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Preface

This dissertation consists of three chapters that examine questions in the fields of international trade and development economics. Specifically, I study how resource demand shocks in the global market affect economic outcomes in resource-exporting countries, and how industrial policy affects firms' outcomes in developing economies.

Chapter 1 is titled "The Impact of Resource Demand Shocks on Manufacturing: Evidence from Indonesia". Rising global demand for vegetable oils has driven the expansion of oil palm plantations and of the vegetable oil industry in Indonesia. I use the palm oil boom in Indonesia as a natural experiment to examine the impact of the expansion of resource-based industries on other manufacturing sectors. In particular, I examine whether competition for intermediate inputs plays a role in propagating the effects of the commodity boom. First, to identify local shocks, I exploit regional variation in suitability for oil palm cultivation at the district level, obtained from Gehrke and Kubitza (2021). Second, to investigate potential crowding-out effects in input markets, I construct a measure of input similarity using sector-level input-output data. Then, I examine how exposure to the boom affects local employment and manufacturing outcomes, such as sales and labor productivity.

I find that highly exposed regions tend to have higher growth in total employment, which is mainly driven by higher growth in agricultural employment. While the export boom led to growth in the vegetable oil industry, it reduced sales and labor productivity in other manufacturing sectors. In terms of employment, there was no significant effect on total manufacturing employment, but the growth of non-production workers in highly exposed regions was slower than that in less exposed regions. I also find that the negative effects of the boom were particularly pronounced among industries that use inputs similar to those of the vegetable oil industry. The findings suggest that competition between the commodity and manufacturing sectors occurred not only in labor markets but also in intermediate input markets.

Chapter 2 is titled "Quantifying the Effects of Commodity Booms on Regional and Sectoral Outcomes". Based on the empirical evidence from Chapter 1, I develop a dynamic spatial equilibrium model that builds on Desmet et al. (2018) and Conte et al. (2021) to quantify the aggregate and welfare effects of the commodity boom. My main contribution is to revisit the 'Dutch disease' hypothesis using a multi-sector spatial model that incorporates both static and dynamic externalities in the manufacturing sectors. The model also features sectoral linkages, internal migration, and both internal and international trade. I calibrate the model to the Indonesian economy, taking 2000 as the baseline year, and simulate the response to the commodity boom that the country experienced in the 2000–2011 period. I then use the calibrated model to quantify the effects of the commodity boom by shutting down the commodity export shocks in the 2000s.

First, I find that while the commodity boom increased GDP during the boom period, it potentially reduced welfare. Second, the effects of the commodity boom varied across sectors. By the end of the boom period, the GDP shares of the commodity and service sectors increased (by 7.86 percentage points (p.p.) and 2.40 p.p., respectively), while manufacturing contracted. In particular, the non-food manufacturing share declined by 7.67 p.p. Third, the impact of the commodity boom was heterogeneous across regions. By the end of the boom period, regions outside Java experienced a 10.62% increase in GDP, while Java—the more industrialized region—experienced a 4.61% decline. Lastly, I show that agglomeration economies and dynamic externalities (or learning-by-doing) play important roles in amplifying the impact of the commodity boom. Agglomeration economies strengthen the positive impact of the commodity boom on aggregate GDP during the boom period. In contrast, dynamic externalities in manufacturing amplify the negative effects on aggregate GDP and on the regional GDP of the more industrialized areas after the boom period.

Chapter 3 is titled "Firm Responses to Industrial Policy: Evidence from Local Content Requirement (LCR) Policy". Governments in both developing and developed countries increasingly use industrial policy to promote domestic production and technological upgrading. One of the policy instruments is the local content requirement (LCR), which mandates that targeted sectors or firms source a certain proportion of inputs from domestic suppliers. Using detailed manufacturing plant-level data from Indonesia, I study the effects of the LCR policy in the telecommunications sector. First, I investigate how the LCR policy affects firms' input composition and cost structure. Second, I estimate the impacts of the policy on firm-level outcomes, such as sales, employment, and value-added. Lastly, I examine whether firms in upstream sectors benefit from the policy through production linkages.

To identify causal effects, I exploit cross-plant variation in exposure to the LCR policy in the telecommunications sector. I measure plant-level exposure based on the share of LCR-targeted products in each plant's output. I use pre-policy data from 2006 to mitigate endogeneity concerns, as firms may have adjusted their product mix in response to the LCR policy. Then, I use a Two-Way Fixed Effects (TWFE) model and a dynamic extension of the TWFE model to examine both static and dynamic effects. While the policy is intended to promote local sourcing, the results suggest they have no significant impact on firm sales. Firms tend to experience higher labor costs and a decline in labor productivity. There are short-term positive effects on employment among upstream firms, but these effects dissipate in the longer run.

Chapter 1

The Impact of Resource Demand Shocks on Manufacturing: Evidence from Indonesia

1.1 Introduction

Primary commodities remain an important source of export earnings for many low- and middle-income countries. When global demand for raw materials rises, resource-rich economies often experience rapid expansion in commodity-producing sectors. Although commodity booms often increase incomes for workers and landowners within these sectors, they may indirectly constrain other tradable sectors, such as manufacturing, through increased competition for factors of production and intermediate inputs. Crowding-out effects in factor markets are among the key mechanisms discussed in the 'Dutch disease' literature (Corden and Neary (1982), Krugman (1987)), which highlights the potential adverse effects of commodity booms on other tradable sectors.

In this chapter, I study the impact of resource demand shocks on local manufacturing in the context of a developing economy. I use the palm oil boom in Indonesia as a natural experiment to examine the impact of the expansion of resource-based industries on other manufacturing sectors. As shown in Figure 1.1, vegetable oil export values increased substantially after 2005 and remained high even after the decline in vegetable oil prices in 2011, suggesting continuous production to meet foreign demand. This trend is different from other main commodities, such as mineral products and rubber, whose export values declined after 2010. Rising demand for vegetable oils has driven the expansion of oil palm plantations and the vegetable oil industry in Indonesia. Palm oil is primarily used as an input for processed food, consumer and industrial products, and bio-diesel[1].

Following Gehrke and Kubitza (2021) and Edwards (2024a), I exploit regional variation in suitability for oil palm cultivation to measure local exposure to the palm oil boom. Suitability is measured using district-level oil palm attainable yield data from Gehrke and Kubitza (2021), based on the Food and Agriculture Organization–Global Agro-Ecological Zones (FAO-GAEZ) dataset. I then examine how exposure to the boom affects local employment and manufacturing outcomes, such as sales and labor productivity. To investigate potential crowding-out effects in input markets, I construct a measure of input similarity using sector-level input-output data.

I document several findings. First, highly exposed regions tend to have a higher growth in total employment, mainly driven by a higher growth in agricultural employment. Second, while the export boom led to growth in the vegetable oil industry, it reduced sales and labor productivity in other manufacturing sectors. Third, the adverse effects of the boom are particularly pronounced among industries that use similar inputs to the vegetable oil industry, suggesting that competition in intermediate input markets is an important channel. Lastly, although there is no significant effect on total manufacturing employment, growth in non-production workers was slower in more exposed regions.

This paper contributes to the literature on the economic impacts of natural resource booms and resource-based specialization (van der Ploeg (2011), Cust and Poelhekke (2015)). While some studies predict and find empirical evidence of negative impacts on manufacturing sectors (Harding and Venables (2016), Haas and Poelhekke (2019), Benguria et al. (2023), Branstetter and Laverde-Cubillos (2024), Kedrosky and Palma (2023)), other studies find evidence that challenges the Dutch disease hypothesis (Allcott and Keniston (2018), Cust et al. (2019), Kraus et al. (2023)). These studies highlight several channels through which resource booms may benefit local manufacturing, including increased local demand, improved public goods provision, and production linkages with resource sectors. Despite these contributions, there is limited empirical evidence on whether resource booms crowd out other sectors through competition in intermediate input markets. I contribute to this literature by providing suggestive evidence that competition for inputs

[1]This is based on the 2010 Indonesian Input-Output Table.

can be an important channel through which resource booms affect local manufacturing.

Outline The remainder of this chapter is structured as follows. Section 1.2 provides background on commodity export growth in Indonesia and describes the data used in the analysis. Section 1.3 presents the empirical strategy, and Section 1.4 presents the results. Section 1.5 concludes.

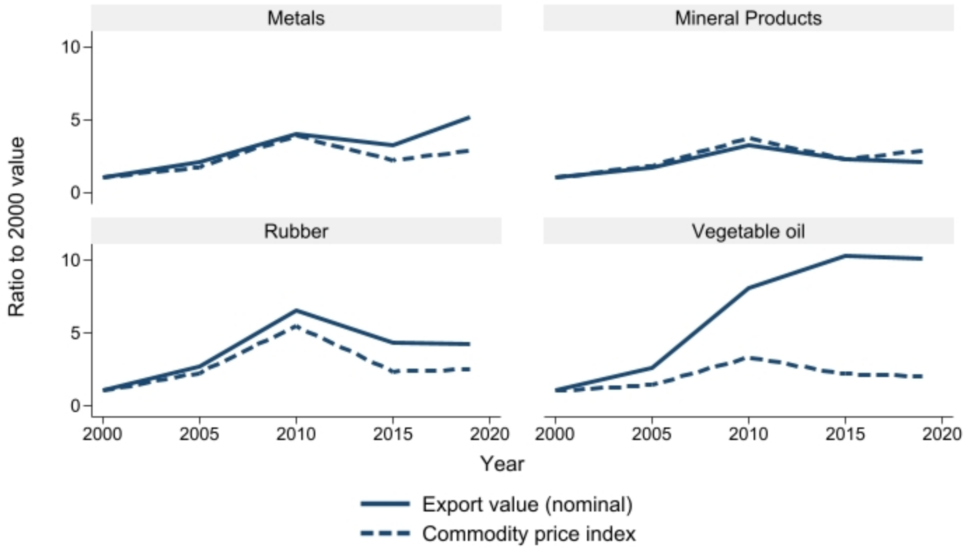


Figure 1.1: Indonesia's export value (nominal, ratio to 2000): main commodities

Notes: Data sources: UN Comtrade and IMF Primary Commodity Price System databases. The coal price index is used for mineral products, and the palm oil price index is used for vegetable oils. Coal and palm oil are Indonesia's main export commodities.

1.2 Background and data

1.2.1 Commodity export growth in Indonesia

During the 2000s commodity boom, the composition of Indonesia's exports changed substantially[2]. Table 2.A.1 reports the sectoral shares of real export values in 2000 and 2010. Over this period, commodity-based sectors, such as mining and quarrying, estate crops, manufacture of food, beverage, and tobacco, and manufacture of basic metals, recorded the largest increases in their share of total real exports.

