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# China Shock or China Boost? Intermediate Inputs and Manufacturing Resilience in Poland

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**Abstract**

We analyze the effects of increased trade exposure to China on the Polish labor market during the period 2011–2019. Utilizing detailed industry-level data and an instrumental variable strategy based on trade flows from other Visegrad Group countries, we disentangle the impacts of import competition and access to imported intermediate inputs. We find that while import competition induced job losses in specific sectors, industries benefiting from access to Chinese intermediate inputs experienced substantial employment gains. Critically, this positive input channel effect was sufficient to offset the majority of displacement losses caused by import competition. Although manufacturing as a whole faced a slight net decline, the aggregate economy experienced net employment expansion. These results identify a "China Boost" driven by intermediate inputs, suggesting that Chinese imports act as strategic complements to domestic labor in Poland, contrasting sharply with the "China Shock" observed in the United States.

**Keywords:**
China shock, global value chain, intermediate input, Poland.

**JEL Classification:**
F14, F16, F66, P33

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# 1 Introduction

The global economic landscape of the last three decades has been defined by the profound reorganization of production, often described as the "second unbundling" of globalization (Baldwin, 2016). No single event catalyzed this transformation more than China's accession to the World Trade Organization (WTO) in 2001. China's integration into the world economy unleashed a massive expansion of manufacturing capacity, fundamentally altering international trade patterns and domestic labor markets globally.

A large and influential body of literature, originating in the United States, has meticulously documented the disruptive labor market consequences of this integration. Autor et al. (2013) provided stark evidence that U.S. local labor markets with greater exposure to import competition from China experienced profound, persistent negative effects. These impacts included significant declines in manufacturing employment, reduced wages, lower labor force participation, and even broader social distress. This narrative of Chinese imports as a primary driver of de-industrialization in the West became the dominant paradigm. Subsequent studies focusing on other mature, high-wage Western European economies often found similar, albeit sometimes less pronounced, negative competition effects.

However, this dominant narrative presents an incomplete picture, largely because its persistent focus on mature, high-income economies constitutes a significant sample selection bias. This gap overlooks the divergent experiences of emerging nations, particularly the transition economies of Central and Eastern Europe (CEE). Unlike the United States, the primary objective in CEE was not managing de-industrialization, but rapid re-industrialization, a process that inherently generated an immense demand for imported inputs to fuel its new supply chains. Furthermore, the narrative is mechanistically incomplete, as it predominantly focuses on the displacement effects of final goods competition. It often ignores that access to cheaper or more varied foreign intermediate inputs can act as a significant positive productivity shock, which can lower production costs, enhance firm efficiency, and ultimately boost employment. The net effect, therefore, is not monolithic but context-dependent, critically mediated by a country's industrial structure and GVC integration.

From the perspective of Poland, the context presents a striking paradox to the standard "China shock" narrative. Superficially, Poland's trade relationship with China resembles the American experience: both nations run persistent, large, and widening bilateral trade deficits, and Poland's imports from China have surged exponentially (see Figure A1 in the Appendix A). According to the US-based evidence, such a deepening deficit should portend severe manufacturing job losses. Yet, the data reveal a trajectory diametrically opposite to that of the United States. Instead of contracting, Poland's manufacturing sector has expanded. As shown in Figure 1, while the import penetration from China rose from 2 percent in 2005 to 11 percent by 2021, Poland's employment rate climbed steadily from roughly 54 percent to nearly 70 percent during the same period. We posit that the resolution to this paradox lies in the distinct composition of Poland's trade deficit. In contrast to the United States, Poland's imports are more heavily concentrated in intermediate inputs (see Figure 2 ). For an emerging manufacturing hub integrated into European supply chains, these Chinese inputs do not replace domestic labor; rather, they act as a strategic complement. Access to cost-effective intermediate goods constitutes a positive productivity shock, allowing Polish firms to lower production costs and expand their market share in downstream EU markets. In this context, the trade deficit is not a sign of weakness, but a mechanism of vertical specialization that fuels domestic employment growth.

Our paper contributes to the literature on the labor market effects of the "China shock" in Central and Eastern European (CEE) transition economies. Although previous studies identify import competition as a primary driver of manufacturing decline in mature, high-income nations, they contribute little to answering the question of how such trade shocks operate in advanced emerging markets undergoing rapid re-industrialization, and whether the impact differs across the supply chain. We contribute to this strand of literature by providing the causal estimates that explicitly disentangle the upstream (input) and downstream (output) channels of trade exposure in this novel context. We show that labor market outcomes in Poland are not driven by the simple displacement effects observed in the West, but rather by the heterogeneous impact of industrial structure, where access to intermediate inputs acts as a complement to domestic labor. Such differentiation allows for a more accurate understanding of how industrial roles mediate the relationship between global trade and local employment — an insight that is critical for reassessing the universality of the "China shock" narrative and designing industrial policies for emerging manufacturing hubs.

To empirically test these arguments, we construct a comprehensive panel of Polish manufacturing

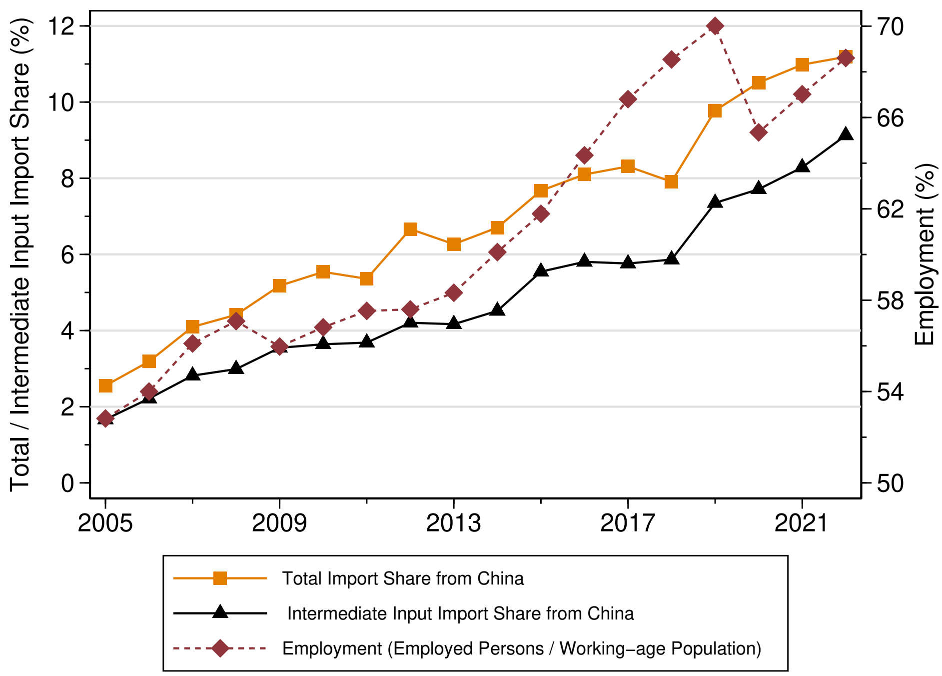


Figure 1: Poland's import share from China (left scale) vs. its employment rate (right scale). The employment rate is defined as employed persons divided by the working-age population. Sources: the UN Comtrade (imports) and Statistical Yearbook of Poland (employment).

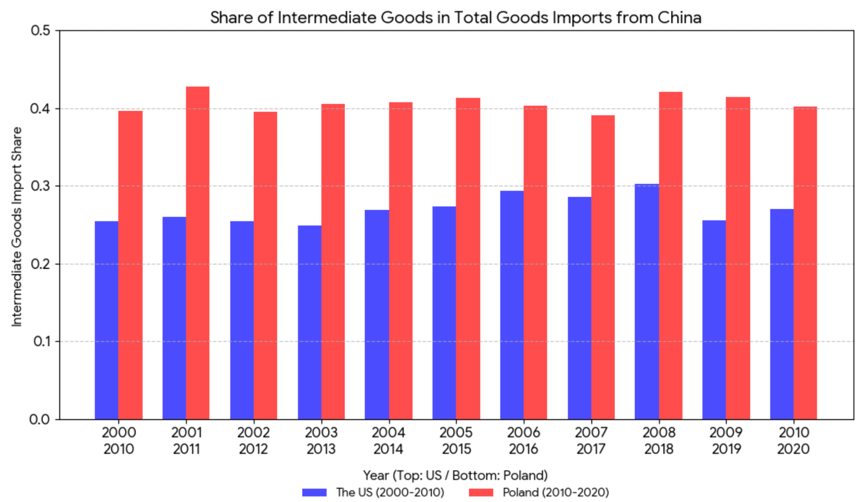


Figure 2: The figure shows the share of intermediate goods in total goods imports from China for the US (2000-2010) and Poland (2010-2020). Data is calculated based on HS 6-digit import/export data from the UN Comtrade database. Intermediate goods are defined according to the Broad Economic Categories (BEC) classification. The time spans are selected to correspond with the "China shock" literature and the period of analysis in this study.

industries spanning 2005 to 2019. Addressing the potential endogeneity of trade flows, whereby demand shocks might simultaneously drive domestic growth and imports, is central to our identification strategy. To this end, we employ a robust instrumental variable approach, instrumenting Polish imports from China with contemporaneous import flows into the other three *Visegrád Group* countries. This strategy effectively isolates supply-side shocks originating from China, filtering out Poland-specific demand factors. Our baseline estimates show that a one standard deviation increase in exposure to Chinese intermediate inputs raises employment in Polish manufacturing by approximately 2.16 percentage points. Crucially, even after accounting for import competition effects, the positive effect from the intermediate input channel is sufficient to offset the vast majority of job losses. This finding resolves the puzzle presented by the stylized facts: far from being a "shock", the influx of Chinese intermediate goods has acted as a critical propellant for Poland's manufacturing resilience.

The rest of the paper is organized as follows. Section 2 reviews the related literature, positioning our study within the broader debate on trade shocks and global value chains. Section 3 details our empirical identification strategy and variable construction. Section 4 describes the data used and presents descriptive statistics. Section 5 presents the estimation results, exploring the mechanisms driven by intermediate inputs and quantifying the net employment impact on the Polish economy. Section 6 verifies the robustness of our findings by employing alternative sample periods and different data sources. Section 7 concludes.

