), by the early 1980s it was clear that eliminating formal tariffs alone had not created a fully integrated market, primarily due to border checks and divergent national regulations acting as NTBs.[39] The economic weight of these barriers was considerable. IMF (2024) estimates that, still in 2020, the remaining NTBs within the EU were equivalent to an ad-valorem tariff of approximately 44 percent for goods and 110 percent for services.

To dismantle these regulatory barriers, the ESM employed two main mechanisms. First, legislative harmonization replaced varied national rules with common EU regulations in areas such as product safety and environmental protection, allowing European firms to produce a single version of a product for the entire European market. Second, the prin-

[37]Completing the Internal Market: White Paper from the Commission to the European Council (1985).

[38]Percentages derived from Ragonnaud (2023) briefing.

[39]For instance, Italy required that all pasta contain 100 percent durum semolina, while Germany only allowed four ingredients in beer, based on the 1815 Bavarian Purity Law.

ciple of mutual recognition established that a product lawfully marketed in one member state must generally be allowed in others, shifting the burden of proof to importing authorities and limiting protectionist uses of national rules.

According to Head and Mayer (2021), the ESM significantly reduced intra-EU trade costs. While these costs had fallen 15 to 18 percent from the mid-1960s until the early 1990s, progress had stalled.[40] The ESM reignited this decline, leading to a 25 percent total reduction by 2004 relative to the mid-1960s. Notably, the ESM also reduced trade costs between the EU and the rest of the world by a similar magnitude. These external trade costs had stagnated in the 1980s after an initial decline but fell again post-ESM, from a 17 percent reduction (relative to the mid-1960s) in 1993 to a 25 percent reduction by the mid-2000s (Head and Mayer 2021).

The ESM was transformative for key sectors of the Spanish economy. Harmonized standards enabled the automotive industry to integrate Spanish plants into pan-European networks, enabling substantial economies of scale (CaixaBank Research 2021). Similarly, unified food safety standards facilitated access to northern European markets for Spanish agriculture, contributing to a positive sectoral trade balance from 1995 onwards (Broberg 2007).

Beyond trade in goods, the ESM advanced the free movement of capital. Although such movement was originally envisioned by the Treaty of Rome, practical progress was minimal until the ESM addressed loopholes allowing protective capital controls, common in the 1970s-80s. The ESM's capital liberalization prompted two distinct FDI waves in Spain. The first, after the 1986 EU accession, was primarily market-seeking to access the domestic market (Clusa 2025). The second, post-1993 ESM implementation saw investors increasingly use Spain as an export platform, substantially boosting capital inflows (Banco de España 2025; Flam and Nordström 2008).

Concurrently with the creation of the ESM, the EU expanded funding programs, creating the European Cohesion Fund (CF) alongside the existing Regional Development Fund (ERDF). Spain was a primary beneficiary of both, receiving significant transfers in the 1990s and early 2000s, as documented by Fuente and Boscà (2010) and Fuente and Boscà

[40] Head and Mayer (2021) estimate that in 1980 goods' trade costs had already declined by around 12 percent, while in 1993 the decline was only 5 or 6 additional percentage points.

(2013).

Finally, with the ESM, Spain also achieved free movement of people within Europe. Transitional labor restrictions from the 1986 accession had expired by 1992, coinciding with the ESM launch (Barker 2024). This change, coupled with integration-led economic growth, reversed Spain's historical pattern of emigration. Starting in the mid-1990s, the country became a major destination for foreign workers, supplying labor to its expanding economy (González-Páramo 2011, Carrasco and Jimeno 2015).

C Simulation to Validate RIF-IV

While Firpo et al. (2009) do not develop or discuss an IV application for their RIF-OLS method, the linearity of the RIF equation makes its extension to a 2SLS (IV) framework a natural one. This appendix details a simulation exercise conducted to validate the use of a 2SLS IV method in recentered influence function regressions. The objective is to demonstrate that this RIF-IV approach can successfully correct for endogeneity—specifically, omitted-variable bias (OVB)—and recover the true causal parameters of interest across the outcome distribution.

Our simulation proceeds in three steps. We establish a benchmark by generating data for 1 million observations with a known causal structure and no endogeneity. We create an outcome variable (Y) and a variable of interest (X_1). We also generate a covariate X_2, which by construction affects both Y and X_1, and an instrument Z, which affects X_1 but is not directly related to Y. Finally, we create an additional exogenous control, X_3.

C.1 Step 0: Validating Manual RIF-OLS Results vs. "rifreg"'s Results

A preliminary step was necessary to validate our RIF-IV procedure. Because no official Stata command exists for RIF-IV, we first had to confirm that our manual RIF-OLS implementation was identical to the “rifreg” command created by Rios-Avila (2021), which is based on the methodology in Firpo et al. (2009). To do this, we used the "clean" benchmark data to estimate the model in two ways. First, we estimate our results using the “rifreg” command at the 10th, 50th, and 90th percentiles. Second, we manually construct the RIF for each quantile (10th, 50th, and 90th) using the kernel density estimator, and then regress this RIF on X_1, X_2, and X_3 using the standard regression command in Stata (“reg”). The results in columns (1) and (2) of Table C.1 confirm that the two methods are functionally identical. This validation confirmed that our manual RIF procedure provides a reliable foundation for the 2SLS extension.

C.2 Step 1: Unbiased RIF-OLS (Benchmark)

In the first step, unbiased RIF-OLS (benchmark), we estimate the "true" causal parameters by fitting a correctly specified RIF-OLS model to the data-generating process. We run RIF-OLS regressions for the 10th, 50th, and 90th percentiles, crucially including all relevant covariates: the variable of interest X_1, the exogenous control X_3, and the confounding variable X_2. By explicitly controlling for X_2, we prevent X_1 from being correlated with the error term, thus satisfying the OLS exogeneity assumption. This model suffers from no endogeneity bias, and its estimates, shown in column (2) of Table C.1, serve as our unbiased benchmark.