[2]This study focuses on the post-2000 commodity boom, particularly the 2005–2011 period. For historical context, see Hill and Pasaribu (2024), which reviews Indonesia's resource booms in the 1970s and 2000s.

In terms of the spatial distribution of export activity, Table 2.A.2 presents the regional shares of total real export values in 2000 and 2010. Apart from the capital region of Jakarta, the provinces with the largest increases in export shares were Riau (+9 p.p.) and South Kalimantan (+3 p.p.). Both are major exporters of commodities. In contrast, West Java, which hosts a large share of non-commodity manufacturing firms, experienced the largest decline, with its share of total real exports falling by 24 p.p.

Palm oil sector Over the past few decades, Indonesia has become the world's largest exporter of palm oil. In 2019, it produced around 42.5 million tons–accounting for approximately 58% of global supply (USDA Foreign Agricultural Service (2019)). Figure 1.2 illustrates the surge in Indonesia's palm oil exports, with the sharpest increase in nominal export value occurring between 2006 and 2011. Most of these exports went to major markets such as China and India[3]. While the export boom was large, not all Indonesian provinces are suitable for oil palm cultivation. Most palm oil production is concentrated on the islands of Sumatra and Borneo (Kalimantan), which also contain a large share of the country's tropical forests[4].

The expansion of Indonesia's palm oil sector occurred not only through the growth of plantation areas but also through a sharp increase in palm oil processing industry. According to the Indonesian Annual Census of Manufacturing, the number of manufacturing plants in the vegetable oil sector rose from 292 in 2000 to 842 in 2015. Most of these are palm oil mills that convert oil palm kernels into crude palm oil (CPO), as well as refineries that further process CPO into refined palm oil. Once processed, CPO and refined palm oil are either exported or used domestically as inputs in downstream industries. Palm oil is primarily used in processed food (80%), with the remainder used in consumer and industrial products–such as basic chemicals, soap, and cosmetics (7%)–and biodiesel (13%) (Edwards (2024b)).

[3]According to data from Statistics Indonesia, China and India accounted for 26.6% and 15.8% of Indonesia's total palm oil export volume in 2012, respectively.

[4]The expansion of palm oil plantations has been closely linked to deforestation (see Naylor et al. (2019), Qaim et al. (2020), Cisneros et al. (2021), Balboni et al. (2021), Busch et al. (2022), Hsiao (2024)). Busch et al. (2022) and Hsiao (2024) study how trade policies imposed on the palm oil industry impact global emissions.

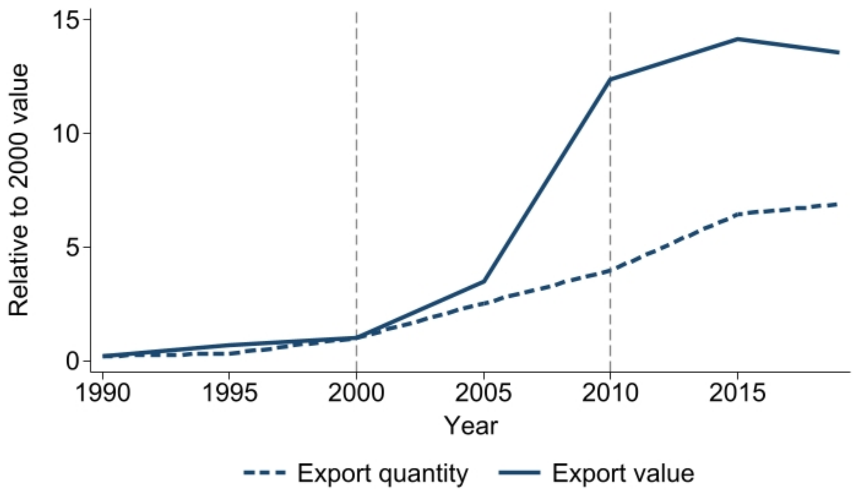


Figure 1.2: Indonesia's palm oil export

Notes: Data source: UN Comtrade (HS code: 1511).

1.2.2 Data

Regional data I construct a district-level panel dataset for the years 1990, 2000, and 2010 by combining data on oil palm plantation area, agro-climatic suitability, employment, population, and other district characteristics. A district is an administrative unit within a province and is equivalent to a city. I obtain data on crop plantation area from the Ministry of Agriculture database and palm oil attainable yield from Gehrke and Kubitza (2021). Data on employment, population, and other characteristics are obtained from the Population Census, the Integrated Public Use Microdata Series (IPUMS) database (Ruggles et al. (2024)), and the World Bank's Indonesia Database for Policy and Economic Research (INDO-DAPOER). The district-level panel is constructed based on 1993 administrative boundaries to match the spatial aggregation of the palm oil attainable yield data from Gehrke and Kubitza (2021).

Manufacturing data I use data from the Indonesian Annual Survey of Manufacturing Plants, which covers medium and large firms with 20 or more employees. The dataset includes plant-level information on sales, employment, industry classification (up to five-digit ISIC codes), and plant location. I use sales and employment as the main outcome variables. For the main analysis, I aggregate the data to the four-digit ISIC level for the years 2001 and 2011, and merge it with the district-level panel dataset described above.

Inter-sectoral linkages I merge the district-sector dataset with inter-industry linkage information from the 2010 Indonesian Input–Output (IO) matrix, which includes 185 sectors. While most sectors are defined at the four-digit ISIC level, some are aggregated at the three-digit level. This IO matrix is used to construct a sector-level measure of input similarity.

1.3 Empirical strategy

Regional exposure to the palm oil boom I use the Indonesian palm oil boom as a natural experiment to investigate the impact of the expansion of resource-based industries on local employment and manufacturing outcomes. Following Gehrke and Kubitza (2021) and Edwards (2024a), I use variation in agro-climatic suitability for oil palm cultivation across districts to measure regional exposure to palm oil demand shocks. I obtain oil palm agro-climatic suitability data from Gehrke and Kubitza (2021). They calculate the average agro-climatically attainable yield for oil palm at the district level using the FAO-GAEZ database. Specifically, they use the agro-climatically attainable yield for rain-fed oil palm under low-input conditions for the period 1961–1990.

I construct a continuous measure of regional exposure (R_r) by interacting time-invariant district-level palm oil attainable yield (in ton/ha) with the observed expansion in oil palm plantation area (in ha) at the national level between 2000 and 2010:

$$R_r \;=\; \text{AttainableYield}_r \times \Delta\text{OilPalmArea}^{IDN}_{2000-2010} \tag{1.1}$$

Regions with high exposure are those where land is highly suitable for oil palm cultivation.

District-level analysis Using the regional exposure measure defined in equation (1.1), I estimate the impact of the palm oil boom on local employment:

$$\Delta y_r = \alpha\, R_r + \phi_m + X'_{rt_0}\,\delta + v_r \tag{1.2}$$

where Δy_r is the change in total employment in district r between 2000 and 2010. Although most of the variation in R_r comes from geographic factors such as soil and climate, which are plausibly exogenous, it may still be correlated with a district's initial level of development. Table 1.1 compares observable characteristics between districts with regional exposure above

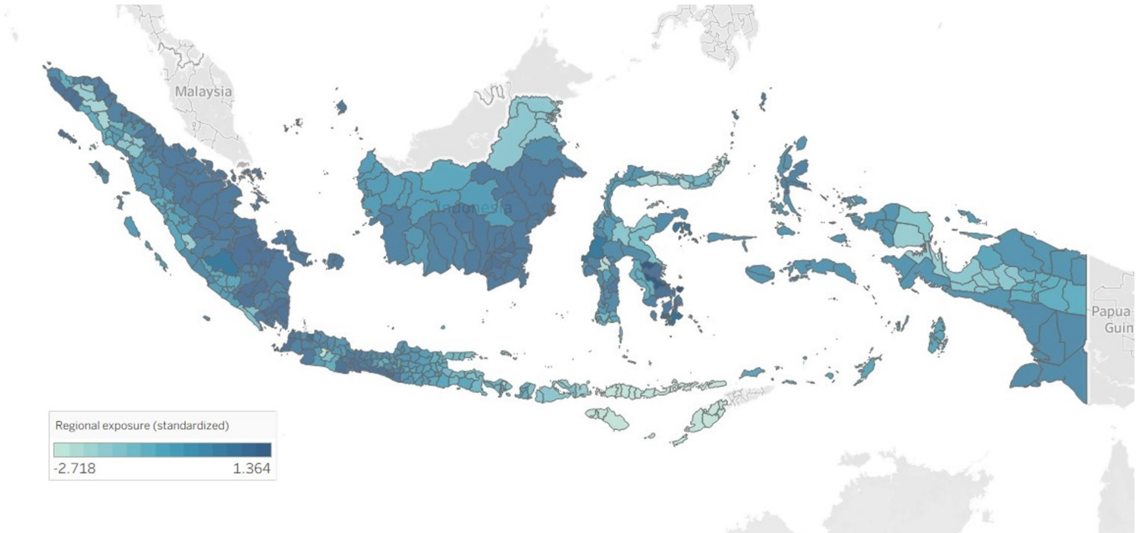


Figure 1.3: Regional exposure to the palm oil boom

Notes: This figure shows the spatial distribution of R_r in Equation (1.1), which measures regional exposure to palm oil demand shocks at the district level.

and below the median. Districts with higher exposure have a lower share of female workers, a higher share of workers with at least a high school education, and greater access to electricity. They also tend to have fewer agricultural workers. To account for observable differences in initial district conditions that may influence outcome trends, I include a set of pre-shock controls, X_{rt_0}. I also include broader region fixed effects, ϕ_m, which refers to main island fixed effects.