## 2 Related Literature

The emergence of China as a major economic power has profoundly reshaped global trade patterns. A vast body of literature, often termed the "China shock", initially focused on the disruptive effects observed in the United States. Seminal work by Autor et al. (2013) demonstrated that regions with higher exposure to Chinese import competition experienced significant, persistent reductions in manufacturing employment and wages. Pierce and Schott (2016) further linked these adjustments to the removal of trade policy uncertainty (PNTR), which incentivized offshoring. Expanding the scope of impact beyond direct competition, scholars identified amplification mechanisms that exacerbated these losses: Xu et al. (2023) found that import exposure depressed local housing values, while Acemoglu et al. (2016) emphasized that negative shocks propagated upstream to supplier industries, thereby depressing overall job growth across the US economy.

However, this pessimistic narrative presents an incomplete picture. Subsequent research has highlighted that a country's specific position within global supply chains and its labor market institutions can fundamentally alter the net outcome. Dauth et al. (2014) provided early evidence of this heterogeneity, finding that in Germany, job losses in import-competing sectors were more than offset by gains in export-oriented industries. Similarly, in the context of Austria's opening to Eastern Europe, Brülhart et al. (2012) found that border regions experienced statistically significant increases in wages and employment, suggesting that improved market access can outweigh competitive shocks. This European resilience is not uniform: Balsvik et al. (2015) found that in Norway, well-functioning labor market institutions cushioned wage effects despite job displacement, whereas Donoso et al. (2015) observed that in Spain, characterized by more rigid labor markets, the China shock had a pronounced negative impact similar to the US experience.

In fact, scholars have explicitly distinguished between competition in final goods and the sourcing of intermediate inputs. Theoretically, this line of inquiry is grounded in Melitz (2003), who established that exposure to trade induces a reallocation of market shares towards more productive firms, thereby driving aggregate industry productivity growth. Complementing this theoretical foundation, early work by Feenstra and Hanson (1999) highlighted that outsourcing intermediate inputs shifts relative labor demand in a manner analogous to skill-biased technical change. This mechanism echoes the seminal finding by Amiti and Konings (2007) in Indonesia, who demonstrated that reducing tariffs on intermediate inputs boosts firm productivity significantly more than reducing tariffs on final goods. Re-examining the US case, Wang et al. (2018) argued that when the downstream benefits of cheaper intermediate inputs are accounted for, the net impact of trading with China becomes positive, primarily by stimulating job creation in the non-manufacturing sector. This finding is supported by Caliendo et al. (2019), who modeled how access to intermediates facilitates labor reallocation into services, and by Goldberg et al. (2010), who documented similar product scope effects from imported inputs in India. This positive "input channel" is further corroborated by evidence from other developed economies, including France (Aghion et al., 2024) and Japan (Taniguchi, 2019), while Bloom et al. (2016) showed that import competition induced European firms to increase innovation and technology adoption.

While the positive role of intermediate inputs is increasingly established, evidence from emerging markets remains scarce and inconclusive. Analyzing the Indian experience, Topalova (2010) provided crucial evidence on the role of factor immobility, finding that rural districts more exposed to trade liberalization experienced slower poverty reduction due to the inability of labor to reallocate across sectors. Adão et al. (2022), studying Ecuador, found that import channels primarily benefited capital owners, exacerbating inequality. Yet, the institutional and industrial context of Central and Eastern Europe (CEE) diverges significantly from this narrative due to its rapid re-industrialization and deep integration into GVCs. Halpern et al. (2015) utilized firm-level data from Hungary to show that accessing imported inputs increased firm-level productivity by 30 percent, attributing half of this gain to the quality channel of foreign goods. Marin (2006) described this integration as "a new international division of labor", where Western European firms improved competitiveness by offshoring production stages to CEE countries (Geishecker, 2006). Hagemejer and Mućk (2019) demonstrated that export expansion driven by GVC integration has been a primary driver of economic convergence in the CEE region. Ando and Kimura (2013) further characterized the region as a crucial bridge connecting East Asian production networks to European markets. Silgoner et al. (2015) found no evidence of China crowding out CEE exports; instead, both have managed to expand market shares simultaneously within the EU-15. This complementarity is partly driven by the rising domestic value-added and sophistication in China's exports (Kee and Tang, 2016), suggesting a relationship of strategic partnership rather than pure substitution.

Despite these structural complementarities, empirical studies on specific China-CEE economic cooperation present a mixed picture regarding their effectiveness. On the macro level, Mau and Seuren (2023) found positive spillovers from the Belt and Road Initiative (BRI), noting that improved railway connections increased export revenues. Conversely, Stanojevic et al. (2021) analyzed the "16+1 Cooperation" mechanism and found no significant trade creation. Beneath these high-level initiatives, sectoral analysis reveals persistent asymmetries: Palonka (2010) noted that CEE countries typically export low-value raw materials while importing Chinese high-value electronics. Crucially, the drivers of this trade appear to be market-based rather than political. Matura (2019) found no correlation between bilateral political friendliness and trade volumes, arguing that flows are driven by multinational corporate strategies. Finally, Megits et al. (2020) highlighted the region's continued vulnerability to external shocks, such as the COVID-19 pandemic. Our study aims to bridge these strands of literature by empirically testing the "input channel" hypothesis within the specific context of Poland's manufacturing industries.

## 3 Estimation Strategy

Our study examines the structural impact of China's export expansion on Polish manufacturing employment, explicitly accounting for inter-industry input-output linkages. To ensure comparability with Acemoglu et al. (2016), we adopt their core methodological framework, but with two crucial modifications. First, we redefine the downstream exposure channel by isolating imported intermediate inputs from final goods. This distinction permits a more precise identification of shocks transmitted through the supply chain, as final goods do not function as inputs for downstream industries. Second, we employ balanced panel data rather than a long-difference approach. This modification is necessitated by data availability constraints. Input-output tables from Statistics Poland detail only 77 industry divisions (of which 24 are in manufacturing), yielding a significantly smaller cross-section than that of previous relevant studies. Therefore, to ensure that the sample size is sufficient, our unit of analysis is the industry-year. Furthermore, this panel structure is informed by a change in Poland's industrial classification (from CPA 2002 to CPA 2008). The 2010 IO table was the first to be standardized under the new system. Consequently, our regressions primarily utilize the post-2010 sample period to construct a consistent, balanced panel. A secondary advantage of this time frame is the exclusion of the confounding effects of the 2008 Great Recession and the COVID-19 pandemic in 2020. Due to data limitations, especially the lack of detailed service trade data, our subsequent regressions are mainly based on data from the manufacturing sector.[1]

[1] More importantly, despite the lack of precise data on the import and export of services between China and Poland, we can infer from a broader perspective. China's share of the EU's service trade is significantly lower than its standing in goods trade: China accounts for only around 5 percent of both EU service imports and exports, which is markedly lower than its respective share of goods imports and exports (21 percent and 8 percent in 2024). Furthermore, on a global scale, China's service exports are only about 15 percent of its total goods exports. Based on these facts, we can reasonably conclude that the scale of China's service exports to Poland is negligible when compared to its goods trade.

### 3.1 Specification

We mainly run the following regression:

$$\Delta L_{j,t} = \beta_0 + \beta_1 \Delta Direct_{j,t} + \beta_2 \Delta Down_{j,t} + \beta_3 \Delta Up_{j,t} + X_{j,2010} + \lambda_J + \alpha_t + \varepsilon_{j,t}, \tag{1}$$

where $\Delta L_{j,t}$ is 100 times the annual change of log employed persons in Poland manufacturing industry division $j$ over year $t$, from 2010-2019.[2] $\Delta Direct_{j,t}$, $\Delta Up_{j,t}$ and $\Delta Down_{j,t}$ are 100 times the annual change in Direct, Upstream, and Downstream trade exposures in industry division $j$, respectively. They will be defined in more detail below. $X_{j,2010}$ is a set of industry-specific start-of-period controls, including cost structures (share of material and energy, share of external services, and share of wages, respectively, in total costs) in 2010. These controls are crucial for mitigating omitted variable bias. The purpose of including these start-of-period characteristics is to control for pre-existing heterogeneity across industries that could affect both future employment trends and future trade exposure. For example, an industry with a high share of wages in 2010 might have already been on a path of employment decline due to pressures like automation, regardless of the new trade shocks. Without controlling for this initial condition, the regression might incorrectly attribute this pre-existing downward trend to the trade variable, thus biasing the estimate of $\beta_1$. By including $X_{j,2010}$, we effectively hold constant these initial industry characteristics, allowing us to better isolate the true, net impact of the change in trade exposure on the change in employment. The elements in $X_{j,2010}$ are each normalized with mean zero so that we can identify the change in the outcome variable conditional only on the variable of our interest. $\lambda_J$ are the manufacturing type fixed effects.[3] $\alpha_t$ are the time fixed effects. $\varepsilon_{j,t}$ is the residual. Regression estimates are weighted by industry division's employed

[2] Employed persons are those who, during the reference week: (1) worked 1 hour for pay/income (as paid employees, self-employed in agriculture/non-agriculture, or unpaid family workers). (2) formally retained employment despite temporary absence (3 months, or ¿3 months with 50% prior pay for salaried workers). Full-time/part-time status is self-declared based on the main job. More details can be found in chapter VII of Statistical Yearbooks of Poland.

[3] It should be noted that these are not industry division level ($j$) fixed effects. Since both our explanatory and dependent variables are specified in first-difference form, any time-invariant industry-division level effects have, in fact, already been eliminated. The manufacturing type is a higher level of aggregation. The 24 manufacturing divisions are divided into 4 types: labor-intensive, capital/resource-intensive, technology-intensive and others. The specific categorization can be found in Table A1 in the Appendix A.

persons in 2010, and standard errors are clustered at the manufacturing type level to allow for arbitrary error correlations within similar industries over time.

A primary challenge in this analysis is the potential endogeneity of Chinese imports. OLS estimates could be biased by simultaneity: unobserved domestic demand shocks within Poland might simultaneously reduce domestic employment and decrease the demand for imports from China. This would create a spurious correlation. To address this, we employ a two-stage least squares (2SLS) strategy. We instrument for Poland's trade exposure to China using the concurrent trade exposure of the other three *Visegrád Group* countries: Hungary, the Czech Republic, and Slovakia.