TABLE C.1: SIMULATION ESTIMATES

	"rifreg"	RIF-OLS	Biased RIF-OLS	RIF-IV
10th Percentile				
X_1	0.210***	0.210***	0.256***	0.210***
	[0.001]	[0.001]	[0.001]	[0.001]
N	1,000,000	1,000,000	1,000,000	1,000,000
50th Percentile				
	"rifreg"	RIF-OLS	Biased RIF-OLS	RIF-IV
X_1	0.289***	0.289***	0.339***	0.289***
	[0.001]	[0.001]	[0.001]	[0.001]
N	1,000,000	1,000,000	1,000,000	1,000,000
90th Percentile				
	"rifreg"	RIF-OLS	Biased RIF-OLS	RIF-IV
X_1	0.358***	0.358***	0.415***	0.357***
	[0.001]	[0.001]	[0.001]	[0.002]
N	1,000,000	1,000,000	1,000,000	1,000,000

Note: Table C.1 displays coefficient estimates for X_1 from the simulation exercise, with standard errors in brackets. All models include the exogenous control X_3. Column (1) shows estimates from the "rifreg" command on the full, unbiased specification (controlling for X_2). Column (2) uses a manual RIF-OLS procedure on the same full specification, serving as the benchmark. Column (3) shows results from a biased RIF-OLS model that omits the confounder X_2. Column (4) applies the RIF-IV (2SLS) procedure to the biased specification, instrumenting X_1 with Z. All estimations are based on $N = 1,000,000$ observations. * $p < 0.10$, ** $p < 0.05$ *** $p < 0.01$

C.3 Step 2: Biased RIF-OLS

In the second step, we simulate a realistic research scenario by introducing an omitted variable bias in our estimation. We again run RIF-OLS regressions for the same three quantiles, but this time we exclude the confounding variable X_2 from the specification. This mimics a situation where a researcher cannot observe a key confounding variable. In our case, this variable could be labor supply. Because X_2 is correlated with both X_1 and Y by construction, omitting X_2 from the regression makes X_1 correlated with the error term, violating the core OLS assumption and leading to biased and inconsistent estimates. As shown in column (3) of Table C.1, the coefficient for X_1 at the different percentiles is biased, differing meaningfully from the true parameters and our benchmark results.

C.4 Step 3: Unbiased RIF-IV

In the third and final step, we apply our RIF-IV strategy to the biased specification from the previous step. We again omit the unobserved X_2 but now explicitly treat X_1 as endogenous. The critical insight validated by this step is that the RIF, once computed, serves as a standard linear dependent variable. Because the RIF regression is linear in its parameters, it can be seamlessly integrated into a 2SLS framework to address endogeneity. We therefore simply use standard instrumental variable commands to estimate the model, specifying the RIF as the outcome and instrumenting X_1 with the valid instrument Z. This RIF-IV procedure directly corrects the endogeneity bias. The resulting estimates, shown in column (4) of Table C.1, are consistent and virtually identical to the true benchmark parameters from the first step.

The findings from this three-step simulation provide a clear conclusion. The exercise demonstrates that while the standard RIF-OLS specification fails to recover the true parameters in the presence of omitted variable bias, the RIF-IV approach effectively corrects for this endogeneity. The RIF-IV estimates are virtually identical to the unbiased benchmark parameters from the correctly specified model. This simulation, therefore, provides strong evidence that extending the RIF methodology to a 2SLS framework is a valid and robust strategy, allowing for the identification of causal effects at different points along the outcome distribution even when confounders are unobserved.

D IV Validity: Methodological Details and Additional Results

This appendix provides additional methodological details and results for our IV validity exercises. Our second set of validity exercises in the main text tests whether future instrument values are correlated with pre-ESM province outcomes. We conduct a falsification test to assess the validity of our instrumental variable, following the ideas in Mitaritonna et al. (2017) and the approach in Hernandez Martinez (2025). This exercise examines whether our instrument, designed to capture trade dynamics specifically related to ESM entry from 1993 onward, spuriously correlates with Spanish labor market outcomes in the years before this integration (1987-1992). Finding such a correlation would suggest that the instrument is picking up pre-existing trends, violating the exclusion restriction.

In practice, we estimate variations of our equation (5), but regress past outcomes on the future value of the instrument:

$$Y_{i,p,k,t} = \beta_1 \ln TO^{IV}_{p,t+Lag} + \beta X_{i,p,k,t} + \alpha_i + \epsilon_{i,p,k,t} \tag{D.1}$$

where t ranges from 1987 to 1992, and $Y_{i,p,k,t}$ represents the individual labor market outcomes in the pre-ESM period (log earnings, log hourly wages, log hours worked, a low-skill dummy, and an unemployment dummy). The key regressor in equation (D.1), $\ln TO^{IV}_{p,t+Lag}$ is our instrument shifted forward by Lag years, where Lag ranges from 6 to 12 years (ensuring the instrument always corresponds to the post-1993 period and the pre-period has full data coverage).

For the estimation, we stack the data across all possible values of Lag from 6 to 12. Because stacking artificially inflates the number of observations by duplicating outcome data for different instrument lags, we draw a random sample from the stacked dataset equal in size to our original estimation sample. In all specifications, we include our standard set of fixed effects ($X_{i,p,k,t}$ and α_i) and cluster standard errors at the province level. Under the null hypothesis that our instrument is valid and uncorrelated with pre-existing trends, the coefficient β_1 should be statistically insignificant and close to zero across all outcomes and specifications.

Table VIII in the main text presents results for the pre-trend falsification test using the stacked dataset, regressing pre-ESM outcomes (1987-1992) on the future instrument values 1. Panel (a) shows that the future total trade openness instrument does not significantly predict past earnings, wages, hours worked, or unemployment status. Panel (b) confirms this lack of predictive power when using the future import and export openness instruments simultaneously for all outcomes. While the coefficient for the Low-Skill dummy in Panel (a) is statistically significant at the 5 percent level, its small magnitude, combined with the insignificant results across other outcomes and the lack of joint predictive power, reinforces the overall conclusion that significant pre-trends correlating with the future instrument are absent.

Overall, these results strongly support the validity of our instrument. The consistent finding that the future instrument does not predict past labor market outcomes aligns with the null hypothesis and provides evidence against confounding, pre-existing trends. Although one coefficient is marginally significant, the overall pattern across multiple outcomes, instruments, and specifications reinforces our confidence in the exclusion restriction.

Our final validity exercise conducts a joint test of pre-existing trends, assessing whether the evolution of various covariates before ESM accession predicts future variation in our instrument. This approach directly tests the exclusion restriction by checking if factors potentially correlated with the error term (pre-period outcomes) are also correlated with the instrument.