Table 1.1: Initial district characteristics (1990)

	Districts with regional exposure:						
	Below Median			Above Median			
	N	Mean	sd	N	Mean	sd	Diff
Log population	134	13.04	0.84	132	13.11	0.89	0.074
Log working-age population (15-64yo)	134	12.52	0.86	132	12.58	0.89	0.064
Log population density	134	5.60	1.59	132	5.64	2.00	0.034
Log agriculture workers	134	10.86	1.60	132	10.41	1.91	-0.451**
Log manufacturing workers	134	9.03	1.97	132	9.29	1.50	0.254
Log service and other workers	134	10.80	1.09	132	11.06	1.01	0.253*
Share of female workers (15-64yo)	134	0.30	0.08	132	0.27	0.07	-0.022**
Share of workers (high school or higher)	134	0.16	0.11	132	0.20	0.14	0.042***
Share of manufacturing workers	134	0.10	0.08	132	0.11	0.09	0.008
HH share: access to electricity	134	0.42	0.26	132	0.48	0.28	0.066**
HH share: access to piped water	134	0.14	0.18	132	0.18	0.22	0.034

Notes: Table shows averages for baseline. The last column is the coefficient of a simple regression of treatment status (above median) on the variable, with clustered standard errors at the district level. Stars indicate whether this difference is significant. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Sectoral analysis: Manufacturing Next, I estimate the effects of the commodity export shocks on local manufacturing industries that are not directly linked to the booming resource sectors. To do so, I exclude the vegetable oil and coke and refined petroleum industries from the analysis. I also report results including the vegetable oil industry in the Appendix. As shown in Table 1.A.4, employment growth in this sector is significantly higher in highly exposed regions compared to other manufacturing industries in the same areas. To examine the indirect effects of the palm oil boom, I use a panel of district-industry pairs at the four-digit ISIC level and estimate the following equation:

$$\Delta y_{jr} = \beta \, R_r + X'_{rt_0} \, \delta + \phi_p + \phi_s + \epsilon_{jr} \tag{1.3}$$

where Δy_{jr} is the annualized change in outcome variables for manufacturing industry j in district r between 2001 and 2011. I include province fixed effects ϕ_p to control for province-specific factors that are constant over time. Two-digit industry fixed effects, ϕ_s, control for industry-specific trends in manufacturing outcomes.

Input similarity to the palm oil processing industry To examine potential crowding-out effects in intermediate input markets, I construct a measure of input similarity to the palm oil industry using the 2010 Indonesian Input-Output[5]. This proxy captures the extent to which an industry relies on similar inputs to those used in palm oil processing, which expanded rapidly during the commodity boom.

The 2010 Input-Output matrix does not report intermediate inputs specifically for the palm oil processing industry. Input use is reported at the broader level of the vegetable oil sector. Although this sector also includes producers of other oils, such as coconut oil, approximately 83% of manufacturing plants in this category produce palm oil products, based on the 2010 Annual Survey of Manufacturing Plants. Therefore, I use input data from the vegetable oil sector to proxy input use in palm oil processing[6].

I construct a continuous measure of input similarity between industry j

[5] The 2010 Input-Output table is used instead of the 2000 version due to its finer sectoral disaggregation (185 sectors compared to 30 sectors in the 2000 table).

[6] An alternative source for the input data is the Annual Manufacturing Survey, which includes detailed input data at the plant level. However, the dataset is limited to tradable inputs and excludes detailed information on services.

and the vegetable oil industry as follows:

$$InputSimilarity_{jv} = \sum_{s=1}^{J} \theta_{sj}\, \theta_{sv} \tag{1.4}$$

where $\theta_{sj} = \frac{p_s x_{sj}}{p_j y_j}$ denotes the share of inputs from industry s in the total sales of industry j, and $\theta_{sv} = \frac{p_s x_{sv}}{p_v y_v}$ denotes the share of inputs from industry s in the total sales of vegetable oil industry[7]. This measure captures the extent to which industry j uses the same inputs as the vegetable oil industry, which is used here as a proxy for the palm oil processing industry. I classify industries as having high input similarity with the palm oil sector if $InputSimilarity_{jv}$ is above the mean. Table 1.A.3 lists the manufacturing industries that meet this criterion. I then estimate the following equation:

$$\Delta y_{jr} \;=\; \beta_1\, R_r \times IS_j \;+\; \beta_2\, R_r \;+\; \beta_3\, IS_j \;+ X'_{rt_0}\,\delta + \;\phi_p \;+\; \phi_s \;+\; \epsilon_{jr} \tag{1.5}$$

where IS_j is a dummy variable equal to one for industries with high input similarity to the vegetable oil industry.

1.4 Results

Effects on local employment Column (1) of Table 1.2 shows the regression results of equation (1.2). A one-standard-deviation increase in district-level exposure to the palm oil boom is associated with a 3.05 p.p. higher employment growth from 2000 to 2010. This estimate corresponds to approximately 11% of the standard deviation in the change in local employment across districts during the same period.

Columns (2)-(4) of Table 1.2 present the effects on sectoral employment. As can be seen in Column (2), increase in local employment growth in highy exposed regions is mainly driven by increase in agriculture employment, although it is only significant at the 10% level. Districts with one standard deviation higher exposure to the palm oil boom experienced a 2.63 p.p. greater increase in agricultural employment between 2000 and 2010. This estimate represents approximately 9.3% of the standard deviation in the change in agricultural employment across districts over the same period.

[7] I adapt the similarity measure from Boehm et al. (2022), which calculates similarity as the product of input shares. The main modification lies in the normalization. Instead of dividing by total intermediate input expenditure, I divide by total industry sales.

Effects on manufacturing outcomes Next, I present the regression results for growth in manufacturing employment, sales, and labor productivity. Column (1) of Table 1.3 shows no significant effect of the palm oil boom on overall manufacturing employment growth. However, the results are different once I consider the type of workers. In regions more exposed to the palm oil boom, the growth of non-production workers in manufacturing is significantly lower, while there is no effect on the growth of production workers. Column (3) of Table 1.3 shows that a one-unit increase in exposure is associated with a 1.49 p.p. lower annual growth rate of non-production workers. This effect represents about 8.5% of the standard deviation in the annual growth rate of non-production workers between 2000 and 2010.

In terms of sales and labor productivity—measured by sales per worker—I find that manufacturing industries in highly exposed regions experienced lower growth in both outcomes. As shown in Table 1.4, one unit increase in exposure reduces annual sales growth by 2.18 p.p. and labor productivity growth by 1.29 p.p. These effects correspond to approximately 11% of the standard deviation in the annual growth rates of sales and labor productivity over the same period.

Heterogeneous effects: Sectors with high input similarity Table 1.6 presents evidence of heterogeneous effects on sales and labor productivity, depending on the degree of input similarity to the vegetable oil industry. However, as shown in Table 1.5, there is no statistically significant difference in employment effects between industries with low and high input similarity.

Among industries with low input similarity, a one-unit increase in regional exposure is associated with a 2.6 p.p. decline in annual sales growth (Column 1) and a 1.7 p.p. decline in annual labor productivity growth (Column 2). By contrast, for industries with high input similarity, the adverse effects are substantially larger. A one-unit increase in exposure corresponds to a 4.4 p.p. reduction in annual sales growth and a 2.7 p.p. reduction in annual labor productivity growth. These results suggest that crowding-out effects in intermediate input markets may partially explain the slower growth in manufacturing industries in regions with higher exposure to the palm oil boom. In particular, industries with greater input similarity to the vegetable oil sector appear to be more negatively affected.

Additional results To assess the validity of my identification strategy, I examine baseline differences between regions with high and low exposure to the palm oil boom prior to the boom period. Table 1.A.5 presents the estimation results for the pre-shock period, 1990–2000. I find no significant differences in total or sectoral employment growth between regions with high and low exposure, which supports the parallel trends assumption.

Table 1.2: Effects on local employment

Dependent Variable:	Δ Log employment (2000-2010)			
	Total (1)	Agriculture (2)	Manufacturing (3)	Services (4)
Regional exposure: palm oil boom	0.030**	0.026*	-0.013	-0.013
	(0.012)	(0.015)	(0.034)	(0.016)
District characteristics (pre-shock)	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
Observations	266	266	266	266
R^2	0.335	0.289	0.436	0.200

Notes: District controls (1990): share of female workers, share of workers who completed at least high school, share of households with electricity, and population density. Standard errors in parentheses are clustered at the district. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.3: Effects on manufacturing employment (2001-2011, annualized)

Dependent Variable:	Δ Log employment (2001-2011, ann.)		
	Total (1)	Production (2)	Non-production (3)
Regional exposure: palm oil boom	-0.007	-0.007	-0.015**
	(0.005)	(0.005)	(0.007)
District characteristics (pre-shock)	✓	✓	✓
Province FE	✓	✓	✓
Two-digit industry FE	✓	✓	✓
Observations	2,708	2,708	2,708
R^2	0.060	0.062	0.050

Notes: Exclude vegetable oil and coke and refined petroleum industries. District controls (1990): share of female workers, share of workers who completed at least high school, share of households with electricity. Standard errors in parentheses are clustered at the district. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.4: Effects on manufacturing sales and productivity (2001-2011, annualized)

Dependent Variable:	Δ Log Sales	Δ Log Sales per worker
	(1)	(2)
Regional exposure: palm oil boom	-0.022***	-0.013***
	(0.007)	(0.005)
District characteristics (pre-shock)	✓	✓
Province FE	✓	✓
Two-digit Industry FE	✓	✓
Observations	2,708	2,708
R^2	0.076	0.075

Notes: Exclude vegetable oil and coke and refined petroleum industries. District controls (1990): share of female workers, share of workers who completed at least high school, share of households with electricity. Standard errors in parentheses are clustered at the district. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.5: Heterogeneous effects on manufacturing employment: by input similarity (2001-2011, annualized)

Dependent Variable:	Δ Log employment (2001-2011, ann.)		
	Total	Production	Non-production
	(1)	(2)	(3)
Regional exposure: palm oil boom × High input similarity	-0.006	-0.006	-0.011
	(0.006)	(0.006)	(0.007)
Regional exposure: palm oil boom	-0.008	-0.008	-0.018**
	(0.007)	(0.007)	(0.009)
Upstream and downstream of vegetable oil industry	✓	✓	✓
District characteristics (pre-shock)	✓	✓	✓
Province FE	✓	✓	✓
Two-digit Industry FE	✓	✓	✓
Observations	2,708	2,708	2,708
R^2	0.061	0.063	0.051

Notes: Exclude vegetable oil and coke and refined petroleum industries. District controls (1990): share of female workers, share of workers who completed at least high school, share of households with electricity. Standard errors in parentheses are clustered at the district. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.6: Heterogeneous effects on manufacturing sales and productivity: by input similarity (2001-2011, annualized)

Dependent Variable:	Δ Log Sales	Δ Log Sales per worker
	(1)	(2)
Regional exposure: palm oil boom × High input similarity	-0.018**	-0.010*
	(0.009)	(0.006)
Regional exposure: palm oil boom	-0.026***	-0.017***
	(0.009)	(0.006)
Upstream and downstream of vegetable oil industry	✓	✓
District characteristics (pre-shock)	✓	✓
Province FE	✓	✓
Two-digit Industry FE	✓	✓
Observations	2,708	2,708
R^2	0.077	0.076

Notes: Exclude vegetable oil and coke and refined petroleum industries. District controls (1990): share of female workers, share of workers who completed at least high school, share of households with electricity. Standard errors in parentheses are clustered at the district. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1.5 Conclusion

This chapter examines how a large resource demand shock affected local manufacturing outcomes in Indonesia. Exploiting plausibly exogenous variation in regional suitability for oil palm cultivation, I estimate the impact of the resource boom on local employment and manufacturing outcomes.