The validity of this instrument relies on two core assumptions. First, for instrument relevance, the other three *Visegrád Group* countries must serve as a strong proxy for the supply-driven component of Chinese imports to Poland. This assumption is well-grounded. The other three *Visegrád Group* countries and Poland share similar economic structures, cultural characteristics, and institutional histories. Crucially, they all joined the EU simultaneously (2004) and share similar geography. Therefore, a common supply shock from China is expected to affect import penetration in all four countries in a highly correlated manner. This assumption is validated by the first-stage estimation results (Table 1). The robust standard errors and F-statistic confirm that the instrument is statistically significant and is not a weak instrument. Second, the exclusion restriction requires that the instrument is uncorrelated with Poland's error term—that is, Poland's idiosyncratic (or domestic) demand shocks. The motivation is that while these economies are similar, their domestic, industry-specific demand shocks are unlikely to be perfectly correlated. A shock to the Polish labor market should not be systematically related to concurrent domestic shocks in Hungary, the Czech Republic, or Slovakia. Thus, the instrument plausibly affects Polish employment only through its correlation with the exogenous, supply-driven component of Chinese trade exposure.

## 3.2 Measuring Direct and Indirect Exposure to China Trade Shocks

To empirically assess the impact of trade with China on Poland's labor market, we construct the following industry-level measures of trade exposures:

Table 1: First stage results of IV regression

| | **Direct** | **Downstream** | **Upstream** |
|---|---|---|---|
| IV: Direct | **0.231*** ** | 0.028 | 0.001 |
| | (0.067) | (0.033) | (0.023) |
| IV: Downstream | -0.224*** | **0.161*** ** | -0.122*** |
| | (0.029) | (0.054) | (0.014) |
| IV: Upstream | 0.192 | 0.174*** | **0.305** ** |
| | (0.300) | (0.045) | (0.153) |
| Robust First Stage F Statistics | 155.316 | 1247.55 | 806.325 |
| Partial R-squared | 0.1163 | 0.1067 | 0.1058 |
| Shea's Partial R-squared | 0.1137 | 0.0918 | 0.1030 |

*Note:* $N$=216, covering 24 manufacturing divisions from 2011-2019. All regressions include a constant term. Dependent variable is 100 times annual changes of Direct / Downstream / Upstream Exposure respectively. Independent variables are 100 times Instrumental variables for annual changes of Direct / Downstream / Upstream Exposure. Initial industry controls are demeaned cost structures which are included in the regression. Manufacturing type fixed effects and time fixed effects are included. All regression estimates are weighted by industry divisions' employed persons in 2010. Standard errors are clustered at the manufacturing type level. Levels of significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

#### 3.2.1 Direct Exposure

A Direct Exposure to Chinese imports for industry division $j$ is defined as total imports from China divided by total absorption in that industry division:

$$\Delta Direct_{j,t} = \frac{M_{j,t}^{PC} - M_{j,t-1}^{PC}}{Y_{j,2015}^{P*} + M_{j,2015}^{P*} - E_{j,2015}^{P*}}, \tag{2}$$

where for industry division $j$ at year $t$, $M_{j,t}^{PC}$ is the imports from China and $Y_{j,2015}^{P*} + M_{j,2015}^{P*} - E_{j,2015}^{P*}$ is the absorption measured as year 2015's output plus imports minus exports.[4]

While China's export expansion is predominantly driven by its internal supply factors, concurrent demand-side disturbances in Polish sectors may bias bilateral trade flow measurements. To instrument the Direct Exposure, we use sum of imports from China in other three *Visegrád Group* countries as the numerator. The denominator is replaced by the 5-year lagged value:

$$\Delta Direct_{j,t}^{IV} = \frac{M_{j,t}^{OV} - M_{j,t-1}^{OV}}{Y_{j,2010}^{P*} + M_{j,2010}^{P*} - E_{j,2010}^{P*}}, \tag{3}$$

#### 3.2.2 Indirect Exposure with Sectoral Linkages

Input-output linkages enable trade exposure in a given industry to generate impacts that transcend its own sector, propagating through both upstream and downstream production networks. We use Poland's 2010 input-output table to compute the weights in linkages. The selection of the 2010 input-output table is primarily motivated by two considerations: First, its compilation predates our sample period (2010–2019), ensuring that the measured inter-industry linkages remain exogenous to subsequent China-induced trade shocks. Second, this temporal alignment mitigates potential endogeneity concerns arising from reverse causality between evolving production networks and trade exposure dynamics.

The Upstream Exposure captures the indirect competitive pressure transmitted through supply chains when downstream industries face direct import competition from China. Formally, we quantify the Upstream

[4] The year 2015 is selected for denominator construction due to the quinquennial (five-year) publication cycle of sectorally disaggregated manufacturing output data by Statistics Poland. Given our study's focus spanning 2010 to 2019, the year 2015 output values provide the most temporally centered and structurally representative benchmark for normalizing trade exposure metrics across industry divisions.

Exposure for industry division $j$'s Upstream Exposure with the following equation:

$$\Delta Up_{j,t} = \sum_{g} w_{j,g}^{up} \Delta Direct_{g,t}, \tag{4}$$

which is equal to the sale-weighted average change in industry $j$'s Direct Exposure across all its downstream industries, indexed by $g$. The weights $w_{j,g}^{up}$ are defined as:

$$w_{j,g}^{up} = \frac{\mu_{j,g}^{up}}{\sum_{g'} \mu_{j,g'}^{up}}, \tag{5}$$

where the denominator represents Poland industry $j$'s total output sales to its downstream industry divisions $g'$. The numerator is the output sale of industry $j$ to a single industry $g'$. $w_{j,g}^{up}$ serves as a sectoral dependency metric, representing the proportional significance of each downstream industry $g'$ within industry $j$'s total output distribution.

Analogous to the Upstream Exposure, the Downstream Exposure which describes how Poland industry $j$ is affected by its upstream suppliers $g'$ can be defined as:

$$\Delta Down_{j,t} = \sum_{g} w_{j,g}^{down} \Delta Directint_{g,t}, \tag{6}$$

where

$$w_{j,g}^{down} = \frac{\mu_{j,g}^{down}}{\sum_{g'} \mu_{j,g'}^{down}}. \tag{7}$$

Importantly in equation (6), we use imports of intermediate goods instead of all commodities from China to measure the Downstream Exposure, following Wang et al. (2018):

$$\Delta Directint_{g,t} = \frac{Mint_{g,t}^{PC} - Mint_{g,t-1}^{PC}}{Yint_{g,2015}^{P*} + Mint_{g,2015}^{P*} - Eint_{g,2015}^{p*}}. \tag{8}$$

The denominator in equation (8) is the total absorption of intermediate inputs in the upstream suppliers $g$ (intermediate products output plus intermediate products imports minus intermediate products exports), while the numerator is the imports of intermediate inputs from China. The denominator in equation (7) is total intermediate inputs for industry $j$, whereas the numerator is the intermediate inputs from industry $j$'s upstream supplier $g$.

To instrument the Upstream Exposure and the Downstream Exposure, we replace the $\Delta Direct_{g,t}$ in equation (4) and equation (6) by $\Delta Direct_{j,t}^{IV}$ and $\Delta Directint_{j,t}^{IV}$:

$$\Delta Up_{j,t}^{IV} = \sum_{g} w_{j,g}^{up} \Delta Direct_{g,t}^{IV}, \tag{9}$$

and

$$\Delta Down_{j,t}^{IV} = \sum_{g} w_{j,g}^{down} \Delta Directint_{g,t}^{IV}, \tag{10}$$

where $\Delta Directint_{g,t}^{IV}$ is defined similar to equation (8), with simply replacing the numerator by other three *Visegrád Group* countries' intermediate products import from China:

$$\Delta Directint_{g,t}^{IV} = \frac{Mint_{g,t}^{OV} - Mint_{g,t-1}^{OV}}{Yint_{g,2010}^{P*} + Mint_{g,2010}^{P*} - Eint_{g,2010}^{P*}}. \tag{11}$$

$w_{j,g}^{up}$ and $w_{j,g}^{down}$ are the same as defined in equation (5) and equation (7).

# 4 Data and Descriptive Statistics

Our empirical analysis relies on several datasets. The following details the data sources, processing, and concordance procedures used to construct our variables for employment, trade flows, and industry linkages.

**Labor Market and Employment Definitions:** Our main sources of data on Poland labor's market are Statistical Yearbook of the Republic of Poland (2005-2023) and Yearbook of Labor Statistics (2012, 2015, 2017, 2021 and 2023) by Statistics Poland. The former presents data on the economic activity of the Polish population, employed persons, average paid employment, working conditions, wages, etc for the manufacturing divisions, while the latter supplements data for the non-manufacturing industry divisions. In order to ensure data reliability, we use data from Statistical Yearbook of Industry (2005-2023) to validate and complement data related to manufacturing divisions. Statistical Yearbook of Industry also provides us with data about characteristics of the manufacturing divisions to serve as control variables in our identification.

**Trade Flows and Concordance:** Data on international trade flows are from the UN Comtrade Database, which gives bilateral imports for 6-digit HS products. To concord these data to our input-output tables which adopt CPA 2008 classification, we first use the publicly available concordance tables from the Jordan Industrial Observatory, which provides a widely used mapping from 6-digit HS codes to 4-digit ISIC Rev.4 industries. Then we use the ISIC-NACE correspondence tables from UNSD to match ISIC 4-digit codes and NACE 2 codes. Finally, as the ISIC-NACE correspondence is not perfectly one-to-one at the 2-digit level, we manually verify the resulting NACE 2 codes against the CPA 2008 division list to ensure a complete and accurate concordance.

To isolate intermediate goods, we first filter the 6-digit HS data using the UN's Broad Economic Categories (BEC) classification, retaining only goods classified as intermediate inputs. After this filtering step, the remaining 6-digit HS codes are aggregated to the CPA 2008 classification using the identical concordance procedure described above.