Specifically, we estimate regressions where the future value of the instrument is the dependent variable, and the past values of our primary outcome variables are the regressors:

$$\ln TO^{IV}_{p,t+Lag} = \sum_{Y} \delta_Y Y_{i,p,k,t} + \beta X_{i,p,k,t} + \alpha_i + \epsilon_{i,p,k,t} \tag{D.2}$$

Here, the dependent variable $\ln TO^{IV}_{p,t+Lag}$ is our instrument shifted forward by Lag years (where Lag ranges from 6 to 12 years). The right-hand side includes the vector of individual pre-ESM characteristics $Y_{i,p,k,t}$ from 1987 to 1992. In line with the remaining specifications of the paper, we include our standard set of fixed effects ($X_{i,p,k,t}$ and α_i), and cluster the standard errors at the province level. As before, we estimate this specification by stacking the data across all possible lags and then drawing a random sample from the stacked dataset equal in size to our original estimation sample.

The key test is the joint significance of the coefficients δ_Y on the pre-period outcome variables. If the instrument is valid and uncorrelated with pre-existing trends, these characteristics should have no joint predictive power for the future instrument. We will test this using an F-statistic for the joint null hypothesis that all $\delta_Y = 0$. Failure to reject this null provides further evidence supporting the validity of our instrument.

Table IX in the main text presents the results of the joint pre-trend test using the stacked dataset, regressing future instruments for trade, import, and export openness on individual labor market outcomes from the pre-ESM period (1987-1992). Across all three specifications, the F-statistic is low (2.16 for trade openness and 2.06 for import and export openness). The F-statistic is insignificant for import and export openness and only marginally significant at the 10 percent level for trade openness. This indicates that the pre-period outcomes, taken together, have very weak predictive power for the future variation in our instrument. Examining the individual coefficients, we find that past earnings, wages, and unemployment status are never significantly correlated with the future instrument values. We do observe a small, statistically significant positive coefficient on the pre-period Low-Skill dummy across all three specifications. Nevertheless, the overall lack of joint predictive power, as evidenced by the low F-statistics, is the main takeaway.

These results support the validity of our instrument. The weak correlation between past outcomes and the future instrument suggests that our IV is unlikely to be confounded by pre-existing trends in these key labor market variables. The failure to reject the joint null hypothesis (that pre-period outcomes do not predict the future instrument) provides support for the validity of the exclusion restriction.

E Model Solution

This appendix outlines the steps used to compute the equilibrium responses of wages to changes in trade costs in the model. We begin by presenting the equations that solve the model's equilibrium. We then present the log-linearized model and subsequently demonstrate how we perform the quantitative analyses.

E.1 Final equations

After using the goods market-clearing condition, we get the following expressions for labor demand for the non-tradable sector in the region r:

$$L_r^N = (1-\beta)\left(\frac{\alpha_r^N}{w_r^L}\right)(\bar{L}w_r^L + \bar{H}_r w_r^H),$$
$$H_r^N = (1-\beta)\left(\frac{1-\alpha_r^N}{w_r^H}\right)(\bar{L}w_r^L + \bar{H}_r w_r^H).$$

And the following labor demand for the tradables sector in region r:

$$\begin{aligned}
L_r^T &= \frac{\beta}{(A_r^T)^{1-\sigma}}\left(\frac{\alpha_r^T}{w_r^L}\right)^{1-(1-\sigma)\alpha_r^T}\left(\frac{1-\alpha_r^T}{w_r^H}\right)^{(\sigma-1)(1-\alpha_r^T)} \times \\
&\times \left[\frac{\theta_1^\sigma(\bar{L}_r w_r^L + \bar{H}_r w_r^H)}{(P_r^{TB})^{1-\sigma}} + \frac{\theta_2^\sigma(\bar{L}_{r'} w_{r'}^L + \bar{H}_{r'} w_{r'}^H)}{(P_{r'}^{TB})^{1-\sigma}} + \frac{\bar{B}(\tau_r^X)^{1-\sigma}}{\beta}\right], \\
H_r^T &= \frac{\beta}{(A_r^T)^{1-\sigma}}\left(\frac{\alpha_r^T}{w_r^L}\right)^{(\sigma-1)\alpha_r^T}\left(\frac{1-\alpha_r^T}{w_r^H}\right)^{\alpha_r^T+\sigma(1-\alpha_r^T)} \times \\
&\times \left[\frac{\theta_1^\sigma(\bar{L}_r w_r^L + \bar{H}_r w_r^H)}{(P_r^{TB})^{1-\sigma}} + \frac{\theta_2^\sigma(\bar{L}_{r'} w_{r'}^L + \bar{H}_{r'} w_{r'}^H)}{(P_{r'}^{TB})^{1-\sigma}} + \frac{\bar{B}(\tau_r^X)^{1-\sigma}}{\beta}\right],
\end{aligned}$$

where the terms in the denominators that are functions of the price indices for the tradable bundles are

$$
\begin{aligned}
(P_r^{TB})^{1-\sigma} &= \theta_1^{\sigma}\left(\frac{1}{A_r^T}\right)^{1-\sigma}\left(\frac{w_r^L}{\alpha_r^T}\right)^{\alpha_r^T(1-\sigma)}\left(\frac{w_r^H}{1-\alpha_r^T}\right)^{(1-\alpha_r^T)(1-\sigma)} \\
&+ \theta_2^{\sigma}\left(\frac{1}{A_{r'}^T}\right)^{1-\sigma}\left(\frac{w_{r'}^L}{\alpha_r^T}\right)^{\alpha_{r'}^T(1-\sigma)}\left(\frac{w_{r'}^H}{1-\alpha_{r'}^T}\right)^{(1-\alpha_{r'}^T)(1-\sigma)} \\
&+ \theta_M^{\sigma}(\tau_r^M)^{1-\sigma}, \\
(P_{r'}^{TB})^{1-\sigma} &= \theta_1^{\sigma}\left(\frac{1}{A_{r'}^T}\right)^{1-\sigma}\left(\frac{w_{r'}^L}{\alpha_{r'}^T}\right)^{\alpha_{r'}^T(1-\sigma)}\left(\frac{w_{r'}^H}{1-\alpha_{r'}^T}\right)^{(1-\alpha_{r'}^T)(1-\sigma)} \\
&+ \theta_2^{\sigma}\left(\frac{1}{A_r^T}\right)^{1-\sigma}\left(\frac{w_r^L}{\alpha_{r'}^T}\right)^{\alpha_r^T(1-\sigma)}\left(\frac{w_r^H}{1-\alpha_r^T}\right)^{(1-\alpha_r^T)(1-\sigma)} \\
&+ \theta_M^{\sigma}(\tau_{r'}^M)^{1-\sigma}.
\end{aligned}
$$

E.2 Log-linearization

We denote $\hat{x} = d\log(x)$ as the percentage change in the variable x around the initial equilibrium. As already mentioned, we will later impose $w_1^L = 1$ as the numeraire $\hat{w}_1^L = 0$.