I find that regions with greater exposure to the palm oil boom experienced higher local employment growth, largely driven by increases in agricultural employment. While the boom led to an expansion of the vegetable oil industry in these regions, other manufacturing industries experienced declines in both sales and labor productivity. In terms of employment, there is no significant effect on total manufacturing employment, but the growth of non-production workers is slower in highly exposed regions relative to less exposed ones.

The boom also had heterogeneous effects across manufacturing industries. Specifically, industries that use inputs similar to those in the vegetable oil industry experienced slower growth in both sales and labor productivity during the boom period. These results remain robust after controlling for upstream and downstream linkages with the vegetable oil industry. Overall, the findings suggest that competition between the commodity and manufacturing sectors occurred not only in labor markets but also in intermediate input markets.

This study has several limitations. First, the reduced-form analysis captures only local effects and does not capture the overall impact of the palm oil boom at the aggregate level. Second, prior research suggests that commodity booms often stimulate growth in service sectors. However, due to limited access to micro-level data on services, this channel is not fully captured in the current analysis. To address these limitations and better understand how the resource boom affects factor reallocation across sectors and regions, I develop a quantitative spatial model calibrated to the Indonesian economy in the next chapter. This framework allows for counterfactual simulations to assess the aggregate and distributional effects of the commodity boom.

References

Allcott, H. and D. Keniston (2018). Dutch disease or agglomeration? The local economic effects of natural resource booms in modern America. *Review of Economic Studies 85*(2), 695–731.

Balboni, C., R. Burgess, A. Heil, J. Old, and B. A. Olken (2021). Cycles of fire? politics and forest burning in indonesia. In *AEA Papers and Proceedings*, Volume 111, pp. 415–419. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Benguria, F., F. Saffie, and S. Urzua (2023). The Transmission of Commodity Price Super-Cycles. *The Review of Economic Studies 00*(0), 1–33.

Boehm, J., S. Dhingra, and J. Morrow (2022). The comparative advantage of firms. *Journal of Political Economy 130*(12), 000–000.

Branstetter, L. G. and N. R. Laverde-Cubillos (2024). The dark side of the boom: Dutch disease, competition with china, and technological upgrading in colombian manufacturing. *Journal of International Economics 148*, 103818.

Busch, J., O. Amarjargal, F. Taheripour, K. G. Austin, R. N. Siregar, K. Koenig, and T. W. Hertel (2022). Effects of demand-side restrictions on high-deforestation palm oil in europe on deforestation and emissions in indonesia. *Environmental Research Letters 17*(1), 014035.

Cisneros, E., K. Kis-Katos, and N. Nuryartono (2021). Palm oil and the politics of deforestation in indonesia. *Journal of Environmental Economics and Management 108*, 102453.

Corden, M. and P. Neary (1982). Booming Sector and De-Industrialisation in a Small Open Economy. *The Economic Journal 92*(368), 825–848.

Cust, J., T. Harding, and P.-L. Vézina (2019). Dutch Disease Resistance: Evidence from Indonesian Firms. *Journal of the Association of Environmental and Resource Economists 6*(6), 1205–1237.

Cust, J. and S. Poelhekke (2015). The local economic impacts of natural resource extraction. *Annual Review of Resource Economics 7*(1), 251–268.

Edwards, R. B. (2024a). Export agriculture and rural poverty: evidence from Indonesian palm oil.

Edwards, R. B. (2024b). Spillovers from agricultural processing.

Gehrke, E. and C. Kubitza (2021). Agricultural productivity and fertility rates: Evidence from the oil palm boom in indonesia. *Journal of Human Resources 59*(1), 316–347.

Haas, R. D. and S. Poelhekke (2019). Mining matters: Natural resource extraction and firm-level constraints. *Journal of International Economics 117*, 109–124.

Harding, T. and A. J. Venables (2016). The Implications of Natural Resource Exports for Nonresource Trade. *IMF Economic Review 64*(2), 268–302.

Hill, H. and D. Pasaribu (2024). Indonesia and the resource curse: Economic and environmental dimensions. In *The Indonesian Economy and the Surrounding Regions in the 21st Century: Essays in Honor of Iwan Jaya Azis*, pp. 65–96. Springer.

Hsiao, A. (2024). Coordination and Commitment in International Climate Action: Evidence from Palm Oil.

Kedrosky, D. and N. Palma (2023). The cross of gold: Brazilian treasure and the decline of Portugal. Technical report, CEPR Press.

Kraus, S., R. Heilmayr, and N. Koch (2023). Spillovers to manufacturing plants from multi-million dollar plantations: Evidence from the Indonesian palm oil boom. *Journal of the Association of Environmental and Resource Economists*.

Krugman, P. (1987). The narrow moving band, the Dutch disease, and the competitive consequences of Mrs. Thatcher. Notes on trade in the presence of dynamic scale economies. *Journal of Development Economics 27*(1-2), 41–55.

Naylor, R. L., M. M. Higgins, R. B. Edwards, and W. P. Falcon (2019). Decentralization and the environment: Assessing smallholder oil palm development in Indonesia. *Ambio 48*(10), 1195–1208.

Qaim, M., K. T. Sibhatu, H. Siregar, and I. Grass (2020). Environmental, Economic, and Social Consequences of the Oil Palm Boom. *Annual Review of Resource Economics 12*(1), 321–344.

Ruggles, S., L. Cleveland, R. Lovaton, S. Sarkar, M. Sobek, D. Burk, D. Ehrlich, Q. Heimann, and J. Lee (2024). Integrated Public Use Microdata Series, International: Version 7.5 [dataset]. Accessed via IPUMS.

USDA Foreign Agricultural Service (2019). Crop explorer: Palm oil - world production. Online report, USDA Foreign Agricultural Service.

van der Ploeg, F. (2011). Natural Resources : Curse or Blessing? *Journal of Economic Literature 49*, 366–420.

Appendix

1.A Additional tables

Table 1.A.1: Summary statistics: regional exposure to palm oil boom and district employment

Variable	Mean	Std. Dev.	Min.	Max.	N
Regional exposure: palm oil boom (std)	-0.005	1.007	-2.884	1.472	266
Δ Log number of workers (15-64 yo):					
Total (all sectors)	0.404	0.273	-0.177	2.331	266
Agriculture	0.155	0.281	-0.402	2.129	266
Manufacturing	0.565	0.566	-1.617	2.580	266
Services	0.602	0.278	0.056	2.500	266

Notes: Log differences are measured between 2000 and 2010.

Table 1.A.2: Summary statistics: manufacturing outcomes

Variable	Mean	Std. Dev.	Min.	Max.	N
Δ Log number of workers:					
Total	0.008	0.143	-0.627	0.717	2,795
Production	0.006	0.146	-0.639	0.760	2,795
Non-production	0.007	0.177	-0.912	0.839	2,795
Δ Log real sales	0.021	0.204	-0.897	0.882	2,795
Δ Log real value-added	0.028	0.208	-0.964	0.943	2,795
Δ Log real sales/worker	0.015	0.121	-0.679	0.597	2,795

Notes: Log differences are measured between 2001 and 2011 (annualized).

Table 1.A.3: Examples of sectors with high input similarity to the vegetable oil industry

No.	Industry (4-digit ISIC)
1	Manufacture of other food products n.e.c.
2	Manufacture of bakery products
3	Manufacture of dairy products
4	Manufacture of prepared animal feeds
5	Manufacture of perfumes and cosmetics
6	Manufacture of grain mill products (copra)
7	Manufacture of soap and detergents
8	Manufacture of botanical products (medicine)

Table 1.A.4: Effects on manufacturing employment: vegetable oil vs other industries (2001-2011, annualized)

Dependent Variable:	Δ Log employment (2000-2010, ann.)		
	Total	Production	Non-production
	(1)	(2)	(3)
Regional exposure: palm oil boom $\times$ VegOil	0.098***	0.090***	0.135***
	(0.027)	(0.026)	(0.044)
Regional exposure: palm oil boom	-0.007	-0.008	-0.015**
	(0.005)	(0.005)	(0.007)
District characteristics (pre-shock)	✓	✓	✓
Province FE	✓	✓	✓
Two-digit Industry FE	✓	✓	✓
Observations	2,783	2,783	2,783
R^2	0.060	0.061	0.054

Notes: District controls (1990): share of female workers, share of workers who completed at least high school, share of households with electricity. Standard errors in parentheses are clustered at the district. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.A.5: Effects on local employment in the pre-shock period

Dependent Variable:	Δ Log employment (1990-2000)			
	Total	Agriculture	Manufacturing	Services
	(1)	(2)	(3)	(4)
Regional exposure: palm oil boom	0.011	0.062	-0.015	0.008
	(0.020)	(0.049)	(0.079)	(0.033)
District characteristics (pre-shock)	✓	✓	✓	
Region FE	✓	✓	✓	✓
Observations	266	266	266	266
R^2	0.103	0.148	0.092	0.050

Notes: District controls (1990): share of female workers, share of workers who completed at least high school, share of households with electricity, and population density. Standard errors in parentheses are clustered at the district. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 2

Quantifying the Effects of Commodity Booms on Regional and Sectoral Outcomes

2.1 Introduction

The reduced-form results in Chapter 1 suggest that commodity booms can have negative effects on the manufacturing sector. This contraction is particularly concerning when manufacturing exhibits learning-by-doing, as productivity growth depends on the accumulation of experience and knowledge over time. Depending on the size and duration of the commodity boom, a country may experience the 'Dutch disease' phenomenon, where commodity booms lead to permanent adverse effects on manufacturing and reduce long-term welfare (Krugman (1987), Matsuyama (1992)).

To quantify the aggregate and welfare effects, I develop a dynamic spatial equilibrium model that builds on Desmet et al. (2018) and Conte et al. (2021). My main contribution is to revisit the 'Dutch disease' hypothesis using a multi-sector spatial model that incorporates both static and dynamic externalities in manufacturing sectors. The model also incorporates sectoral linkages, internal migration, and both domestic and international trade. I calibrate the model to the Indonesian economy with 2000 as the initial year and simulate the response to the commodity boom that the country experienced in the 2000–2011 period. I then use the calibrated model to quantify the effects of the commodity boom by shutting down the commodity export shocks in the 2000s.

In this model, technology follows the multi-sector spatial model of Caliendo et al. (2018) with local productivity spillovers as in Desmet and Rossi-Hansberg (2014) and Desmet et al. (2018). Firms produce varieties of intermediate goods using labor, land, and materials. Firms hire two types of workers which are production and non-production workers or innovation workers. One of the key features of the model is that I assume that local sectoral productivity depends on fundamental productivity and agglomeration economies. For non-commodity sectors, I assume that sectoral productivity benefits from local population density. For manufacturing sectors, I also assume that manufacturing productivity is determined by two factors: local past productivity with spatial spillovers and local past innovation. To proxy local innovation, I use the number of non-production workers with at least a college degree.