**Input-Output Linkages** A final data source used in our analysis is the Poland input-output table (2005, 2010, 2015, 2020) from statistics Poland, which helps us to compute indirect trade exposure by upstream and downstream linkages between industries. Each of these input-output tables contains three sub-tables for Poland's total inputs and outputs (including imports and exports), imported input tables and domestic output tables, allowing us to make substitutions for the type of IO tables in the robustness tests. There is a one-to-one correspondence for dependent variables and independent variables in the manufacturing section, all of which have 24 divisions. In the non-manufacturing sections, however, some dependent variables are more aggregate, where one division of dependent variable may contain multiple divisions for independent variables. We use the division's output as the weight to sum up the exposure of multiple divisions for independent variables to match the granularity of the dependent variables. Domestic output data are also provided by the IO tables.

Table 2 reports the descriptive statistics of variables used in our estimates, covering 24 manufacturing divisions from 2011-2019 ($N$=216). Key manufacturing indicators show positive trends, with the value of fixed assets growing by an average of 6.308 percent annually, sold production by 6.123 percent, and real wage by 4.026 percent. Employment in the manufacturing sector has shown significant growth momentum, increasing by an average of 1.618 percent per year. The mean of the direct exposure across manufacturing industries exhibited an annualized increase of 0.67 percentage points. Change of the downstream exposure is very similar to that of the direct exposure, with a mean of 0.603 percentage points. But the upstream exposure is much smaller (0.375), partly because the imports of intermediate goods from China has grown faster than the imports of final goods. All three exposure variables show high volatility, with large standard deviations and wide ranges. The distribution of all exposure changes displays substantial rightward skewness in manufacturing industry divisions, as the mean far exceeds the median. This distributional pattern persists in our broader sample of other three *Visegrád Group* countries employed for instrumental variable construction, confirming the validity of our instrumental variables again.

Table 2: Descriptive Statistics

| **Variables** | **Obs** | **Mean** | **SD** | **Med** | **Min** | **Max** |
|---|---|---|---|---|---|---|
| 100*ΔDirect | 216 | 0.670 | 1.399 | 0.171 | -5.166 | 11.478 |
| 100*ΔDownstream | 216 | 0.603 | 1.066 | 0.228 | -1.195 | 6.955 |
| 100*ΔUpstream | 216 | 0.375 | 0.592 | 0.213 | -2.321 | 3.241 |
| 100*ΔDirect (IV) | 216 | 0.246 | 1.638 | 0.024 | -13.176 | 9.618 |
| 100*ΔDownstream (IV) | 216 | 0.237 | 1.011 | 0.069 | -12.209 | 5.039 |
| 100*ΔUpstream (IV) | 216 | 0.166 | 0.688 | 0.084 | -6.923 | 5.300 |
| (Demeaned) cost share of materials and energy | 216 | 0.040 | 0.114 | 0.068 | -0.433 | 0.213 |
| (Demeaned) cost share of external services | 216 | 0.002 | 0.035 | -0.015 | -0.089 | 0.079 |
| (Demeaned) cost share of wages and salaries | 216 | 0.006 | 0.056 | -0.008 | -0.115 | 0.157 |
| 100*Annual changes of employed persons | 216 | 1.618 | 3.478 | 1.660 | -13.291 | 12.903 |
| 100*Annual changes of economic entities | 216 | 0.422 | 3.612 | 0.870 | -20.067 | 22.314 |
| 100*Annual changes of value of fixed assets | 216 | 6.308 | 4.658 | 6.794 | -9.285 | 29.560 |
| 100*Annual changes of sold production | 216 | 6.123 | 6.620 | 5.958 | -23.832 | 35.279 |
| 100*Annual changes of real wage | 216 | 4.026 | 2.035 | 4.551 | -4.991 | 9.451 |

*Note:* $N$=216, covering 24 manufacturing divisions from 2011-2019. Variables regarding cost of shares are each normalized with mean zero. All observations are weighted by industry divisions' employed persons in 2010.

Furthermore, Figure A3 in the Appendix A illustrates 100 times changes of trade exposures across three channels from 2011 to 2019 within the Polish input-output table. It shows that the direct competition channel mainly affects manufacturing divisions that China has comparative advantage in, or runs a large trade surplus from processing and assembling trade, such as textile products, computer and electronic products. The indirect upstream and downstream shocks propagated through the value chain. Upstream impacts predominantly concentrated in manufacturing industries while demonstrating limited influence on service and primary sections. Downstream effects, however, exhibit broader economic penetration, exerting positive influences across nearly all divisions.

# 5 Estimation Results

In this section, we present the causal impact of China's trade expansion on the Polish economy. We begin with our benchmark estimates for the manufacturing sector, followed by an analysis of the underlying economic mechanisms. We conclude by aggregating the net employment effects and extending these findings to estimate the impact on the non-manufacturing sector.

## 5.1 Benchmark Regression Results

Table 3 presents the benchmark estimation results for the impacts of trade exposures on 24 manufacturing industry divisions. The dependent variable, as specified in the table, is 100 times the annual changes of log employed persons for each division. We test various specifications, defined in equation (1), including OLS and 2SLS estimations, and sequentially add or remove time fixed effects, manufacture type fixed effects, and initial industry controls. While the OLS results in Column (1) align with our hypothesis, they are likely biased by endogeneity. To address this critical issue, Columns (2)-(10) employ a 2SLS strategy, instrumenting with contemporaneous changes in other *Visegrád Group* countries.

Crucially, the 2SLS estimates provide robust evidence for our proposed mechanism. The results are stable and significant across different specifications. Focusing on our preferred model in Column (9) (which includes all three exposure variables), we find that a direct trade shock reduces manufacturing employment (elasticity of -0.827), and upstream exposure shows a similar negative impact (-2.339). The most striking finding, however, is the highly significant positive effect of downstream exposure (2.156). This demonstrates that downstream integration, through access to intermediate goods, leads to a net expansion of the manufacturing sector. This finding presents a significant departure from the literature; for instance, the seminal study by Acemoglu et al. (2016), which our estimates are otherwise comparable to, found no evidence of such a positive downstream effect.

Finally, to ensure our estimates for the direct effect are comparable to other studies, Column (10) isolates this variable (while still including all fixed effects and controls). The resulting elasticity of -0.393 is consistent with the literature, such as the -0.54 elasticity found in Autor et al. (2013), further validating the credibility of our model.

Table 3: Effect of Direct, Downstream and Upstream on Employment

**Dependent variable: 100×annual changes of employed persons**

| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** | **(9)** | **(10)** |
|---|---|---|---|---|---|---|---|---|---|---|
| Direct | -0.278** | -1.145*** | -1.138*** | -1.023*** | -1.017*** | -0.984*** | -0.940*** | -0.984*** | -0.827*** | -0.393* |
| | (0.058) | (0.314) | (0.288) | (0.341) | (0.170) | (0.301) | (0.158) | (0.301) | (0.151) | (0.212) |
| Downstream | 0.677*** | 2.386*** | 2.357*** | 1.809*** | 2.941*** | 1.767*** | 2.848*** | 1.767*** | 2.156*** | |
| | (0.054) | (0.179) | (0.216) | (0.225) | (0.309) | (0.293) | (0.258) | (0.293) | (0.251) | |
| Upstream | -0.089 | -2.041 | -2.367* | -0.866 | -3.241** | -1.289* | -3.738*** | -1.289* | -2.339*** | |
| | (0.381) | (1.347) | (1.365) | (0.777) | (1.394) | (0.783) | (1.373) | (0.783) | (0.554) | |
| Estimation Method | OLS | 2SLS | 2SLS | 2SLS | 2SLS | 2SLS | 2SLS | 2SLS | 2SLS | 2SLS |
| Time Fixed Effects | Yes | No | No | Yes | No | Yes | No | Yes | Yes | Yes |
| Manufacture Type Fixed Effects | Yes | No | No | No | Yes | No | Yes | Yes | Yes | Yes |
| Initial Industry Controls | Yes | No | Yes | No | No | Yes | Yes | No | Yes | Yes |
| Observations | 216 | 216 | 216 | 216 | 216 | 216 | 216 | 216 | 216 | 216 |

*Note:* $N$=216, covering 24 manufacturing divisions from 2011-2019. All regressions include a constant term. Dependent variable is 100 times annual changes of log employed persons. The employed persons data are collected from Statistical Yearbooks of Poland. Independent variables are 100 times annual changes of Direct / Downstream / Upstream Exposure. Initial industry controls are demeaned cost structures. All regression estimates are weighted by industry divisions' employed persons in 2010. Standard errors are clustered at the manufacturing type level. Levels of significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

### 5.2 Employment Effect

In the previous section, our analysis established the significant channel of the three trade exposures on manufacturing employment. To convert these elasticities into their more intuitive economic magnitude, we calculate the specific number of jobs gained or lost due to trade exposures. Again, focusing on the 2SLS estimates from column (9) of Table 3, we combine these coefficients with the values of the regressors reported in Table 2. Using the framework from equation 1, we can write the impacts of direct, downstream, and upstream exposures on manufacturing division $j$'s employment in year $t$:

$$\Delta L_{j,t}^{direct} = L_{j,t} \times \hat{\beta}_1 \times \Delta \widetilde{Direct}_{j,t}, \tag{12}$$

$$\Delta L_{j,t}^{down} = L_{j,t} \times \hat{\beta}_2 \times \Delta \widetilde{Down}_{j,t}, \tag{13}$$

$$\Delta L_{j,t}^{up} = L_{j,t} \times \hat{\beta}_3 \times \Delta \widetilde{Up}_{j,t}, \tag{14}$$

where $\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$ are the 2SLS coefficient estimates from column (5) of Table 3. $\Delta \widetilde{Direct}_{j,t}$ $\Delta \widetilde{Down}_{j,t}$ and $\Delta \widetilde{Up}_{j,t}$ are the actual trade exposures from China in division $j$ and year $t$. We estimate these variables by multiplying the observed trade exposures from China with the Shea's partial R-squared from the first-stage regression in Table 1, which has a value of 0.1137, 0.0918, 0.1030, respectively. We accumulate the implied employment effects for each manufacturing division $j$ over the time span of 2011 to 2019, and report them in Table 4.