Non-tradable labor demand. We start by log-linearizing the non-tradable labor demands. To do this we first define labor income share (at the initial SS) as follows:

$$
s_r^L = \frac{w_r^L \bar{L}_r}{E_r}, \quad s_r^H = \frac{w_r^H \bar{H}_r}{E_r}
$$

Then we get labor demand in the non-tradable low-skill sector in region r:

$$
\begin{aligned}
\hat{L}_r^N &= -\hat{w_r^L} + d\ln\Big(\bar{L}w_r^L + \bar{H}_r w_r^H\Big), \\
\hat{L}_r^N &= -\hat{w_r^L} + s_r^L \hat{w}_r^L + s_r^H \hat{w}_r^H,
\end{aligned}
$$

Using the labor share definition and the fact that $\hat{x} = \frac{dx}{x}$

$$
\boxed{\hat{L}_r^N = (s_r^L - 1)\hat{w}_r^L + s_r^H \hat{w}_r^H}, \tag{E.1}
$$

Then we get labor demand for the non-tradable high-skill sector in region r:

$$\boxed{\hat{H}_r^N = s_r^L \hat{w}_r^L + (s_r^H - 1)\hat{w}_r^H}, \tag{E.2}$$

Tradable labor demand. Now we proceed to log-linearize the tradable labor demand. As this step is more involved, we proceed in several steps, as detailed below.

$$L_r^T = \frac{\beta}{A_{rT}^{1-\sigma}} \left(\alpha_r^T\right)^{1-(1-\sigma)\alpha_r^T} \left(1-\alpha_r^T\right)^{(\sigma-1)(1-\alpha_r^T)} \left(\frac{1}{w_r^L}\right)^{1-(1-\sigma)\alpha_r^T} \left(\frac{1}{w_r^H}\right)^{(\sigma-1)(1-\alpha_r^T)} \times$$
$$\times \underbrace{\left[\frac{\theta_1^\sigma(\bar{L}_r w_r^L + \bar{H}_r w_r^H)}{(P_r^{TB})^{1-\sigma}} + \frac{\theta_2^\sigma(\bar{L}_{r'} w_{r'}^L + \bar{H}_{r'} w_{r'}^H)}{(P_{r'}^{TB})^{1-\sigma}} + \frac{\bar{B}(\tau_r^X)^{1-\sigma}}{\beta}\right]}_{:=\Phi_r^T}$$

For simplicity, define $\bar{B}$ as the constant terms in the export equation, and Φ_r^T as detailed in the previous equation.

Step 1: Log-linearize in terms of prices, and then replace log-linearized prices.

$$L_r^T = \frac{\beta}{A_{rT}^{1-\sigma}} \left(\alpha_r^T\right)^{1-(1-\sigma)\alpha_r^T} \left(1-\alpha_r^T\right)^{(\sigma-1)(1-\alpha_r^T)} \left(\frac{1}{w_r^L}\right)^{1-(1-\sigma)\alpha_r^T} \left(\frac{1}{w_r^H}\right)^{(\sigma-1)(1-\alpha_r^T)} \Phi_r^T()$$
$$\hat{L}_r^T = (-1)(1-(1-\sigma)\alpha_r^T)\hat{w}_r^L + (-1)(\sigma-1)(1-\alpha_r^T)w_r^H + d\ln\Phi_r^T$$
$$\hat{L}_r^T = -[(1-(1-\sigma)\alpha_r^T)]\hat{w}_r^L - [(\sigma-1)(1-\alpha_r^T)]w_r^H + d\ln\Phi_r^T$$

Step 2: Log-linearize Φ_r^T in terms of prices and total income.

$$\ln \Phi_r^T(w_r^j, p_r^T, ..) = \ln \underbrace{\left[\frac{\theta_1^\sigma(\bar{L}_r w_r^L + \bar{H}_r w_r^H)}{(P_r^{TB})^{1-\sigma}} + \frac{\theta_2^\sigma(\bar{L}_{r'} w_{r'}^L + \bar{H}_{r'} w_{r'}^H)}{(P_{r'}^{TB})^{1-\sigma}} + \frac{\bar{B}(\tau_r^X)^{1-\sigma}}{\beta} \right]}_{:=\Phi_r^T}$$

$$\ln \Phi_r^T(w_r^j, p_r^T, ..) = ln \left[\frac{\theta_1^\sigma(E_r)}{(P_r^{TB})^{1-\sigma}} + \frac{\theta_2^\sigma(E_{r'})}{(P_{r'}^{TB})^{1-\sigma}} + \frac{\bar{B}(\tau_r^X)^{1-\sigma}}{\beta} \right]$$

Note that $\Phi_r^T(w_r^j, p_r^T, ..)$ becomes a wired addition of total expenditure in terms of prices. Define the following shares in equilibrium:

$$\Lambda_{\Phi_r^T}^{Tr} := \frac{\theta_1^\sigma(E_r)}{(P_r^{TB})^{1-\sigma}} \frac{1}{\Phi_r^T} > 0, \quad \Lambda_{\Phi_r^T}^{Tr'} := \frac{\theta_2^\sigma(E_{r'})}{(P_{r'}^{TB})^{1-\sigma}} \frac{1}{\Phi_r^T} > 0, \quad \Lambda_{\Phi_r^T}^{Xr} := \frac{\bar{B}(\tau_r^X)^{1-\sigma}}{\beta} \frac{1}{\Phi_r^T} > 0,$$

$$\hat{\Phi}_r^T = \left[\frac{\theta_1^\sigma(E_r)}{(P_r^{TB})^{1-\sigma}} [\hat{E}_r + (\sigma - 1)\hat{P}_r^{TB}] + \frac{\theta_2^\sigma(E_{r'})}{(P_{r'}^{TB})^{1-\sigma}} [\hat{E}_{r'} + (\sigma - 1)\hat{P}_{r'}^{TB}] + \frac{\bar{B}(\tau_r^X)^{1-\sigma}}{\beta} [\hat{\tau}_r^X(1 - \sigma)] \right] \frac{1}{\Phi_r^T}$$

$$\hat{\Phi}_r^T = \left[\Lambda_{\Phi_r^T}^{Tr} [\hat{E}_r + (\sigma - 1)\hat{P}_r^{TB}] + \Lambda_{\Phi_r^T}^{Tr'} [\hat{E}_{r'} + (\sigma - 1)\hat{P}_{r'}^{TB}] + \Lambda_{\Phi_r^T}^{Xr} [\hat{\tau}_r^X(1 - \sigma)] \right]$$

Step 3. Replace $\hat{E}_r$ and P^{TB} with their log-linearized equations in terms of wages.