In this economy, workers' utility not only depends on their consumption of goods and services, but also on local amenities. I assume that local amenities are subject to congestion effects, where higher population density negatively affects local amenities. Workers are allowed to move across regions, subject to moving costs. As in Desmet et al. (2018), I assume that bilateral moving costs can be decomposed into origin-specific and destination-specific components. This assumption on moving costs simplifies the dynamic optimization made by workers. They only have to pay the flow utility moving cost, which is destination-specific, during their stay in the host region.

I calibrate the model to the Indonesian economy with 2000 as the baseline year. The model includes 25 provinces in Indonesia[1] and two foreign countries: China and the rest of the world. One of the challenges is obtaining the initial productivity for 108 sector-regions and the initial amenities for 27 regions. To recover these parameters, I follow the quantification strategy in Desmet et al. (2018) and Conte et al. (2021). By inverting the model, I back out the fundamental productivity and amenities relative to utility so that the model matches the data in 2000 [2].

In the quantitative analysis, I allow fundamental productivity of manufacturing sectors to evolve endogenously. I estimate the elasticity of productivity with respect to local innovation using model-generated productivity data

[1] I adjust the regional aggregation within Indonesia. The details are provided in Section 2.3.1

[2] The data includes land area, sectoral employment, wages, and bilateral trade costs. I obtain the parameters on bilateral trade costs by implementing a two-step procedure proposed by Yotov et al. (2016). Using trade value data from the Indonesian Inter-Regional-Input-Output (IRIO) table, I estimate a gravity equation and use the point estimates to construct the bilateral trade cost matrix.

and local innovation worker data obtained from the National Labor Survey. I calibrate the fundamental productivity of commodities and services in Indonesia, as well as all four sectors in foreign countries, exogenously. Following Eaton et al. (2016) and Fadinger et al. (2024), I calibrate sectoral productivity changes based on observed values of sectoral price indices, wages, rents, and domestic trade shares. The model is able to produce the distribution of GDP by sector-region from 2001 to 2010 as observed in the data.

Using the calibrated model, I quantify the effects of the commodity boom. First, I analyze the effects on aggregate outcomes. In the baseline economy, export revenues grow by approximately 10% per year in nominal terms. In a counterfactual experiment, I eliminate the commodity export boom between 2000 and 2010. To do this, I set the productivity growth of the commodity sector in Indonesia to 2-3% per year, resulting in commodity export growth of less than 1% per year.

First, I find that while the commodity boom increased GDP during the boom period, it potentially reduces welfare. The commodity boom increased aggregate GDP by 1.48% by the end of the boom period. However, it potentially reduces welfare by approximately 0.32%[3]. Second, the effects of the commodity boom varied across sectors. By the end of the boom period, the commodity and service sectors gained larger shares of GDP (7.86 p.p. and 2.40 p.p., respectively), while manufacturing contracted significantly. In particular, the non-food manufacturing share declined by 7.67 p.p. Third, the impact of the commodity boom is heterogeneous across regions[4]. By the end of the boom period, regions outside Java experienced a 10.62% increase in GDP, while Java experienced a 4.61% decline.

Lastly, I also show that agglomeration economies and dynamic externalities, or learning-by-doing, play important roles in amplifying the impact of the commodity boom. Agglomeration economies strengthen the positive impact of the commodity boom on aggregate GDP during the boom period. In contrast, dynamic externalities in manufacturing amplify the negative effects on aggregate GDP and the regional GDP of more industrialized areas after the boom ends.

[3]I simulate the response of the economy over 40 years and compute the discounted utility of workers.

[4]In this analysis, I compare regions on Java Island with those outside Java. Java is more industrialized, accounting for 61% of total GDP and 57% of the population as of 2010 (Statistics Indonesia, 2010). According to the 2010 Annual Manufacturing Survey, approximately 75% of non-agriculture-based manufacturing plants were located on Java.

Related literature This study is particularly related to Dutch Disease literature that focus on the effects of resource booms in the presence of learning-by-doing in manufacturing sectors (van Wijnbergen (1984), Krugman (1987), Matsuyama (1992), Sachs and Warner (1995), Gylfason et al. (1999)) and the extended works with productivity spillovers across sectors (Torvik (2001), Bjørnland and Thorsrud (2016), Bjørnland et al. (2019)). Focusing on local economic impacts, prior research also finds positive spillover effects on local labor market outcomes (Michaels (2011), Aragón and Rud (2013), Cust and Poelhekke (2015), Costa et al. (2016), Allcott and Keniston (2018), Edwards (2024a), Edwards (2024b)). I contribute to this literature by quantifying the effects of commodity booms on sectoral and regional outcomes using a dynamic spatial equilibrium framework that incorporates both static externalities (through agglomeration economies) and dynamic externalities (through local innovation)[5].

There are two recent studies (Baldomero-Quintana (2025) and Benguria et al. (2024)) that also quantify the effects of commodity booms using spatial equilibrium models. Relative to Baldomero-Quintana (2025), I quantify the long-term effects of commodity booms in the presence of internal migration. Relative to Benguria et al. (2024) who also quantify the effects using a dynamic spatial model, I incorporate externalities in spatial equilibrium framework.

In terms of the model setup, the model in this paper builds on a quantitative spatial model framework (Allen and Arkolakis (2014), Redding (2016), Redding and Rossi-Hansberg (2017), Caliendo et al. (2018)) and is closely related to spatial models that allow regional productivity to evolve over time (Desmet et al. (2018), Desmet and Rossi-Hansberg (2014), Eckert and Peters (2018), Nagy (2023), Conte et al. (2021), Allen and Donaldson (2020)). Relative to these studies, I incorporate sectoral linkages to capture potential crowding-out effects in the intermediate input market. Note that Baldomero-Quintana (2025) and Benguria et al. (2023) also incorporate sectoral linkages in quantifying the effects of commodity booms, but abstracts from the role of agglomeration economies and dynamic externalities. Furthermore, compared to Desmet et al. (2018) and Conte et al. (2021), I estimate the elasticity of productivity with respect to local innovation using Indonesian microdata and productivity parameters generated by the model.

[5]This paper also relates to the broader literature on agglomeration economies (Ciccone and Hall (1996), Ellison and Glaeser (1997), Duranton and Puga (2004), Rosenthal and Strange (2004), Desmet and Henderson (2015), Combes and Gobillon (2015)).

Lastly, this study is also related to the application of quantitative spatial models for within-country analysis with migration and trade (Fan (2019), Faber and Gaubert (2019), Tombe and Zhu (2019), and Ma and Tang (2020) in a static framework, and Caliendo et al. (2019), Allen and Donaldson (2020), and Cai et al. (2025) in a dynamic framework). Among these studies, the most closely related papers are Cai et al. (2025) as they also feature endogenous productivity. In a one-sector model, Cai et al. (2025) model productivity evolution as a function of migration and trade between regions. In this paper, I closely follow Desmet et al. (2018), assuming that local sectoral productivity growth depends on past local innovation, with spatial diffusion of technology determined by exogenous geographical distance.

Outline The remainder of this chapter is structured as follows. I propose a quantitative model in Section 2.2. Section 2.3 presents data used to calibrate the model. Using the calibrated model, I conduct the quantitative analysis presented in Section 2.4. Lastly, Section 2.5 concludes.

2.2 Model

To quantify the aggregate and welfare effects of a commodity boom, I develop a dynamic spatial model with spatial frictions that builds on Desmet and Rossi-Hansberg (2014) and Desmet et al. (2018) with multiple sectors and sectoral linkages as in Caliendo et al. (2018).

There are $N+1$ regions, indexed by r or s, comprising N domestic regions and one additional region representing the rest of the world. Time is discrete and indexed by t. There are four sectors indexed by j or k: commodities (C), food manufacturing (F), non-food manufacturing (M), and services (S). The economy has two factors, which are labor and a composite factor that consists of land and structures. Total labor in the economy is denoted by $\bar{L}$. The initial population distribution is given by $\tilde{L}_{rt_0}$. Each region r is endowed with a fixed factor denoted by H_r.

2.2.1 Preferences

A worker i who lives in region r in period t with location history $\bar{r}_0 = \{r_0, ..., r_{t-1}\}$ enjoys utility:

$$U_{irt}^{\bar{r}_0} = a_{rt}\, C_{rt}\, \frac{1}{m_{rt}^{\bar{r}_0}}\, \varepsilon_{irt} \tag{2.1}$$

where a_{rt} is the local amenities in region r, C_{rt} is the consumption bundle of goods and services in region r, $m_{rt}^{\bar{r}_0}$ is the moving cost when the worker is residing in region r in period t, and ε_{irt} is an idiosyncratic preference shock.

Each worker i has a set of idiosyncratic preference ε_{irt} for residing in different regions within the country. I assume that ε_{irt} follows a Fréchet distribution with shape parameter η:

$$Pr[\varepsilon_{irt} \leq z] = e^{-z^{-\eta}} \tag{2.2}$$

where the shape parameter η controls the dispersion of preferences across workers for each region. A smaller value of η indicates greater variation in taste (i.e., the worker's utility is less sensitive to amenity-adjusted real income) and therefore a stronger incentive to disperse spatially.

Workers in region r consume a bundle of goods and services, C_{rt}, from each sector $j \in \{C, F, M, S\}$ according to the following form:

$$C_{rt} = \prod_{j \in \{C,F,M,S\}} \left[\int (c_{jrt}^{\omega})^{\rho} d\omega \right]^{\frac{\chi_j}{\rho}} \tag{2.3}$$

where parameter $\rho = \frac{\sigma}{\sigma-1}$ determines the elasticity of substitution between varieties ω within sector j. Workers spend a constant fraction of their income on each good j, which is equal to χ_j and $\sum_{j \in \{C,F,M,S\}} \chi_j = 1$.

Local amenities I assume that there are congestion effects in local amenities in region r which takes the following form:

$$a_{rt} = \bar{a}_r \left(\frac{\tilde{L}_{rt}}{H_r} \right)^{-v}, \qquad v > 0 \tag{2.4}$$

where $\bar{a}_r$ is region r's fundamental amenity. $\left(\frac{\tilde{L}_{rt}}{H_r} \right)^{-v}$ is a dispersion force that stems from local population density. Note that the greater the value of v, the stronger the dispersion force.