Table 4 shows that direct trade shocks and upstream exposures exerted significant negative pressure on employment, accounting for a combined loss of 14,841 and 21,754 jobs, respectively. However, the most striking finding from this quantification is the overwhelmingly positive and substantial role played by the downstream exposure channel. During the same period, downstream integration (such as gaining access to intermediate goods) generated a net total of 29,562 jobs. The magnitude of this positive effect is remarkable; it not only completely offset the losses from direct shocks but also surpassed the negative impact from the upstream channel. While the manufacturing sector as a whole still registered a net decline of 7,033 jobs, the data clearly demonstrates that without the powerful cushion provided by the downstream channel, the total employment loss would have been far more severe (totaling -36,595 jobs). This positive downstream contribution was especially pronounced in key sectors like "Electrical Equipment" (+4,867), "Repair And

Table 4: Employment Effects on Manufacturing Divisions, 2011-2019

| **Division Name** | **Direct** | **Downstream** | **Upstream** | **Net** |
|---|---|---|---|---|
| Food Products | 1 | 273 | -142 | 132 |
| Beverages | -1 | 65 | -12 | 51 |
| Tobacco Products | 5 | 9 | 0 | 15 |
| Textiles | -780 | 787 | -1543 | -1536 |
| Wearing Apparel | -1849 | 1459 | -894 | -1284 |
| Leather And Related Products | -533 | 106 | -866 | -1293 |
| Wood, Cork, Straw And Wicker Products | -120 | 248 | -1278 | -1151 |
| Paper And Paper Products | -68 | 181 | -232 | -119 |
| Printing And Reproduction Of Recorded Media | 0 | 135 | -45 | 90 |
| Coke And Refined Petroleum Products | -3 | 11 | -18 | -10 |
| Chemicals And Chemical Products | -171 | 309 | -588 | -451 |
| Pharmaceutical Products | -65 | 66 | -62 | -62 |
| Rubber And Plastic Products | -597 | 1217 | -1742 | -1122 |
| Other Non-Metallic Mineral Products | -504 | 581 | -609 | -532 |
| Basic Metals | -105 | 417 | -788 | -476 |
| Metal Products | -1247 | 2359 | -2411 | -1299 |
| Computer, Electronic And Optical Products | -1212 | 1934 | -1864 | -1142 |
| Electrical Equipment | -2428 | 4867 | -2460 | -22 |
| Machinery And Equipment N.E.C. | -1039 | 3012 | -1105 | 867 |
| Motor Vehicles, Trailers And Semi-Trailers | -304 | 6367 | -641 | 5422 |
| Other Transport Equipment | -193 | 1342 | -237 | 913 |
| Furniture | -2030 | -97 | -2460 | -4586 |
| Other Manufacturing | -1596 | 810 | -1133 | -1920 |
| Repair And Installation Of Machinery And Equipment | 0 | 3105 | -623 | 2483 |
| Total | -14841 | 29562 | -21754 | -7033 |

*Note:* Each column represents the estimated impact of different channels on the number of people employed in each manufacturing division in Poland from 2011 to 2019 based on equation (12), (13) and (14).

Installation Of Machinery And Equipment" (+3,105), and "Machinery And Equipment N.E.C." (+3,012), where the downstream gains were more than sufficient to reverse the negative shocks from other channels.

The analysis thus far has focused exclusively on the manufacturing sector. However, the economic implications of trade exposures inevitably spill over into the non-manufacturing sector, which relies heavily on manufactured goods as intermediate inputs (for example, computers for IT services, vehicles for logistics, and building materials for construction). Due to data limitations, we are unable to independently estimate the elasticity of Polish non-manufacturing industries. However, given that prior literature (Acemoglu et al., 2016; Wang et al., 2018) indicates that results remain robust when non-manufacturing sectors are included, we assume the elasticities are comparable.[5] Consequently, we apply the manufacturing-derived coefficients to the exposure profiles of the non-manufacturing sector. Readers should interpret these results with caution, as they serve as a broad indication of employment trends rather than an exact calculation.

Additionally, unlike the manufacturing sector, since the Polish Statistical Office does not provide data on non-manufacturing employment corresponding to the industry-division, but only provides data corresponding to industry-section level, we use the variable "Average Paid Employment" to help the calculation.[6] According to Statistics Poland, average paid employment is defined as full-time paid employees as well as part-time paid employees in terms of full-time paid employees, while employed persons is a direct sum of numbers of full-time paid employees and part-time paid employees. We use the average paid employment to calculate the proportion of employment in each division to the total employment in the section, and then use this proportion to calculate the employment effect of trade exposure on each non-manufacturing division.[7] Specifically, we first calculate the effects on average paid employment for each division $j$, and then obtain the effects on employed persons by multiplying the ratio of employed persons and average paid employment in the corresponding section with estimated effects on average paid employment, that is for each non-

[5] In the robustness checks below, we also extend the regression to include non-manufacturing industries. While the direct and upstream competition effects lose statistical significance, they retain their negative signs; meanwhile, the positive downstream effect remains significant.

[6] In the input-output table, the Polish economy is divided into 20 sections or 77 divisions, with each section consisting of multiple divisions.

[7] This calculation relies on the implicit assumption that the ratio of full-time to part-time employees is uniform across all divisions within the same section.

manufacturing division $j$ in section $s$:

$$\Delta L_{j,t}^{direct} = \frac{L_t^s}{APL_t^s} \times APL_{j,t} \times \hat{\beta}_1 \times \Delta \widetilde{D}irect_{j,t}, \tag{15}$$

$$\Delta L_{j,t}^{down} = \frac{L_t^s}{APL_t^s} \times APL_{j,t} \times \hat{\beta}_2 \times \Delta \widetilde{D}own_{j,t}, \tag{16}$$

$$\Delta L_{j,t}^{up} = \frac{L_t^s}{APL_t^s} \times APL_{j,t} \times \hat{\beta}_3 \times \Delta \widetilde{U}p_{j,t}, \tag{17}$$

The employment effect on each non-manufacturing division can be found in Table A2 in the Appendix A. Figure 3 reports the cumulative implied employment effects for manufacturing, non-manufacturing and total divisions based on the equations above.[8] Despite the negative impact on manufacturing employment, Chinese exports to Poland boosted non-manufacturing as well as overall employment, especially in non-manufacturing. This is because for non-manufacturing industries, they are rarely affected by direct exposure. And according to our estimates, the positive downstream effect significantly outweighs the negative upstream effect, ultimately leading to an increase in employment by about 26,000 and 19,000 in non-manufacturing and all divisions respectively as a result of the Chinese trade shock. Let us illustrate this situation with a simple example. For example, Polish office administrators do not directly "import" administrative services from China, but may be able to import large quantities of cheaper office supplies and electronics from China, reducing the opportunity cost of hiring clerical staff and thus expanding their own recruitment. It should be emphasized that the Polish labor market has expanded very rapidly over the past decade. Chinese trade exposures can explain only a small part of it and is not a decisive factor. We just want to point out that China's trade with Poland is, on the whole, favorable for local employment in Poland.

### 5.3 Other Industry Outcomes

Our analysis thus far has concentrated on trade exposure's employment effects, which is a single dimension of industry adjustment. To comprehensively assess alternative adaptation mechanisms, we examine the impact of trade exposure on the Value of Fixed Assets (Column (1)), Sold Production (Column (2)), Economic Entities (Column (3)), Real Wage (Column (4)), and the Share of Material in Total Costs

[8] We only calculated the employment effects of China's trade exposure for 68 out of a total of 77 divisions as there are 9 non-manufacturing divisions for which data is not available.

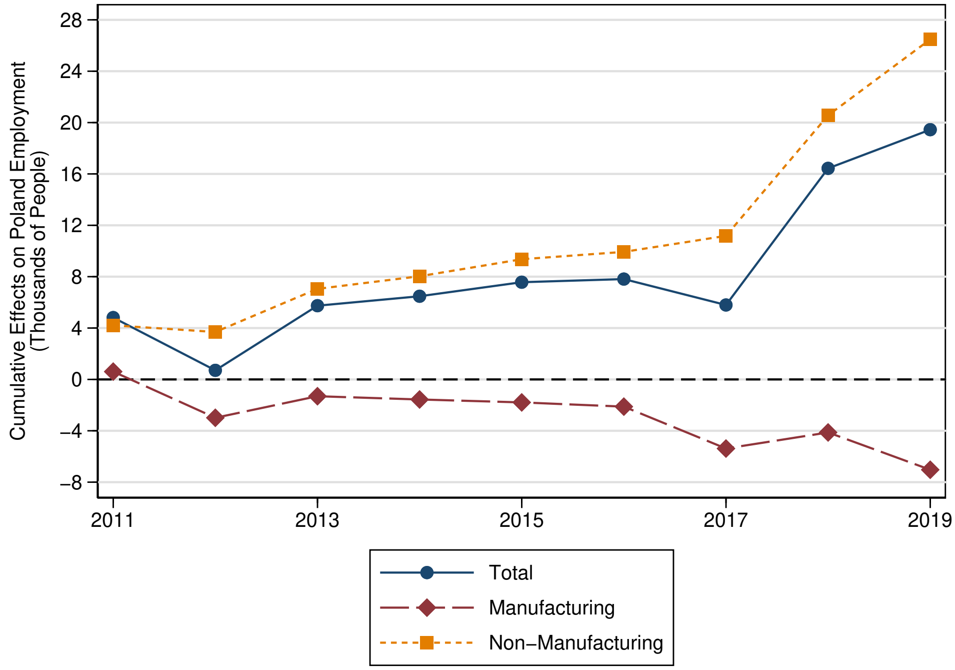


Figure 3: Cumulative Effects on Poland Employment, 2011-2019

(Column (5)) in Table 5. The regression model used is the same as equation 1, except that the explained variable on the left side of the equation has been replaced.

Consistent with our employment findings, downstream exposure exhibits a significant positive correlation with the value of fixed assets, sold production, and the number of economic entities. Conversely, upstream exposure shows a significant negative effect on these three variables. It is worth noting that although the estimated coefficient for upstream exposure is large in magnitude, the intensity of upstream exposure is inherently smaller than that of direct and downstream exposure. Therefore, the shock from Chinese intermediates competing with Polish suppliers may not be as high as the elasticity suggests.