For this, remember that

$$\hat{E}_r = s_r^L \hat{w}_r^L + s_r^H \hat{w}_r^H,$$

We now turn to P^{TB}. First, we rewrite the equation, then log-linearize and simplify it in terms of notation, and define a new set of constants. Then we express its log-linear version in terms of wages.

Define $\kappa_r^T = \left(\frac{1}{A_r^T}\right)^{1-\sigma} \left(\frac{1}{\alpha_r^T}\right)^{\alpha_r^T(1-\sigma)} \left(\frac{1}{1-\alpha_r^T}\right)^{(1-\alpha_r^T)(1-\sigma)}$.

Then the price equations become:

$$
\begin{aligned}
(P_r^{TB})^{1-\sigma} &= \theta_1^\sigma \left(\frac{1}{A_r^T}\right)^{1-\sigma} \left(\frac{w_r^L}{\alpha_r^T}\right)^{\alpha_r^T(1-\sigma)} \left(\frac{w_r^H}{1-\alpha_r^T}\right)^{(1-\alpha_r^T)(1-\sigma)} \\
&+ \theta_2^\sigma \left(\frac{1}{A_{r'}^T}\right)^{1-\sigma} \left(\frac{w_{r'}^L}{\alpha_{r'}{}^T}\right)^{\alpha_{r'}^T(1-\sigma)} \left(\frac{w_{r'}^H}{1-\alpha_{r'}^T}\right)^{(1-\alpha_{r'}^T)(1-\sigma)} \\
&+ \theta_M^\sigma (\tau_r^M)^{1-\sigma}, \\
(P_r^{TB})^{1-\sigma} &= \theta_1^\sigma \kappa_r^T \left(w_r^L\right)^{\alpha_r^T(1-\sigma)} \left(w_r^H\right)^{(1-\alpha_r^T)(1-\sigma)} \\
&+ \theta_2^\sigma \kappa_{r'}^T \left(w_{r'}^L\right)^{\alpha_{r'}^T(1-\sigma)} \left(w_{r'}^H\right)^{(1-\alpha_{r'}^T)(1-\sigma)} \\
&+ \theta_M^\sigma (\tau_r^M)^{1-\sigma},
\end{aligned}
$$

$$
\begin{aligned}
(P_{r'}^{TB})^{1-\sigma} &= \theta_1^\sigma \left(\frac{1}{A_{r'}^T}\right)^{1-\sigma} \left(\frac{w_{r'}^L}{\alpha_{r'}^T}\right)^{\alpha_{r'}^T(1-\sigma)} \left(\frac{w_{r'}^H}{1-\alpha_{r'}^T}\right)^{(1-\alpha_{r'}^T)(1-\sigma)} \\
&+ \theta_2^\sigma \left(\frac{1}{A_r^T}\right)^{1-\sigma} \left(\frac{w_r^L}{\alpha_r{}^T}\right)^{\alpha_r^T(1-\sigma)} \left(\frac{w_r^H}{1-\alpha_r^T}\right)^{(1-\alpha_r^T)(1-\sigma)} \\
&+ \theta_M^\sigma (\tau_{r'}^M)^{1-\sigma}. \\
(P_{r'}^{TB})^{1-\sigma} &= \theta_1^\sigma \kappa_{r'}^T \left(w_{r'}^L\right)^{\alpha_{r'}^T(1-\sigma)} \left(w_{r'}^H\right)^{(1-\alpha_{r'}^T)(1-\sigma)} \\
&+ \theta_2^\sigma \kappa_r^T \left(w_r^L\right)^{\alpha_r^T(1-\sigma)} \left(w_r^H\right)^{(1-\alpha_r^T)(1-\sigma)} \\
&+ \theta_M^\sigma (\tau_{r'}^M)^{1-\sigma},
\end{aligned}
$$

Define the consumption share in the tradable bundle as:

$$\lambda_r^M = \theta_M^\sigma (\tau_r^M)^{1-\sigma}$$
$$\lambda_{r'}^{Tr'} = \theta_1^\sigma \kappa_{r'}^T \left(w_{r'}^L\right)^{\alpha_{r'}^T(1-\sigma)} \left(w_{r'}^H\right)^{(1-\alpha_{r'}^T)(1-\sigma)}$$
$$\lambda_{r'}^{Tr} = \theta_2^\sigma \kappa_{r'}^T \left(w_{r'}^L\right)^{\alpha_{r'}^T(1-\sigma)} \left(w_{r'}^H\right)^{(1-\alpha_{r'}^T)(1-\sigma)}$$

After some algebra and rearranging terms, we get that the log-linearized equations are:

$$\boxed{\hat{P}_r^{TB} = \lambda_r^{Tr}\left[\alpha_r^T \hat{w}_r^L + \hat{w}_r^H(1-\alpha_r^T)\right] + \lambda_{r'}^{Tr}\left[\hat{w}_{r'}^L \alpha_{r'}^T + \hat{w}_{r'}^H(1-\alpha_{r'}^T)\right] + \lambda_r^M \hat{\tau}_r^M} \tag{E.3}$$

$$\boxed{\hat{P}_{r'}^{TB} = \lambda_{r'}^{Tr'}\left[\alpha_{r'}^T \hat{w}_{r'}^L + \hat{w}_{r'}^H(1-\alpha_{r'}^T)\right] + \lambda_r^{Tr'}\left[\hat{w}_r^L \alpha_r^T + \hat{w}_r^H(1-\alpha_r^T)\right] + \lambda_{r'}^M \hat{\tau}_{r'}^M} \tag{E.4}$$

Step 4. Plug the log-linearized prices and expenditure back into $\hat{\Phi}$.

$$\hat{\Phi}_r^T = \left[\Lambda_{\Phi_r^T}^{Tr}[\hat{E}_r + (\sigma-1)\hat{P}_r^{TB}] + \Lambda_{\Phi_r^T}^{Tr'}[\hat{E}_{r'} + (\sigma-1)\hat{P}_{r'}^{TB}] + \Lambda_{\Phi_r^T}^{Xr}[\hat{\tau}_r^X(1-\sigma)]\right]$$