Income and indirect utility I assume that workers maximize utility, U_{irt}, in each period subject to the following budget constraint:

$$w_{rt} + \frac{R_{rt}\, H_r}{\tilde{L}_{rt}} = \sum_{j=1}^{J} P_{jrt}\, C_{jrt} \tag{2.5}$$

A worker in region r supplies one unit of labor inelastically and earns income from work, w_{rt}, and from local land rents. It is assumed that local land rent is distributed equally among the residents of a location. Therefore, each worker receives a proportional share of the local rents, $\frac{R_{rt} H_r}{\tilde{L}_{rt}}$.

In each period workers consume their total income. The indirect utility of a worker in region r is as follows:

$$V_{irt} = a_{rt} \frac{I_{rt}}{m^d_{rt} \prod_{j=1}^{J} (P_{jrt})^{\chi_j}} \varepsilon_{irt} \tag{2.6}$$

where

$$I_{rt} = w_{rt} + \frac{R_{rt} H_r}{\tilde{L}_{rt}} \tag{2.7}$$

and m^d_{rt} is a destination-specific moving cost when the worker is living in region r at time t.

I_{rt} is a nominal income of a worker in region r in period t. P_{jrt} is the price index of sector j at location r in period t:

$$P_{jrt} = \left[\int (p^{\omega}_{jrt})^{\frac{\rho}{\rho-1}} d\omega \right]^{\frac{\rho-1}{\rho}} \tag{2.8}$$

where p^{ω}_{jrt} is the price of variety ω in sector j produced in region r. Thus, we can express indirect utility as:

$$V_{irt} = \frac{a_{rt}\, y_{rt}}{m^d_{rt}} \varepsilon_{irt} \tag{2.9}$$

where y_{rt} is real income of a worker in region r.

Location decision In this setup a worker with location history $\bar{r}_0 = \{r_0, ..., r_{t-1}\}$ who resides in region r at time period t has to pay a utility cost. The moving cost takes the following form:

$$\frac{1}{m^{\bar{r}_0}_{rt}} = \prod_{u=1}^{t} \frac{1}{m(r_{u-1}, r_u)} \tag{2.10}$$

Following Desmet et al. (2018), I assume that bilateral moving costs from origin s at time $t-1$ to destination r at time t can be decomposed into:

$$m(s_{t-1}, r_t) = m^o_{s_{t-1}} m^d_{r_t} \tag{2.11}$$

where $m^o_{(.)}$ is an origin-specific cost and $m^d_{(.)}$ is a destination-specific cost. I assume that there is no moving cost within region r. Thus,

$$m(r_{t-1}, r_t) = m^o_{r_{t-1}}\, m^d_{r_t} = 1 \tag{2.12}$$

$$m^o_{r_{t-1}} = \frac{1}{m^d_{r_t}} \tag{2.13}$$

The assumption imposed on moving costs simplifies the dynamic optimization made by workers. This assumption implies that workers' decision regarding where to locate themselves is based solely on current factors; it is not influenced by past or future economic variables. Appendix 2.B shows the derivation of the value function of a worker living in region r_0 in period 0 after observing a distribution of taste shocks in all locations. As can be seen from Equation (2.B.1), location choice in period 1 is not influenced by the economic variables in period 0 or subsequent periods. In this setup, migrants only have to pay the flow utility moving cost (m^d_{rt}) during their stay in the host region r.

Assuming that ε_{irt} follows a Fréchet distribution, I can obtain a closed-form expression of the proportion of workers moving between regions. The share of workers in region s that relocate to region r:

$$\lambda_t(r, s) = \frac{(v_{rt})^{\eta}\,(m^d_{r_t})^{-\eta}}{\sum_{l=1}^{N}(v_{lt})^{\eta}\,(m^d_{l_st})^{-\eta}} \tag{2.14}$$

where $v_{rt} = a_{rt}\, y_{rt}$, is the amenity-adjusted real income. Note that equation (2.14) determines the evolution of the distribution of workers across regions over time. The number of workers living in region r at time $t+1$ is:

$$\tilde{L}_{rt+1} = \sum_{s=1}^{N} \lambda_t(r, s)\, \tilde{L}_{st} \tag{2.15}$$

Welfare The Fréchet distribution for utility also implies that, conditional on residing in region r, the expected utility of a worker i at time t:

$$\bar{V}_{rt} = E(V_{irt} \mid i \text{ lives in } r) = \Gamma\left(\frac{\eta - 1}{\eta}\right) m^d_{r_t} \left[\sum_{s=1}^{N} (v_{st})^{\eta}\,(m^d_{s_t})^{-\eta}\right]^{\frac{1}{\eta}} \tag{2.16}$$

where $\Gamma(.)$ denotes the gamma function.[6]

[6]To ensure a finite value for expected utility, $\eta > 1$.

2.2.2 Technology

Technology follows the multi-sector spatial model of Caliendo et al. (2018) with local productivity spillovers as in Desmet and Rossi-Hansberg (2014) and Desmet et al. (2018).

Final goods There is a continuum of varieties $\omega \in [0,1]$ in each sector j. Firms in region r combine intermediate goods in sector j to produce a sectoral composite good:

$$Q_{jrt} = \left[\int (\tilde{q}^{\omega}_{jrt})^{\frac{\zeta-1}{\zeta}} d\omega \right]^{\frac{\zeta}{\zeta-1}} \tag{2.17}$$

where Q_{jrt} is the final good in sector j in region r, $\tilde{q}^{\omega}_{jrt}$ is the quantity demanded of an intermediate good from the lowest cost supplier, and ζ is the elasticity of substitution between varieties ω within sector j. Final goods in each sector are used for consumption and as material inputs in the production of intermediate goods in all sectors.

$$Q_{jrt} = C_{jrt} + \sum_{k=1}^{J} M^{j}_{krt} \tag{2.18}$$

M^{j}_{krt} is a composite good j that is used as material inputs in the production of sector k.

Intermediate goods Firms in each sector and region produce varieties of intermediate goods, q^{ω}_{jrt}. A representative firm produces output q^{ω}_{jrt} using labor and land as primary factors, and materials from other sectors. The quality of the firm's technology determines the firm's productivity and it depends on how many resources the firm allocates to innovate. Therefore, in addition to hiring production workers, the firm needs to employ workers who engage in innovation activities. It is important to note that to simplify the model, I assume that workers are homogeneous in terms of their skills or education. Therefore, it is assumed that every worker can perform both production and non-production activities.

The production function takes the following form:

$$q^{\omega}_{jrt} = z^{\omega}_{jrt} \left[(L^{\omega}_{\phi,jrt})^{\vartheta_j} \, (L^{\omega}_{jrt})^{\mu_j} \, (H^{\omega}_{jrt})^{1-\vartheta_j-\mu_j} \right]^{\gamma_j} \prod_{k=1}^{J} (M^{\omega,k}_{jrt})^{\gamma_{j,k}} \tag{2.19}$$

where $L^{\omega}_{\phi,jrt}$ denotes the number of workers hired by the firm to innovate or to perform non-production activities, L^{ω}_{jrt} is the number of workers hired by the firm to produce, H^{ω}_{jrt} denotes land and structures, $M^{\omega,k}_{jrt}$ are material inputs from sector k demanded by a firm in sector j, and z^{ω}_{jrt} is an idiosyncratic productivity shifter.

The parameter $\gamma_j \geq 0$ is the share of value added in the production of a good in sector j, and $\gamma_{j,k} \geq 0$ is the share of materials from sector k in the production of sector j. I assume that the production function exhibits constant returns to scale such that $\sum_{k=1}^{J} \gamma_{j,k} = 1 - \gamma_j$.

I assume that the idiosyncratic productivity shifter z^{ω}_{jrt} is i.i.d across varieties, regions, and time, and drawn from a Fréchet distribution with CDF:

$$Pr(z^{\omega}_{jrt} \leq z) = e^{-(Z_{jrt}/z)^{\theta}} \tag{2.20}$$

By the properties of the Fréchet distribution, Z_{jrt} is the average productivity of sector j in location r at time t. The average productivity depends on fundamental productivity and agglomeration economies,

$$Z_{jrt} = T_{jrt} \left[\frac{\tilde{L}_{rt}}{H_r}\right]^{\alpha_j}, \qquad \alpha_j \geq 0 \tag{2.21}$$

where

$$\tilde{L}_{rt} = \sum_{j=1}^{J} L_{\phi,jrt} + L_{jrt} \tag{2.22}$$

I assume that $\alpha_j > 0$ if sector j belongs to the broad sectors of manufacturing and services and $\alpha_j = 0$ if sector j belongs to the primary commodity sectors. The assumption of $\alpha_j > 0$ implies that sectoral productivity benefits from local agglomeration economies. T_{jrt} is region r's fundamental productivity in sector j at time t. I assume that initial productivity T_{jrt_0} is exogenously given.

Productivity evolution Following Desmet et al. (2018), I assume that regional fundamental productivity, T_{jrt}, evolves according to the following equation:

$$T_{jrt} = \underbrace{(T_{jrt-1})^{\delta} \left[\sum_{s=1}^{N} \iota(r,s)\, T_{jst-1}\right]^{1-\delta}}_{\text{local past sectoral productivity with spatial spillovers}} \qquad \underbrace{(L_{\phi,jrt-1})^{\kappa_j}}_{\text{local past sectoral innovation}} \tag{2.23}$$

where $\sum_{s=1}^{R} \iota(r,s)\, T_{jst-1}$ is the aggregate technology that spill over to region r, weighted by $\iota(r,s)$ that depends on the distance between region r and the other region s. Equation (2.23) shows that, conditional on the spatial distribution of past productivity, T_{jrt-1}, fundamental productivity of sector j in region r at time t is determined by: (1) local past sectoral productivity and the spatial diffusion of past productivity from other regions, and (2) local past sectoral innovation.

I assume $\kappa_j \in (0,1)$ and $\delta \in (0,1]$. Note that $\delta = 1$ implies no spatial diffusion of past productivity. If $\delta \in (0,1)$, the dynamic evolution of a region's technology also depends on the aggregate level of technology. By contrast, if $\delta = 0$ then only the aggregate technology matters.

As in Desmet and Rossi-Hansberg (2014) and Nagy (2023), the timing of technology diffusion or productivity spillovers between regions is as follows:

1. At the beginning of period t, firms in region r start with productivity level T_{jrt}.

2. In period t, workers make decisions about their consumption and their location choices. Given the factor prices, each firm decides how much to innovate, how much to bid for land, how many production workers to hire, and how much materials to buy.

3. All markets clear.

4. Between time periods t and $t+1$, technology diffuses across regions.

5. At the beginning of period $t+1$, firms in region r start with a new productivity level T_{jrt+1} which has evolved according to equation (2.23) where T_{jrt+1} depends on the past productivity level of region r (T_{jrt}) or other regions (T_{jst}) through spatial diffusion, and the past sectoral innovation in region r ($L_{\phi,jrt}$).