The effects of direct exposure are more complex. As shown in Table 5, it has a significant positive impact on the value of fixed assets (Column (1)) and the number of economic entities (Column (3)), but its effect on sold production (Column (2)) is statistically insignificant. This inconsistency may reflect the dual nature of direct exposure: a negative production effect due to competition (similar to the employment effect), and a positive effect from the accession of Chinese goods into Polish manufacturing's sales and

Table 5: Estimates on Other Industry-Level Outcomes

| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** |
|---|---|---|---|---|---|
| | **Value of Fixed Assets** | **Sold Production** | **Economic Entities** | **Real Wage** | **Share of Material in Total Costs** |
| Direct | 1.49*** | 0.01 | 1.35*** | 0.30* | |
| | (0.42) | (0.75) | (0.16) | (0.17) | |
| Downstream | 3.92*** | 3.14*** | 1.31*** | -0.46*** | 0.20** |
| | (0.27) | (1.19) | (0.16) | (0.13) | (0.11) |
| Upstream | -10.35** | -7.94** | -4.70*** | -0.29 | |
| | (4.93) | (3.18) | (1.73) | (0.18) | |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Manufacture Type Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Initial Sector Controls | Yes | Yes | Yes | Yes | Yes |
| Observations | 216 | 216 | 216 | 216 | 216 |

*Note:* $N$=216, covering 24 manufacturing divisions from 2011-2019. All regressions are estimated using Two-Stage Least Squares (2SLS) and include a constant term. The dependent variables are 100 times the annual changes in fixed assets value, sold production, economic entities, real wage, and share of material in total costs, respectively. All dependent variables are computed from Statistical Yearbooks of Industry in Poland. Independent variables are 100 times annual changes of Direct / Downstream / Upstream Exposure. Initial industry controls are demeaned cost structures. Manufacturing type fixed effects and time fixed effects are included. All regression estimates are weighted by industry divisions' employed persons in 2010. Standard errors are clustered at the manufacturing type level. Levels of significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

investment channels.

Regarding real wages (Column (4)), the results are also different. Downstream exposure is significantly negatively correlated with real wages, while direct exposure shows a marginally positive correlation. The effect of upstream exposure is insignificant. The negative wage effect from downstream exposure may be because of the fact that the (previously observed) increase in employment came mainly from low-wage jobs. The aggregate expansion of Plant and Machine Operators and assemblers (ISCO-08 Group 8) supports this mechanism: increase in intermediate inputs appears to have stimulated the growth of routine, lower-paid assembly roles, which structurally pulled down average real wages (see Figure A2 in the Appendix A).

Finally, we examine the share of materials in total costs (Column (5)), which offers compelling support for our core argument. The analysis shows that downstream exposure has a significant positive impact on this share. It suggests that access to Chinese intermediates prompts a strategic shift in production methods. Firms appear to be re-optimizing their cost structure to become more material-intensive, thereby increasing the proportion of material costs in their total costs. This result underlines that these inputs are enabling Polish firms to scale up or specialize, rather than being displaced. Taken together, these results provide strong evidence for our proposed channel: Chinese imports are not merely substituting for Polish workers; they are enhancing the efficiency and scale of Polish manufacturing, which in turn generates a derived demand for labor.

# 6 Robustness Checks

## 6.1 Pooled Regression for Manufacturing and Non-Manufacturing

As mentioned above, we are unable to obtain detailed data on service trade between China and Poland. If we include non-manufacturing industries in the benchmark regression model, the direct exposures for services are all 0, which would seriously affect the accuracy of our estimates. Thus our benchmark regression can only select the manufacturing sector as sample. But to test the results of our previous discussion, we use (100 times) the annual change in average paid employment and the estimated employed persons (obtained from equation (15), (16) and (17)) as the dependent variable to run a pooled regression:

$$\Delta APL_{j,t}(\Delta L_{j,t}) = \beta_0 + \beta_1 \Delta Direct_{j,t} + \beta_2 \Delta Down_{j,t} + \beta_3 \Delta Up_{j,t} + \gamma X_{j,2010} + \lambda_J + \alpha_t + \varepsilon_{j,t}. \tag{18}$$

Unlike the benchmark regression, control variable $X_{j,2010}$ here is demeaned output of each division in 2010. $\lambda_J$ are industry type fixed effects.[9] Regression estimates are weighted by division's average paid employment in 2010, and standard errors are clustered at the sector level. Columns (1) and (2) of Table 6 present the results of pooled manufacturing and non-manufacturing regressions. Although the coefficients on the upstream effects are not statistically significant, the direct and downstream effects are still consistent with those of the benchmark regression. In columns (3) and (4), we keep the samples where $\Delta Direct_{j,t}$ is not 0 (including agriculture, mining, manufacturing, electricity and water supply sections) and run the regression again. The results are closer to the benchmark.

## 6.2 High-Order Input-Output Relationship and Other Robustness Checks on the IO Table

The direct and indirect exposure measures we constructed above actually capture only the first-order effects of trade-induced changes in direct buyer (supplier) demand (supply) on the output of the sector $j$', while neglecting the higher-order impacts arising from subsequent (antecedent) demand (supply) changes through downstream (upstream) networks. In other words, we need to consider suppliers of suppliers, suppliers of suppliers of suppliers, buyers of buyers, buyers of buyers of buyers, etc. To incorporate the full spectrum of upstream and downstream demand linkages, we substitute our initial measures $\Delta Direct_{j,t}$, $\Delta Down_{j,t}$, $\Delta Up_{j,t}$ (and their instrumental variables) with full chain measures derived from the input-output matrix. This is achieved through application of the Leontief inverse matrix to first-order upstream and downstream linkage matrices, following the methodological framework established by Acemoglu et al. (2016).[10] When extending our analysis to higher-order input-output relationships (Column (1) of Table 7), we observe that the estimates are consistent with the first-order effects in terms of direction (positive

[9] For non-manufacturing divisions, we categorized into 18 industry type according to CPA 2008 classification. For manufacturing we followed the previous classification of manufacturing type.

[10] If we stack the elements $w_{j,g}^{up}$ and $w_{j,g}^{down}$ in equation (5) and equation (7) to construct the converting matrices $W_{J\times G}^{up}$ and $W_{J\times G}^{down}$, then first-order exposures $\Delta UP_{J\times T}$ and $\Delta DOWN_{J\times T}$ can be computed from $W_{J\times G}^{up} \times \Delta DIRECT_{J\times T}$ and

Table 6: Pooled Regression for Manufacturing and Non-Manufacturing Average Paid Employment

| | **(1)** | **(2)** | **(3)** | **(4)** |
|---|---|---|---|---|
| | **Average Paid Employment** | **Employed Persons** | **Average Paid Employment** | **Employed Persons** |
| Direct | -0.758* | -0.490 | -0.829*** | -0.798*** |
| | (0.443) | (0.569) | (0.274) | (0.243) |
| Downstream | 1.347* | 1.608** | 1.723*** | 1.950*** |
| | (0.741) | (0.660) | (0.459) | (0.575) |
| Upstream | -1.186 | -2.561 | -2.109* | -2.799*** |
| | (1.522) | (1.582) | (1.242) | (0.947) |
| Time Fixed Effects | Yes | Yes | Yes | Yes |
| Industry Type Fixed Effects | Yes | Yes | Yes | Yes |
| Initial Industry Controls | Yes | Yes | Yes | Yes |
| Observations | 612 | 612 | 306 | 306 |

*Note:* $N$=612 (306), covering 68 manufacturing and non-manufacturing divisions (34 non-service divisions from 2011-2019). All regressions are estimated using Two-Stage Least Squares (2SLS) and include a constant term. Dependent variables are 100 times annual changes of average paid employment and employed persons. Independent variables are 100 times annual changes of Direct / Downstream / Upstream Exposure. Initial industry controls is demeaned output of each division in 2010. Industry type fixed effects and time fixed effects are included. All regression estimates are weighted by industry divisions' average paid employment in 2010. Standard errors are clustered at the manufacturing type level. Levels of significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

downstream and negative upstream). However, the absolute values of the coefficients across all three channels of the China shock shrink. This attenuation is likely due to the increased intensity of trade exposure measurements when replacing first-order links with infinite-order linkages.

Moreover, in our benchmark regressions, calculations for both downstream and upstream exposure rely on Poland's 2010 total input-output table (including both local and imported inputs). However, for downstream exposure, it is analytically more relevant to isolate the allocation of intermediate inputs imported from China. Thus, an IO table comprising only imported goods and services provides more precise information. Conversely, for upstream exposure, the focus is on linkages between local upstream divisions and their buyers. Using the domestic use table excludes the noise of intermediate imports from other countries. After recalculating the weights using these specific tables, the estimates remain robust (Columns (2)-(4) of Table 7). Finally, similar to Wang et al. (2018), we measure upstream exposure excluding the diagonal elements of the input-output matrix.[11] This addresses the potential double-counting problem, as both the direct and upstream exposure channels capture diagonal elements (own-sector effects) and affect employment negatively. Additionally, using identical IO tables for upstream and downstream channels can lead to multicollinearity. The results, shown in Columns (5)-(8) of Table 7, remain consistent with our baseline for the direct and downstream channels, although the upstream effect loses statistical significance while maintaining its negative sign.

## 6.3 Direct Exposure to Net Imports

Although Poland exports to China are much smaller compared to Chinese exports to Poland, in order to more accurately identify the role of direct exposure, we calculate direct exposure by replacing gross imports with net Polish imports from China:

$$\Delta NetDirect_{j,t} = \frac{NetM^{PC}_{j,t} - NetM^{PC}_{j,t-1}}{Y^{P*}_{j,2015} + M^{P*}_{j,2015} - E^{P*}_{j,2015}}, \tag{19}$$

$W^{down}_{J\times G} \times \Delta DIRECT_{J\times T}$, respectively. Replacing $W^{up}_{J\times G}$ and $W^{down}_{J\times G}$ by $W^{upho}_{J\times G} = (I - W^{up}_{J\times G})^{-1}$ and $W^{downho}_{J\times G} = (I - W^{down}_{J\times G})^{-1}$, we can obtain $\Delta UP^{ho}_{J\times T}$ and $\Delta DOWN^{ho}_{J\times T}$.

[11] That is, replace equation (5) by $w^{up}_{j,g\neq j} = \frac{\mu^{up}_{j,g}}{\sum_{g'\neq j}\mu^{up}_{j,g'}}$ and $w^{up}_{j,j} = 0$.