After replacing and re-ordering, we get that:

$$
\begin{aligned}
\hat{\Phi}_r^T &= \hat{w}_r^L[\Lambda_\Phi^{Tr} s_r^L + (\sigma-1)\alpha^T(\Lambda_\Phi^{Tr}\lambda_r^{Tr} + \Lambda_\Phi^{Tr'}\lambda_r^{Tr'})] + \\
&+ \hat{w}_r^H[\Lambda_\Phi^{Tr} s_r^H + (\sigma-1)(1-\alpha^T)(\Lambda_\Phi^{Tr}\lambda_r^{Tr} + \Lambda_\Phi^{Tr'}\lambda_r^{Tr'})] \\
&+ \hat{w}_{r'}^L[\Lambda_\Phi^{Tr'} s_{r'}^L + (\sigma-1)\alpha_{r'}^T(\Lambda_\Phi^{Tr}\lambda_{r'}^{Tr} + \Lambda_\Phi^{Tr'}\lambda_{r'}^{Tr'})] \\
&+ \hat{w}_{r'}^H[\Lambda_\Phi^{Tr'} s_{r'}^H + (\sigma-1)(1-\alpha_{r'}^T)(\Lambda_\Phi^{Tr}\lambda_{r'}^{Tr} + \Lambda_\Phi^{Tr'}\lambda_{r'}^{Tr'})] \\
&+ \hat{\tau}_r^M \Lambda_\Phi^{Tr}\lambda_r^M(\sigma-1) \\
&+ \hat{\tau}_{r'}^M \Lambda_\Phi^{Tr'}\lambda_{r'}^M(\sigma-1) \\
&+ \Lambda_{\Phi_r^T}^{Xr}\hat{\tau}_r^X(1-\sigma)
\end{aligned}
$$

Step 5. Use $\hat{\Phi}$ in the labor demands.

$$
\begin{aligned}
\hat{L}_r^T &= -[(1-(1-\sigma)\alpha_r^T)]\hat{w}_r^L - [(\sigma-1)(1-\alpha_r^T)]\hat{w}_r^H + \\
&+ \hat{w}_r^L[\Lambda_\Phi^{Tr} s_r^L + (\sigma-1)\alpha^T(\Lambda_\Phi^{Tr}\lambda_r^{Tr} + \Lambda_\Phi^{Tr'}\lambda_r^{Tr'})] + \\
&+ \hat{w}_r^H[\Lambda_\Phi^{Tr} s_r^H + (\sigma-1)(1-\alpha^T)(\Lambda_\Phi^{Tr}\lambda_r^{Tr} + \Lambda_\Phi^{Tr'}\lambda_r^{Tr'})] \\
&+ \hat{w}_{r'}^L[\Lambda_\Phi^{Tr'} s_{r'}^L + (\sigma-1)\alpha_{r'}^T(\Lambda_\Phi^{Tr}\lambda_{r'}^{Tr} + \Lambda_\Phi^{Tr'}\lambda_{r'}^{Tr'})] \\
&+ \hat{w}_{r'}^H[\Lambda_\Phi^{Tr'} s_{r'}^H + (\sigma-1)(1-\alpha_{r'}^T)(\Lambda_\Phi^{Tr}\lambda_{r'}^{Tr} + \Lambda_\Phi^{Tr'}\lambda_{r'}^{Tr'})] \\
&+ \hat{\tau}_r^M \Lambda_\Phi^{Tr}\lambda_r^M(\sigma-1) \\
&+ \hat{\tau}_{r'}^M \Lambda_\Phi^{Tr'}\lambda_{r'}^M(\sigma-1) \\
&+ \hat{\tau}_r^X \Lambda_{\Phi_r^T}^{Xr}(1-\sigma)
\end{aligned}
$$

Which can be written as:

$$
\begin{aligned}
\hat{L}_r^T &= \hat{w}_r^L[\Lambda_\Phi^{Tr} s_r^L + (\sigma-1)\alpha^T(\Lambda_\Phi^{Tr}\lambda_r^{Tr} + \Lambda_\Phi^{Tr'}\lambda_r^{Tr'}) - (1+(\sigma-1)\alpha_r^T)] + \\
&+ \hat{w}_r^H[\Lambda_\Phi^{Tr} s_r^H + (\sigma-1)(1-\alpha_r^T)(\Lambda_\Phi^{Tr}\lambda_r^{Tr} + \Lambda_\Phi^{Tr'}\lambda_r^{Tr'}) - (\sigma-1)(1-\alpha_r^T)] \\
&+ \hat{w}_{r'}^L[\Lambda_\Phi^{Tr'} s_{r'}^L + (\sigma-1)\alpha_{r'}^T(\Lambda_\Phi^{Tr}\lambda_{r'}^{Tr} + \Lambda_\Phi^{Tr'}\lambda_{r'}^{Tr'})] \\
&+ \hat{w}_{r'}^H[\Lambda_\Phi^{Tr'} s_{r'}^H + (\sigma-1)(1-\alpha_{r'}^T)(\Lambda_\Phi^{Tr}\lambda_{r'}^{Tr} + \Lambda_\Phi^{Tr'}\lambda_{r'}^{Tr'})] \\
&+ \hat{\tau}_r^M \Lambda_\Phi^{Tr}\lambda_r^M(\sigma-1) \\
&+ \hat{\tau}_{r'}^M \Lambda_\Phi^{Tr'}\lambda_{r'}^M(\sigma-1) \\
&+ \Lambda_{\Phi_r^T}^{Xr}\hat{\tau}_r^X(1-\sigma)
\end{aligned}
$$