Firms compete in perfectly competitive markets, and I assume that land markets are also competitive. In this setup, firms choose how much to innovate to maximize their current profits, which are equivalent to their bids for land. Due to local competition, firms will continue to bid for land until they reach a point where their profits are zero after accounting for innovation costs. Therefore, in each period, firm profits are zero and future gains from innovation will be reflected in the local land price. This implies that the solution to the dynamic innovation decision problem is the same as the solution to a sequence of static innovation decision problems that maximize static profits, as proven in Desmet and Rossi-Hansberg (2014) and discussed in detail in Desmet et al. (2018).

A firm maximizes its static profits subject to its production function:

$$\max_{\{L^{\omega}_{\phi,jrt}, L^{\omega}_{jrt}, H^{\omega}_{jrt}, M^{\omega,k}_{jrt}\}} p^{\omega}_{jrt}\, q^{\omega}_{jrt} - w_{rt}[L^{\omega}_{\phi,jrt} + L^{\omega}_{jrt}] - \sum_{k=1}^{J} p^{\omega}_{krt}\, M^{\omega,k}_{jrt} - R_{rt} H^{\omega}_{jrt} \quad (2.24)$$

Note that the equilibrium local land rent, R_{rt}, is taken as given by the firms. Firms produce in region r if their bid is higher or equal to the equilibrium land rent. Therefore, the firms' decisions of hiring workers and purchasing materials in a given region are independent of the local idiosyncratic productivity draws. $L^{\omega}_{\phi,jrt}$, L^{ω}_{jrt}, $M^{\omega,k}_{jrt}$, H^{ω}_{jrt} are identical across varieties ω. Thus, I can derive the following equations by integrating the first-order conditions of the firm's problem across varieties:

$$L_{\phi,jrt} = \frac{\vartheta_j}{\vartheta_j + \mu_j} \tilde{L}_{jrt} \quad (2.25)$$

$$L_{jrt} = \frac{\mu_j}{\vartheta_j + \mu_j} \tilde{L}_{jrt} \quad (2.26)$$

$$\sum_{k=1}^{J} M^{k}_{jrt}\, P_{krt} = \frac{1 - \gamma_j}{(\vartheta_j + \mu_j)\gamma_j} w_{rt} \tilde{L}_{jrt} \quad (2.27)$$

$$R_{rt} H_{jrt} = w_{rt} \sum_{j=1}^{J} \frac{1 - \vartheta_j - \mu_j}{\vartheta_j + \mu_j} \tilde{L}_{jrt} \quad (2.28)$$

2.2.3 Prices and trade shares

I assume perfect competition in the goods market, which implies that firms sell their products at marginal costs. In this economy, final goods are non-tradable, while intermediate goods in tradable sectors incur some trade cost. Let $\tau(r,s) \geq 1$ be the iceberg trade cost of transporting a good from region s to r. When shipping one unit of an intermediate good in sector j from region s to r, $\tau(r,s) \geq 1$ units must be produced in region s.

The price of good j produced in region s sold in region r:

$$p^{\omega}_{jrt}(r,s) = \frac{c_{jst}\, \tau_j(r,s)}{z^{\omega}_{jst}} \quad (2.29)$$

where c_{jst} is marginal cost of producing good j in region s:

$$c_{jst} = B_j \left[w_{st}^{\mu_j + \vartheta_j}\, R_{st}^{1 - \mu_j - \vartheta_j} \right]^{\gamma_j} \prod_{k=1}^{J} P_{kst}^{\gamma_{j,k}} \quad (2.30)$$

where $B_j = [\gamma_j\, \mu_j^{\mu_j}\, \vartheta_j^{\vartheta_j}\, (1-\mu_j-\vartheta_j)^{1-\mu_j-\vartheta_j}]^{-\gamma_j} \prod_{k=1}^{J} \gamma_{j,k}^{-\gamma_{j,k}}$.

As in Eaton and Kortum (2002), using the properties of the Fréchet distribution, I can derive the share of goods produced in region s that are sold to region r:

$$\pi_{jt}(r,s) = \frac{T_{jst}^{\theta}\,(c_{jst}\,\tau(r,s))^{-\theta}}{\Phi_{jrt}} \tag{2.31}$$

$\Phi_{jrt} = \sum_{v=1}^{N} T_{jvt}^{\theta}(c_{jvt}\,\tau(r,v))^{-\theta}$.

The price index of sector $j \in \{C, F, M\}$ in location r in period t is given by:

$$P_{jrt} = \Lambda \left[\sum_{v=1}^{N} T_{jvt}^{\theta}(c_{jvt}\,\tau(r,v))^{-\theta} \right]^{-\frac{1}{\theta}} \tag{2.32}$$

where $\Lambda = \Gamma\left(1 - \frac{\rho}{(1-\rho)\theta}\right)^{-\frac{1-\rho}{\rho}}$. If j is a non-tradable sector ($j = S$), the price index is equal to $P_{Srt} = \Lambda\; T_{Srt}^{-1}\; c_{Srt}$.

2.2.4 Market clearing and equilibrium

For market clearing to occur, total revenue of firms that produce varieties in sector j in region r has to be equal to total expenditure on these varieties spent by all regions. Total revenue in region r is equal to:

$$TR_{rt} = w_{rt} \sum_{j=1}^{J} \frac{1}{\gamma_j(\mu_j + \vartheta_j)}\, \tilde{L}_{jrt} \tag{2.33}$$

Let X_{jrt} be the total expenditures on varieties in sector j from region r:

$$X_{jrt} = \sum_{s}^{N} \pi_{jt}(s,r) \left[\chi_j(w_{st}\,\tilde{L}_{st} + R_{st}\,H_s) + w_{st} \sum_{k}^{J} \frac{\gamma_{k,j}}{\gamma_k(\mu_k + \vartheta_k)} \tilde{L}_{kst} \right] \tag{2.34}$$

Equation (2.33) must equal to $\sum_{j=1}^{J} X_{jrt}$.

Regional market clearing in final goods requires:

$$\tilde{L}_{rt} C_{jrt} + \sum_{k=1}^{J} M_{krt}^{j} = Q_{jrt} \tag{2.35}$$

Regional labor and land market clearing requires:

$$\sum_{j=1}^{J} \tilde{L}_{jrt} = \tilde{L}_{rt} \tag{2.36}$$

$$\sum_{j=1}^{J} H_{jrt} = H_r \tag{2.37}$$

In the equilibrium, labor and land markets clear across all locations: $\sum_{r=1}^{N} \tilde{L}_{rt} = \tilde{L}$ and $\sum_{r=1}^{N} H_r = H$.

Given a set of locations and their initial distribution of technology, amenity, population, and land $\{T_{jrt_0}, \bar{a}_r, \tilde{L}_{rt_0}, H_r\}$, as well as bilateral trade and migration cost functions $\{\tau(r,s), m_r^d\}$, a competitive equilibrium for this economy is a sequence of functions $\{\tilde{L}_{jrt}, H_{jrt}, M_{jrt}^k, C_{jrt}, w_{rt}, R_{rt}, P_{jrt}, T_{jrt}, a_{rt}, \pi_{jt}(r,s), \lambda_t(r,s), \bar{V}_{rt}\}_{t=0}^{\infty}$, such that for each period t, the optimization conditions for workers and firms hold, all markets clear, aggregate trade is balanced, and utility is equalized across regions. Regional sectoral productivity $\{T_{jrt}\}$ and regional population $\{\tilde{L}_{rt}\}$ evolve according to the law of motions shown in equations (2.15) and (2.23).

2.3 Data and calibration

2.3.1 Data

I calibrate the model to the Indonesian economy, with the baseline year set to 2000.

Regions I use province as the regional unit, with a total of 25 regions within Indonesia. The main data sources are the Indonesian Inter-Regional-Input-Output (IRIO) data for 2000 and 2010 (Statistics Indonesia, (2000, 2010), Resosudarmo and Hartono (2020))[7]. I merge some provinces to align with the regional classifications used in the microdata from the manufacturing plant survey and the labor force survey. I disaggregate the foreign region into China and the rest of the world (RoW), since China is one of the main importers of Indonesia's commodities. The RoW region includes Indonesia's other major trading partners, such as Australia, India, Japan, South Korea, the United States, the United Kingdom, the European Union, Singapore, Malaysia, Thailand, the Philippines, and Vietnam.

Industries There are four sectors in the model: commodities (C), food manufacturing (F), non-food manufacturing (M), and services (S). The commodity sector includes agriculture, animal farming, forestry, fishery, coal mining, and oil and gas extraction. I also classify the vegetable oil industry and the

[7]The 2000 IRIO data cover 30 provinces with 30 sectors in each province, while the 2010 data cover 33 provinces with 35 sectors in each province.

manufacture of coke and refined petroleum products under the commodity sector. Food manufacturing includes food processing, beverages, and tobacco. The services sector refers to non-tradable sectors which also includes construction and utilities.

Regional employment and wages I obtain employment and wage data in the baseline year from the 2001 National Labor Force Survey (*Sakernas*). The survey data in 2001 are representative at the province level. The sectoral information in the National Labor Force Survey data is available at the three-digit ISIC level. The surveyed individuals who were currently working are classified into several groups: self-employed, employers with permanent workers, employees (with contracts), casual workers in agriculture, casual workers in non-agriculture, and unpaid workers. The survey provides data on workers' monthly wages and the number of hours worked, but does not provide information on employers' earnings. Therefore, to construct regional employment data, I sum up the number of workers who are classified as employees (with contracts) and casual workers at the province level for each industry using the sampling weights provided by the Indonesian Statistical Office. Regarding regional wages, I compute the weighted average of hourly wages at the province level.

Value-added, net exports, domestic trade The data sources for value added, net exports, and domestic trade are the Indonesian IRIO data for 2000 and 2010. I deflate domestic trade and value added in the 2010 data using the Wholesale Price Index (WPI), available at the two-digit sector level. To deflate export and import values, I use sectoral export and import price indices, which are also available at the two-digit level.

2.3.2 Parameterization

I obtain values for preference and technology parameters from multiple sources, as summarized in Appendix Table 2.B.5.

Initial regional productivity To obtain initial productivity (T_{jrt_0}), I follow the quantification strategy in Desmet et al. (2018) and Conte et al. (2021). I recover the distributions of the initial fundamental productivity (T_{jrt_0}) by inverting the model. Using the initial distributions of land area (H_r), sectoral employment ($\tilde{L}_{jrt_0}$), wages w_{rt_0}, and bilateral trade cost ($\tau(r,s)^{-\theta}$), I back out the fundamental productivity and amenities relative to utility so that the model matches the data in 2000. Using initial regional wages, I use equation (2.28) to obtain land rents R_{rt_0}. Using equations (2.21), (2.28), and (2.30), I rewrite the price index equation (2.32) of each sector as shown in equations (2.B.4) and (2.B.5) in the appendix. Using market clearing condition and rearranging equation (2.34), the fundamental productivity of commodity and manufacturing sectors can be written as in equations (2.B.7) and (2.B.8).