Table 7: High-Order Input-Output Relationship and Other Robustness Checks on the IO Table

**Dependent variable: 100×annual changes of employed persons**

| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** |
|---|---|---|---|---|---|---|---|---|
| Direct | -0.33 | -0.87*** | -0.89*** | -0.91*** | -1.47*** | -1.30*** | -1.46*** | -1.27*** |
| | (0.60) | (0.20) | (0.14) | (0.19) | (0.50) | (0.33) | (0.53) | (0.36) |
| Downstream | 0.44*** | 1.29*** | 2.10*** | 1.26*** | 2.25*** | 1.34*** | 2.23*** | 1.31*** |
| | (0.04) | (0.14) | (0.25) | (0.14) | (0.18) | (0.13) | (0.17) | (0.13) |
| Upstream | -0.76*** | -1.69*** | -1.94*** | -1.39*** | -0.84 | -1.19 | -0.67 | -0.89 |
| | (0.27) | (0.34) | (0.38) | (0.17) | (1.83) | (1.12) | (1.56) | (1.02) |
| Upstream Type | Higher-Order | Total | Domestic | Domestic | Total | Total | Domestic | Domestic |
| Downstream Type | Higher-Order | Import | Total | Import | Total | Import | Total | Import |
| Including Diagonal | Yes | Yes | Yes | Yes | No | No | No | No |
| Observations | 216 | 216 | 216 | 216 | 216 | 216 | 216 | 216 |

*Note:* $N$=216, covering 24 manufacturing divisions from 2011-2019. All regressions are estimated using Two-Stage Least Squares (2SLS) and include a constant term. Dependent variable is 100 times annual changes of log employed persons. The employed persons data are collected from Statistical Yearbooks of Poland. Independent variables are 100 times annual changes of Direct / Downstream / Upstream Exposure computed by the Leontief inverse method or from different types of IO tables. Initial industry controls are demeaned cost structures, which are included in the regression. Manufacturing type fixed effects and time fixed effects are included. All regression estimates are weighted by industry divisions' employed persons in 2010. Standard errors are clustered at the manufacturing type level. Levels of significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

similarly the instrument variable for $\Delta NetDirect_{j,t}$ will be:

$$\Delta NetDirect^{IV}_{j,t} = \frac{NetM^{OV}_{j,t} - NetM^{OV}_{j,t-1}}{Y^{P*}_{j,2010} + M^{P*}_{j,2010} - E^{P*}_{j,2010}}. \tag{20}$$

As shown in Table 8, replacing the direct effect measure from gross imports to net imports yields qualitatively consistent findings with benchmark results Table 3 and Table 5.

### 6.4 Using WIOD's IO Coefficients as Weights

To alternatively estimate the direct and indirect exposure to Chinese imports, we use Inter-Country Input Output (ICIO) tables from the World Input Output Database (WIOD). The 2016 version data covers 56 industries and 44 countries (including Poland) from 2000 to 2014. We match the HS6 trade data to the WIOD industry classification and replace Poland IO table 2010 and 2015 in equation (5) and (7) with ICIO table 2010 and 2014, respectively. After removing two industries for which we do not have import/export and employment data, we obtain a panel of 54 industries. We still estimate this panel using the benchmark regression to get Table 9. Compared to Table 3 and Table 6, the results are roughly consistent, especially for the indirect effects. Our main story still holds.

## 7 Conclusion

The global economic landscape of the last three decades has been defined by the profound reorganization of production and the integration of China into the world economy. The explosive expansion of China's manufacturing capacity has fundamentally altered international trade patterns. In this paper, we focus on the labor market consequences of this integration for Poland, an advanced emerging market undergoing rapid re-industrialization. Understanding the consequences of these developments is crucial, as the dominant narrative derived from the United States emphasizes the disruptive effects of import competition. We analyze the causal impact of the rise of China on the performance of local labor markets in Poland during the period 2011 to 2019, using an instrumental variable approach that explicitly disentangles the upstream and downstream channels of trade exposure.

The key message derived from our analysis is that trade exposure has acted as a "China Boost" more

Table 8: Accounting for Net Imports in Direct Exposure

| | (1) Employed Persons | (2) Value of Fixed Assets | (3) Sold Production | (4) Economic Entities | (5) Real Wage |
|---|---|---|---|---|---|
| Net Direct | -0.770*** | 1.957*** | 0.460 | 1.621*** | -0.264 |
| | (0.286) | (0.470) | (0.513) | (0.200) | (0.600) |
| Downstream | 2.108*** | 3.982*** | 3.118*** | 1.370*** | -0.415*** |
| | (0.254) | (0.294) | (1.170) | (0.174) | (0.092) |
| Upstream | -2.438*** | -11.338** | -8.855*** | -5.274*** | -0.857 |
| | (0.578) | (4.879) | (2.005) | (1.905) | (1.617) |
| Time Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Initial Industry Controls | Yes | Yes | Yes | Yes | Yes |
| Observations | 216 | 216 | 216 | 216 | 216 |

*Note:* $N$=216, covering 24 manufacturing divisions from 2011-2019. All regressions are estimated using Two-Stage Least Squares (2SLS) and include a constant term. Dependent variable are 100 times annual changes of log employed persons, fixed assets value, sold production, economic entities and real wages, respectively. Independent variables are 100 times annual changes of Direct (net import)/ Downstream / Upstream Exposure. Initial industry controls are demeaned cost structures. Manufacturing type fixed effects and time fixed effects are included. All regression estimates are weighted by industry divisions' employed persons in 2010. Standard errors are clustered at the manufacturing type level. Levels of significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 9: Direct, Downstream and Upstream Effects on Employment Using WIOD

**Dependent variable: 100×annual changes of employed persons**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Direct | -0.969 | -0.048 | -0.667 | 0.100 | -0.266 |
| | (0.744) | (0.693) | (0.735) | (0.623) | (0.651) |
| Downstream | 2.611*** | 3.469*** | 1.825*** | 2.164*** | 2.770*** |
| | (0.225) | (0.443) | (0.083) | (0.009) | (0.604) |
| Upstream | -2.462 | -6.564** | -1.450 | -4.313*** | -4.424** |
| | (2.397) | (2.563) | (1.720) | (1.304) | (1.850) |
| Time Fixed Effects | No | No | Yes | Yes | Yes |
| Industry Type Fixed Effects | No | Yes | No | Yes | Yes |
| Initial Industry Controls | No | Yes | No | Yes | Yes |
| Observations | 171 | 171 | 171 | 171 | 486 |

*Note:* $N$=171(486), covering 19 WIOD manufacturing divisions (total 54 divisions) from 2011-2019. All regressions are estimated using Two-Stage Least Squares (2SLS) and include a constant term. Dependent variable is 100 times annual changes of log employed persons. Independent variables are 100 times annual changes of Direct / Downstream / Upstream Exposure computed from WIOD's IO tables. Initial industry controls are demeaned cost structures. All regression estimates are weighted by industry divisions' employed persons in 2010. Standard errors are clustered at the manufacturing type level. Levels of significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

than a “China Shock”, presenting a trajectory diametrically opposite to the adverse labor market effects observed in the United States. We attribute this divergence to the distinct composition of trade: unlike the U.S. focus on final goods, Poland’s imports are concentrated in intermediate inputs that function as strategic complements to domestic labor, effectively lowering production costs for downstream EU markets. Although direct competition caused job losses in specific sectors like textiles, these were more than offset by productivity-driven gains in industries leveraging these inputs—such as electrical equipment—and by growth in the non-manufacturing sector . Consequently, the trade deficit emerges not as a sign of weakness, but as a mechanism of vertical specialization that fuels aggregate employment growth.

Our conclusions for Poland may be representative for other Central and Eastern European (CEE) economies to the extent that they have also deeply integrated into Global Value Chains. An important avenue for future research would be to investigate whether the positive “input channel” observed here persists in the long run as China moves up the value chain, and to further explore the spillover effects on the service sector with more granular data.

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# A Supplementary Tables and Figures

Table A1: Manufacturing Type for Industry Divisions

| ID | Division Name | Manufacturing Type |
|---|---|---|
| 6 | Food Products | Labor-Intensive |
| 7 | Beverages | Labor-Intensive |
| 8 | Tobacco Products | Capital/Resource-Intensive |
| 9 | Textiles | Labor-Intensive |
| 10 | Wearing Apparel | Labor-Intensive |
| 11 | Leather And Related Products | Labor-Intensive |
| 12 | Wood, Cork, Straw And Wicker Products | Labor-Intensive |
| 13 | Paper And Paper Products | Labor-Intensive |
| 14 | Printing And Reproduction Of Recorded Media | Labor-Intensive |
| 15 | Coke And Refined Petroleum Products | Capital/Resource-Intensive |
| 16 | Chemicals And Chemical Products | Technology-Intensive |
| 17 | Pharmaceutical Products | Technology-Intensive |
| 18 | Rubber And Plastic Products | Capital/Resource-Intensive |
| 19 | Other Non-Metallic Mineral Products | Capital/Resource-Intensive |
| 20 | Basic Metals | Capital/Resource-Intensive |
| 21 | Metal Products | Capital/Resource-Intensive |
| 22 | Computer, Electronic And Optical Products | Technology-Intensive |
| 23 | Electrical Equipment | Technology-Intensive |
| 24 | Machinery And Equipment N.E.C. | Technology-Intensive |
| 25 | Motor Vehicles, Trailers And Semi-Trailers | Technology-Intensive |
| 26 | Other Transport Equipment | Technology-Intensive |
| 27 | Furniture | Labor-Intensive |
| 28 | Other Manufacturing | Other Manufacturing |
| 29 | Repair And Installation Of Machinery And Equipment | Technology-Intensive |

*Note:* The ID and Division Name information are from input-Output tables by Statistics Poland.