Similarly, the high-skill demand equation is given by:

$$
\begin{aligned}
\hat{H}_r^T &= -[(\sigma-1)\alpha_r^T)]\hat{w}_r^L - [(1-\sigma)(\alpha_r^T)+\sigma]\hat{w}_r^H + \\
&+ \hat{w}_r^L[\Lambda_\Phi^{Tr} s_r^L + (\sigma-1)\alpha^T(\Lambda_\Phi^{Tr}\lambda_r^{Tr} + \Lambda_\Phi^{Tr'}\lambda_r^{Tr'})] + \\
&+ \hat{w}_r^H[\Lambda_\Phi^{Tr} s_r^H + (\sigma-1)(1-\alpha^T)(\Lambda_\Phi^{Tr}\lambda_r^{Tr} + \Lambda_\Phi^{Tr'}\lambda_r^{Tr'})] \\
&+ \hat{w}_{r'}^L[\Lambda_\Phi^{Tr'} s_{r'}^L + (\sigma-1)\alpha_{r'}^T(\Lambda_\Phi^{Tr}\lambda_{r'}^{Tr} + \Lambda_\Phi^{Tr'}\lambda_{r'}^{Tr'})] \\
&+ \hat{w}_{r'}^H[\Lambda_\Phi^{Tr'} s_{r'}^H + (\sigma-1)(1-\alpha_{r'}^T)(\Lambda_\Phi^{Tr}\lambda_{r'}^{Tr} + \Lambda_\Phi^{Tr'}\lambda_{r'}^{Tr'})] \\
&+ \hat{\tau}_r^M \Lambda_\Phi^{Tr}\lambda_r^M(\sigma-1) \\
&+ \hat{\tau}_{r'}^M \Lambda_\Phi^{Tr'}\lambda_{r'}^M(\sigma-1) \\
&+ \hat{\tau}_r^X \Lambda_{\Phi_r^T}^{Xr}(1-\sigma)
\end{aligned}
$$

$$
\begin{aligned}
\hat{H}_r^T &= \hat{w}_r^L[\Lambda_\Phi^{Tr} s_r^L + (\sigma-1)\alpha^T(\Lambda_\Phi^{Tr}\lambda_r^{Tr} + \Lambda_\Phi^{Tr'}\lambda_r^{Tr'}) - (\sigma-1)\alpha_r^T)] + \\
&+ \hat{w}_r^H[\Lambda_\Phi^{Tr} s_r^H + (\sigma-1)(1-\alpha^T)(\Lambda_\Phi^{Tr}\lambda_r^{Tr} + \Lambda_\Phi^{Tr'}\lambda_r^{Tr'}) - [\alpha_r^T + \sigma(1-\alpha_r^T)]] \\
&+ \hat{w}_{r'}^L[\Lambda_\Phi^{Tr'} s_{r'}^L + (\sigma-1)\alpha_{r'}^T(\Lambda_\Phi^{Tr}\lambda_{r'}^{Tr} + \Lambda_\Phi^{Tr'}\lambda_{r'}^{Tr'})] \\
&+ \hat{w}_{r'}^H[\Lambda_\Phi^{Tr'} s_{r'}^H + (\sigma-1)(1-\alpha_{r'}^T)(\Lambda_\Phi^{Tr}\lambda_{r'}^{Tr} + \Lambda_\Phi^{Tr'}\lambda_{r'}^{Tr'})] \\
&+ \hat{\tau}_r^M \Lambda_\Phi^{Tr}\lambda_r^M(\sigma-1) \\
&+ \hat{\tau}_{r'}^M \Lambda_\Phi^{Tr'}\lambda_{r'}^M(\sigma-1) \\
&+ \hat{\tau}_r^X \Lambda_{\Phi_r^T}^{Xr}(1-\sigma)
\end{aligned}
$$

Step 6. Define some convenience notation.

Define the vector B^L as follows:

$$
\begin{aligned}
B_1^{Lr} &= \mu_r^{T,L}[\Lambda_\Phi^{Tr} s_r^L + (\sigma-1)\alpha^T(\Lambda_\Phi^{Tr}\lambda_r^{Tr} + \Lambda_\Phi^{Tr'}\lambda_r^{Tr'}) - (1 + (\sigma-1)\alpha_r^T)] \\
B_2^{Lr} &= \mu_r^{T,L}[[\Lambda_\Phi^{Tr} s_r^H + (\sigma-1)(1-\alpha_r^T)(\Lambda_\Phi^{Tr}\lambda_r^{Tr} + \Lambda_\Phi^{Tr'}\lambda_r^{Tr'}) - (\sigma-1)(1-\alpha_r^T)] \\
B_3^{Lr} &= \mu_r^{T,L}[[\Lambda_\Phi^{Tr'} s_{r'}^L + (\sigma-1)\alpha_{r'}^T(\Lambda_\Phi^{Tr}\lambda_{r'}^{Tr} + \Lambda_\Phi^{Tr'}\lambda_{r'}^{Tr'})] \\
B_4^{Lr} &= \mu_r^{T,L}[\Lambda_\Phi^{Tr'} s_{r'}^H + (\sigma-1)(1-\alpha_{r'}^T)(\Lambda_\Phi^{Tr}\lambda_{r'}^{Tr} + \Lambda_\Phi^{Tr'}\lambda_{r'}^{Tr'})] \\
B_5^{Lr} &= \mu_r^{T,L}[\Lambda_\Phi^{Tr}\lambda_r^M(\sigma-1)] \\
B_6^{Lr} &= \mu_r^{T,L}[\Lambda_\Phi^{Tr'}\lambda_{r'}^M(\sigma-1)] \\
B_7^{Lr} &= \mu_r^{T,L}[\Lambda_{\Phi_r^T}^{Xr}(1-\sigma)]
\end{aligned}
$$

Define the vector B^H as follows:

$$
\begin{aligned}
B_1^{Hr} &= \mu_r^{T,L}[\Lambda_{\Phi}^{Tr} s_r^L + (\sigma-1)\alpha^T(\Lambda_{\Phi}^{Tr}\lambda_r^{Tr} + \Lambda_{\Phi}^{Tr'}\lambda_r^{Tr'}) - (\sigma-1)\alpha_r^T)]+ \\
B_2^{Hr} &= \mu_r^{T,L}[\Lambda_{\Phi}^{Tr} s_r^H + (\sigma-1)(1-\alpha^T)(\Lambda_{\Phi}^{Tr}\lambda_r^{Tr} + \Lambda_{\Phi}^{Tr'}\lambda_r^{Tr'}) - [\alpha_r^T + \sigma(1-\alpha_r^T)]] \\
B_3^{Hr} &= \mu_r^{T,L}[\Lambda_{\Phi}^{Tr'} s_{r'}^L + (\sigma-1)\alpha_{r'}^T(\Lambda_{\Phi}^{Tr}\lambda_{r'}^{Tr} + \Lambda_{\Phi}^{Tr'}\lambda_{r'}^{Tr'})] \\
B_4^{Hr} &= \mu_r^{T,L}[\Lambda_{\Phi}^{Tr'} s_{r'}^H + (\sigma-1)(1-\alpha_{r'}^T)(\Lambda_{\Phi}^{Tr}\lambda_{r'}^{Tr} + \Lambda_{\Phi}^{Tr'}\lambda_{r'}^{Tr'})] \\
B_5^{Hr} &= \mu_r^{T,L}\Lambda_{\Phi}^{Tr}\lambda_r^M(\sigma-1) \\
B_6^{Hr} &= \mu_r^{T,L}\Lambda_{\Phi}^{Tr'}\lambda_{r'}^M(\sigma-1) \\
B_7^{Hr} &= \mu_r^{T,L}\Lambda_{\Phi_r^T}^{Xr}(1-\sigma)
\end{aligned}
$$

Step 7. Impose market-clearing conditions to obtain the 3 equations in 3 unknowns as functions of trade cost shocks.