Table A2: Employment Effects on Non-Manufacturing Divisions, 2011-2019

| **Division Name** | **Direct** | **Downstream** | **Upstream** | **Net** |
|---|---|---|---|---|
| Agriculture, Forestry And Fishing | -174 | 5209 | -649 | 4386 |
| Crop And Animal Production, Hunting | 0 | 131 | -130 | 1 |
| Forestry And Logging | 0 | 12 | 0 | 12 |
| Mining Of Coal And Lignite | 0 | 702 | -134 | 568 |
| Other Mining And Quarrying | -2 | 220 | -84 | 134 |
| Electricity, Gas, Steam And Air Conditioning Supply | 0 | 670 | -391 | 279 |
| Water Collection, Treatment And Supply | 0 | 176 | -77 | 99 |
| Sewerage | 0 | 343 | -180 | 163 |
| Waste Collection, Treatment And Disposal Activities | 0 | 162 | -68 | 94 |
| Construction | 0 | 7086 | -756 | 6330 |
| Wholesale And Retail Trade And Repair Of Motor Vehicles | 0 | 2103 | -535 | 1569 |
| Wholesale Trade | 0 | 2730 | -5487 | -2757 |
| Retail Trade | 0 | 2887 | -6395 | -3508 |
| Land And Pipeline Transport | 0 | 5079 | -1806 | 3273 |
| Water Transport | 0 | 412 | -298 | 114 |
| Warehousing; Postal And Courier Services | 0 | 167 | -213 | -46 |
| Accommodation | 0 | 163 | -168 | -4 |
| Food And Beverage Service Activities | 0 | 119 | -213 | -93 |
| Publishing Services | -13 | 57 | -83 | -39 |
| Motion Picture, Video And Television Production | 0 | 13 | -1 | 12 |
| Programming And Broadcasting Services | 0 | 4 | -17 | -13 |
| Telecommunications Services | 0 | 398 | -114 | 284 |
| Computer Programming, Consultancy Services | 0 | 602 | -224 | 378 |
| Information Services | 0 | 26 | -38 | -12 |
| Financial Services | 0 | 371 | -456 | -86 |
| Insurance Services | 0 | 21 | -87 | -66 |
| Services Auxiliary To Financial Services And Insurance Services | 0 | -4 | -41 | -44 |
| Real Estate Activities | 0 | 326 | -278 | 48 |
| Legal And Accounting Services | 0 | 83 | -454 | -370 |
| Management Consulting Services | 0 | 205 | -399 | -194 |
| Architectural And Engineering Services | 0 | 404 | -373 | 31 |
| Scientific Research And Development Services | 0 | 552 | -852 | -299 |
| Advertising And Market Research Services | 0 | 17 | -120 | -103 |
| Other Professional, Scientific And Technical Services | 0 | -27 | -92 | -119 |
| Veterinary Services | 0 | 41 | -2 | 39 |
| Rental And Leasing Services | 0 | 367 | -123 | 244 |
| Employment Services | 0 | 134 | -579 | -445 |
| Tourism Activities | 0 | 7 | -5 | 2 |
| Security And Investigation Services | 0 | 377 | -300 | 77 |
| Services To Buildings And Landscape | 0 | 269 | -227 | 42 |
| Office Administrative And Other Business Support Services | 0 | 40 | -69 | -28 |
| Public Administration Services | 0 | 10494 | -3331 | 7163 |
| Education Services | 0 | 4457 | -1394 | 3063 |
| Human Health Services | 0 | 4643 | -383 | 4260 |
| Social Works Services | 0 | 97 | 0 | 97 |
| Creative, Arts And Entertainment Services | -2 | 148 | -17 | 129 |
| Library, Archive, Museum Services | 0 | 75 | -104 | -30 |
| Gambling And Betting Services | 0 | 14 | 0 | 14 |
| Sporting Services And Amusement And Recreation Services | 0 | 74 | -10 | 64 |
| Services Furnished By Membership Organisations | 0 | 1061 | -227 | 834 |
| Repair Services Of Personal And Household Goods | 0 | 848 | -49 | 799 |
| Other Personal Services | 0 | 461 | -411 | 50 |
| Total | -193 | 55030 | -28444 | 26394 |

*Note:* Each column represents the estimated impact of different channels on the number of people employed in each non-manufacturing division in Poland from 2011 to 2019 based on equation (15) (16) (17). Employment-related data are not available for 9 of the 53 non-manufacturing divisions, so only 44 divisions are shown in this table.

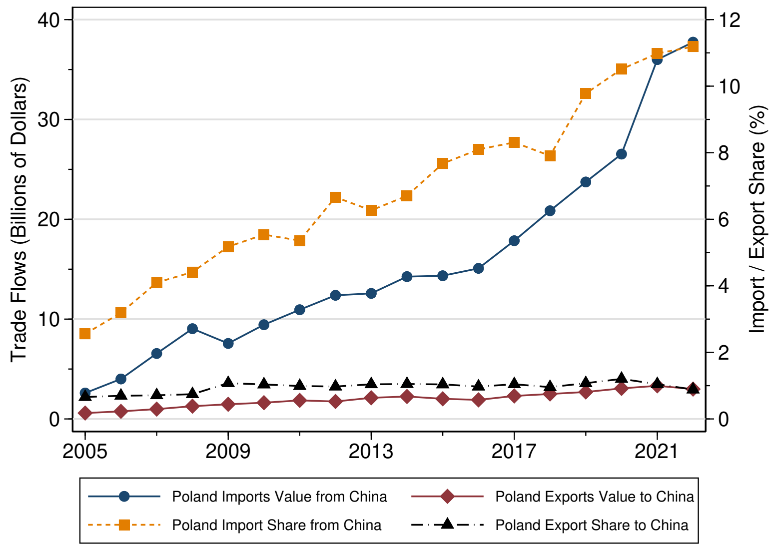


Figure A1: Bilateral trade between Poland and China. Data source: the UN Comtrade.

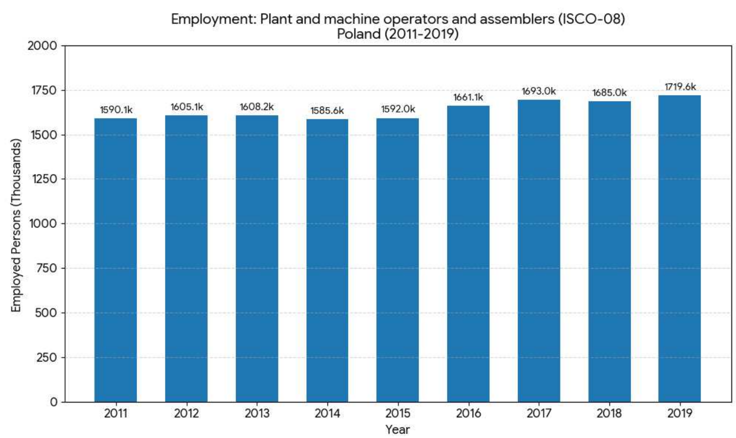


Figure A2: Employment of Plant and machine operators and assemblers in Poland from 2011 to 2019.

Data source: Eurostat LFS series.

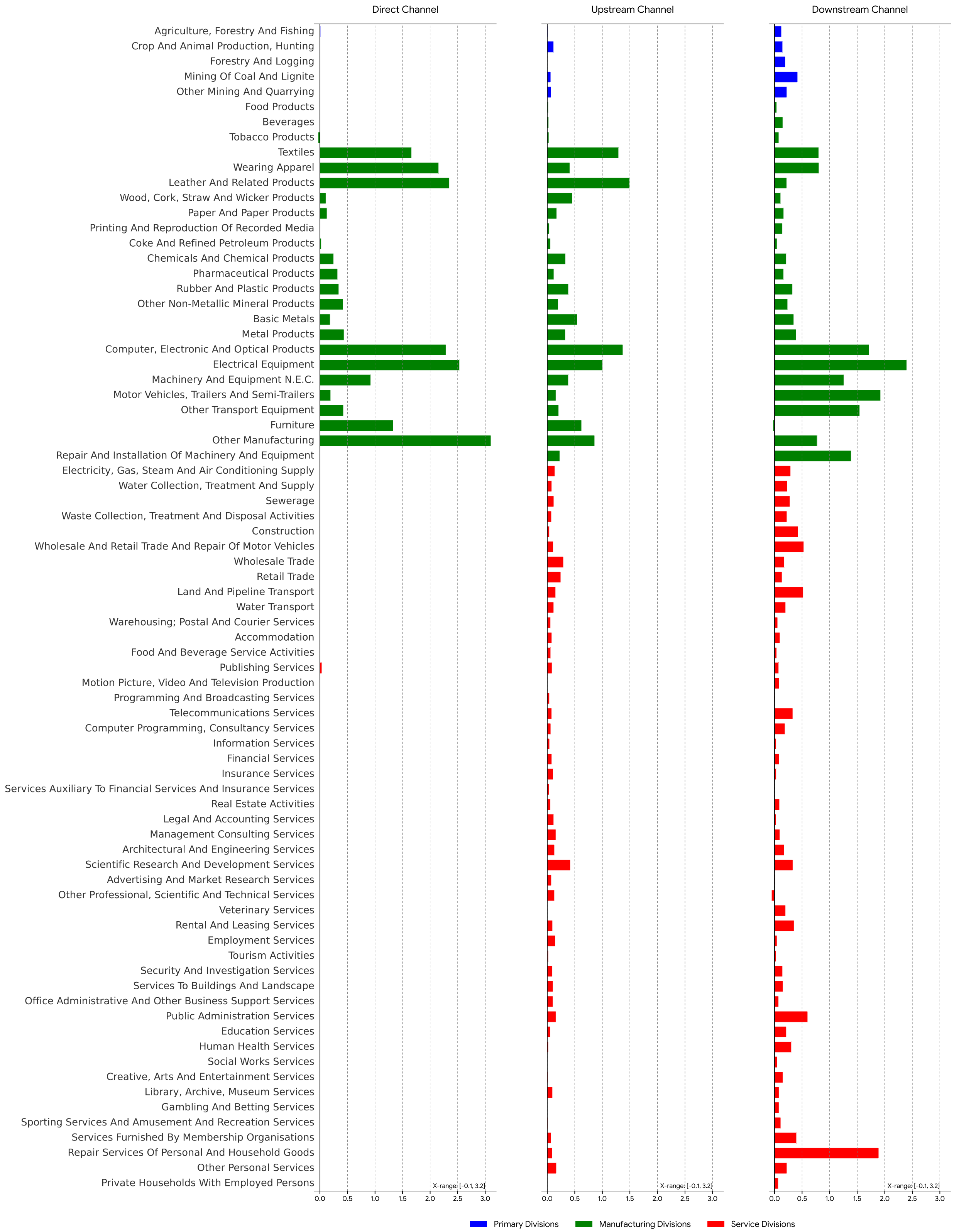


Figure A3: 100 Times Changes of Direct, Downstream and Upstream Exposure, 2011-2019