Define employment shares:

$$\mu_r^{T,L} = \frac{L_r^T}{\bar{L}_r}, \quad \mu_r^{N,L} = \frac{L_r^N}{\bar{L}_r}, \quad \mu_r^{T,H} = \frac{H_r^T}{\bar{H}_r}, \quad \mu_r^{N,H} = \frac{H_r^N}{\bar{H}_r} \tag{E.5}$$

Low-skill labor market clearing becomes:

$$\mu_r^{T,L}\hat{L}_r^T + \mu_r^{N,L}\hat{L}_r^N = 0 \tag{E.6}$$

High-skill labor market clearing becomes:

$$\mu_r^{T,H}\hat{H}_r^T + \mu_r^{N,H}\hat{H}_r^N = 0 \tag{E.7}$$

Market-clearing condition for region r with low skills becomes :

$$0 = [B_1^{Lr} + (1-\mu_r^{T,L})(s_r^L - 1)]\hat{w}_r^L + [B_2^{Lr} + (1-\mu_r^{T,L})s_H^L]\hat{w}_r^H + B_3^{Lr}\hat{w}_{r'}^L$$
$$+ B_4^{Lr}\hat{w}_{r'}^H + B_5^{Lr}\hat{\tau}_r^M + \hat{\tau}_{r'}^M B_6^{Lr} + B_7^{Lr}\hat{\tau}_r^X$$

Note that each constant B_i^{Lr} already has the term $\mu_r^{T,L}$. For each region, we have the following condition:

$$[B_1^{Lr} + (1-\mu_r^{T,L})(s_r^L - 1)]\hat{w}_r^L +$$
$$[B_2^{Lr} + (1-\mu_r^{T,L})s_r^H]\hat{w}_r^H + B_3^{Lr}\hat{w}_{r'}^L + B_4^{Lr}\hat{w}_{r'}^H = -B_5^{Lr}\hat{\tau}_r^M - B_6^{Lr}\hat{\tau}_{r'}^M - B_7^{Lr}\hat{\tau}_r^X$$

Specifically, for region one, the equation simplifies as we have $\hat{w}_r^L = 0$:

$$[B_2^{L1} + (1-\mu_1^{T,L})s_1^H]\hat{w}_1^H + B_3^{L1}\hat{w}_2^L + B_4^{L1}\hat{w}_2^H = -B_5^{L1}\hat{\tau}_1^M - B_6^{L1}\hat{\tau}_2^M - B_7^{L1}\hat{\tau}_1^X$$

For region two, we get:

$$B_3^{L2}\hat{w}_1^L + B_4^{L2}\hat{w}_1^H + [B_1^{L2} + (1-\mu_2^{T,L})(s_2^L - 1)]\hat{w}_2^L +$$
$$[B_2^{L2} + (1-\mu_2^{T,L})s_2^H]\hat{w}_2^H = -B_6^{L2}\hat{\tau}_1^M - B_5^{L2}\hat{\tau}_2^M - B_7^{L2}\hat{\tau}_2^X$$

Lastly, using region one's market-clearing for high-skill labor demand:

$$0 = \left\{ B_1^{Hr}\hat{w}_r^L + B_2^{Hr}\hat{w}_r^H + B_3^{Hr}\hat{w}_{r'}^L + B_4^{Hr}\hat{w}_{r'}^H + B_5^{Hr}\hat{\tau}_r^M + \hat{\tau}_{r'}^M B_6^{Hr} + B_7^{Hr}\hat{\tau}_r^X \right\}$$
$$+ (1-\mu_r^{T,H})(s_r^L - 1)\hat{w}_r^L + (1-\mu_r^{T,H})\hat{w}_r^H s_H^L$$

Which, again, as before given that $\hat{w}_1^L = 0$, we obtain the following condition for region one:

$$[B_2^{H1} + (1 - \mu_1^{T,H})s_1^H]\hat{w}_1^H + B_3^{H1}\hat{w}_2^L + B_4^{H1}\hat{w}_2^H = -B_5^{H1}\hat{\tau}_1^M - B_6^{H1}\hat{\tau}_2^M - B_7^{H1}\hat{\tau}_1^X$$

Now we can solve the system.

Step 8. Impose ex-ante symmetry - across regions. This translates into the following conditions:

$\mu_1^{T,L} = \mu_2^{T,L}; \mu_1^{T,H} = \mu_2^{T,H};\ s_1^H = s_2^H; s_1^L = s_2^L; \lambda_1^{T1} = \lambda_2^{T2}; \lambda_1^{T2} = \lambda_2^{T1}; \lambda_1^M = \lambda_2^M; \Lambda_\Phi^{T2} = \Lambda_\Phi^{T1};$
$\Lambda_\Phi^{X1} = \Lambda_\Phi^{X2}; \alpha_1^T = \alpha_2^T$

E.3 Matrix system

Using the three previous equations, we can rewrite the system of equations in the following matrix form:

$$\mathbf{A}\begin{bmatrix}\hat{w}_1^H\\ \hat{w}_2^L\\ \hat{w}_2^H\end{bmatrix} = \mathbf{C}\begin{bmatrix}\hat{\tau}_1^X\\ \hat{\tau}_2^X\\ \hat{\tau}_1^M\\ \hat{\tau}_2^M\end{bmatrix} \tag{E.8}$$

where **A** is 3×3 and **C** is 3×4. The solution of the model then becomes:

The solution is:

$$\begin{bmatrix}\hat{w}_1^H\\ \hat{w}_2^L\\ \hat{w}_2^H\end{bmatrix} = M \cdot \begin{bmatrix}\hat{\tau}_1^X\\ \hat{\tau}_2^X\\ \hat{\tau}_1^M\\ \hat{\tau}_2^M\end{bmatrix} \tag{E.9}$$

where $M = A^{-1}C$ is a 3×4 matrix that is a function of parameters only.