I solve the equations (2.B.4) and (2.B.7) to obtain P_{Crt_0} and T_{Crt_0}. Similarly, to recover P_{Krt_0} and T_{Krt_0} for $K \in \{F, M\}$, I solve the equations (2.B.5) and (2.B.8). I compute $T_{Srt_0} = 1$ for all regions and compute P_{Srt_0} using equation (2.B.6). Figures 2.1, 2.2, and 2.3 show the spatial distribution of regional productivity of the commodity, food manufacturing, and non-food manufacturing sectors, respectively.

Figure 2.1: Initial regional productivity of the commodity (C) sector

Figure 2.2: Initial regional productivity of the food manufacturing (F) sector

Figure 2.3: Initial regional productivity of the non-food manufacturing (M) sector

Initial regional amenities After solving for regional wage, land rents, and sectoral price indices, I recover the ratio of amenities to utility. Substituting equations (2.4) to the indirect utility, $v_{rt} = a_{rt}\, y_{rt}$, yields:

$$\frac{\bar{a}_r}{v_{rt_0}} = \frac{\prod_{j=1}^{J} (P_{jrt_0})^{\chi_j}}{I_{rt_0}} \left[\frac{L_{rt_0}}{H_r} \right]^{\lambda} \tag{2.38}$$

where $I_{rt_0} = w_{rt_0} + \frac{R_{rt_0} H_r}{\tilde{L}_{rt_0}}$ is worker's nominal income. To recover $\bar{a}_r$, Desmet et al. (2018) use subjective well-being data as a proxy for v_{rt_0}. I use the subjective well-being data at the province level published by the Indonesian Statistical Office. I standardize the provincial data and adjust the mean so that it matches the country data used in Desmet et al. (2018) for Indonesia. Figure 2.4 shows the spatial distribution of initial regional amenities.

Figure 2.4: Initial regional amenities

Technology Regarding the technology parameters, the share of value added in total output, γ_j for $j \in \{C, S\}$, is set equal to 1, while γ_j for $j \in \{F, M\}$ are obtained from the 2000 IRIO data. Manufacturing sectors (both food and non-food industries) use land, labor, and materials as inputs whereas commodity and service sectors only use land and labor. Table 2.B.4 shows the values of $\gamma_{j,k}$. In terms of the land share, I follow Valentinyi and Herrendorf (2008) and set the land share equals 0.32 for commodity, 0.12 for manufacturing, and 0.21 for service sectors.

One of the key parameters affecting productivity evolution is ϑ_j. For commodity sector (C), I set $\vartheta_C = 0.001$ based on the parameter for agriculture sector in Conte et al. (2021). For food manufacturing (F) and non-food manufacturing (M), I use the share of workers that are classified as experts, specialists, or senior managers. This follows the job classification by occupation based on the 2002 National Labor Force Survey (Sakernas). I set $\vartheta_F = 0.0036$ and $\vartheta_M = 0.014$ based on the National Labor Survey (Sakernas) data. I set ϑ_S to be equal to ϑ_M in the main calibration strategy. Regarding the shape parameter for productivity, I follow Simonovska and Waugh (2014) and set the elasticity of trade flows with respect to trade costs equals 4 ($\theta = 4$).

Elasticity of productivity with respect to local innovation I estimate the elasticity of productivity with respect to local innovation by conducting a regression analysis on the log-transformed form of equation (2.23), which models the dynamic evolution of manufacturing productivity. The estimating equation is as follows:

$$\log(T_{jrt}) = \delta \log(T_{jrt-1}) + (1-\delta) \log(\tilde{T}_{jt-1}) + \kappa_j \log(L_{\phi,jrt-1}) + \phi_t + \phi_p + \varepsilon_{jrt} \tag{2.39}$$

where T_{jrt} is model-generated productivity data for sector j in region r at time t, $\tilde{T}_{jt-1}$ is the average of sectoral productivity at time $t-1$ as a proxy for aggregate sectoral productivity, $L_{\phi,jrt-1}$ is the number of innovation workers, proxied by the number of non-production workers with at least a college degree.

To obtain sectoral productivity, I invert the model using observed data on regional wages and sectoral employment from 1990 to 2019. Data on wages, employment, and non-production workers are from the National Labor Survey data. The unit observation is sector $\times$ province. I regress log-transformed productivity on the log of the number of innovation workers from the previous period, controlling for past productivity at both the province and aggregate levels.

Table 2.1 shows the regression results. I find that a 1% increase in the number of innovation workers is associated with a 0.003% increase in manufacturing productivity in the next period. This result suggests a positive and statistically significant relationship between local innovation (proxied by highly educated non-production workers) and productivity in the manufacturing sector.

Table 2.1: Estimation of productivity elasticity with respect to local innovation

Dependent Variables:	Log(Productivity)$_{jrt}$
Log(Productivity)$_{jrt-1}$	0.971***
	(0.004)
Log(Average productivity)$_{jt-1}$	0.012***
	(0.005)
Log(Non-production_workers)$_{jrt-1}$	0.003***
	(0.001)
Province FE	✓
Year FE	✓
Observations	784

Notes: This table presents the regression results of equation (2.39) using annual data from 1990 to 2019. The unit of observation is sector × province. Standard errors are clustered at the province level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Bilateral trade cost To construct bilateral trade cost, I implement a two-stage procedure for cross-section data proposed by Yotov et al. (2016). The bilateral trade costs ($\tau(r,s)^{-\theta}$) are approximated by the logarithm of bilateral distance and an indicator for regional borders. First, using domestic trade values from the 2000 IRIO data, I estimate the following equation using PPML estimator:

$$X_j(r,s) = exp\Big[\phi_r + \phi_s + \beta_1\, ln(distance(r,s)) \\ + \beta_2\, \mathbf{1}\{Contiguity\} + \beta_3\, \mathbf{1}\{InternationalBorder\}\Big] \times \epsilon_j(r,s) \quad (2.40)$$

The origin and destination fixed effects (ϕ_r and ϕ_s) capture the multilateral resistances, outputs, and expenditures. Table 2.2 presents the estimation results. Then, using the point estimates of the effects of distance, contiguity, and international borders, I construct the bilateral trade cost ($\tau(r,s)^{-\theta}$).

Table 2.2: Effects of distance on trade values

Dependent Variables:	Trade values
Log(distance)	-0.280***
	(0.066)
Contiguity=1	2.498***
	(0.322)
International Border=1	-5.719***
	(0.616)
Origin FE	✓
Destination FE	✓
Observations	108,900

Notes: This table presents the regression results of equation (2.40). Standard errors are clustered at the origin-destination pair. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

International trade cost Following Head and Ries (2001)'s approach, I calibrate the changes in international trade costs based on the changes in observed expenditure shares in Indonesia, China, and the rest of the world. Changes in international trade cost between 2000 and 2010 are computed as follows:

$$\hat{\tau}(r,s) = \left(\frac{\hat{\pi}(r,s)\,\hat{\pi}(s,r)}{\hat{\pi}(r,r)\,\hat{\pi}(s,s)} \right)^{\frac{1}{2\theta}} \tag{2.41}$$

where $\hat{\pi}(r,r)$ is the changes in expenditure shares in region r spent on goods produced in its own region.

Table 2.3: Changes in international trade cost ($\hat{\tau}(r,s)$) between 2000 and 2010

Country pairs	Change in trade cost ($\hat{\tau}(r,s) = \frac{\tau_{2010}}{\tau_{2000}}$)
Indonesia - China	0.94
Indonesia - Rest of the World	0.99
China - Rest of the World	0.85

Notes: This table presents the changes in international trade cost between 2000 and 2010 based on equation (2.41).

Changes in sectoral productivity: China and the rest of the world (RoW) China is one of the main destinations for Indonesia's commodity exports. In this model I set productivity of China and the RoW to be exogenous in each period, while manufacturing productivity within Indonesia follows the productivity evolution as in equation (2.23). I follow the approach in Eaton et al. (2016) and Fadinger et al. (2024) to recover the unobserved productivity that rationalizes the observed data. I compute changes in sectoral productivity of

China and the RoW between 2000 and 2010 as follows:

$$\hat{T}_{jr} = \frac{1}{\hat{P}_{jr}} \hat{c}_{jr} \left(\hat{\pi}_j(r,r)\right)^{1/\theta} \tag{2.42}$$

where $\hat{x} = \frac{x_{2010}}{x_{2000}}$, $\hat{T}_{jr}$ is the change in sectoral productivity, $\hat{P}_{jr}$ is the change in sectoral output price index, $\hat{c}_{jr}$ is the change in unit cost that is determined by changes in wage, rent, and intermediate input price index, and $\hat{\pi}_j(r,r)$ is change in domestic trade share. I obtain output and intermediate input price indices and domestic trade shares from the World Input-Output Database (WIOD). Wage data is obtained from the WIOD–Socio-economic Account (SEA) data, and rent is computed using wage data and the assumed parameters for labor and land shares in value added. Table 2.4 shows the changes in sectoral productivity of China and the RoW between 2000 and 2010. I compute the compound annual growth rate based on the values in Table 2.4, then I use the annual growth rate and the initial productivity in 2000 to construct the sequence of sectoral productivity of China and the RoW.

Table 2.4: Changes in sectoral productivity ($\hat{T}_{jr} = \frac{T_{jr,2010}}{T_{jr,2000}}$) between 2000 and 2010

Sector j	China	Rest of the World
Commodities (C)	1.93	1.14
Food manufacturing (F)	1.82	1.05
Other manufacturing (M)	1.55	1.05
Services (S)	2.84	1.16

Notes: This table presents the productivity growth between 2000 and 2010 based on equation (2.42).

Preference The values of χ_j for $j \in \{C, F, M, S\}$ are obtained using sectoral shares of final consumption in the 2000 IRIO data. Regarding the Fréchet shape parameter for migration, I set $\eta = 2.7$ following Bryan and Morten (2019) and Tombe and Zhu (2019). Bryan and Morten (2019) quantify the aggregate productivity effects of internal migration in Indonesia and estimate the Fréchet shape parameter for the distribution of skills equal to 3.2. Note that in their model workers differ in productivity instead of preferences. Tombe and Zhu (2019) suggest that in a setup in which workers differ by preference, Bryan and Morten (2019)'s estimates for the Fréchet parameter equal to 2.7.

Destination-specific moving cost Using migration flow from region s to r, $L(r,s)$, from the 2000 Population Census data, I estimate the following

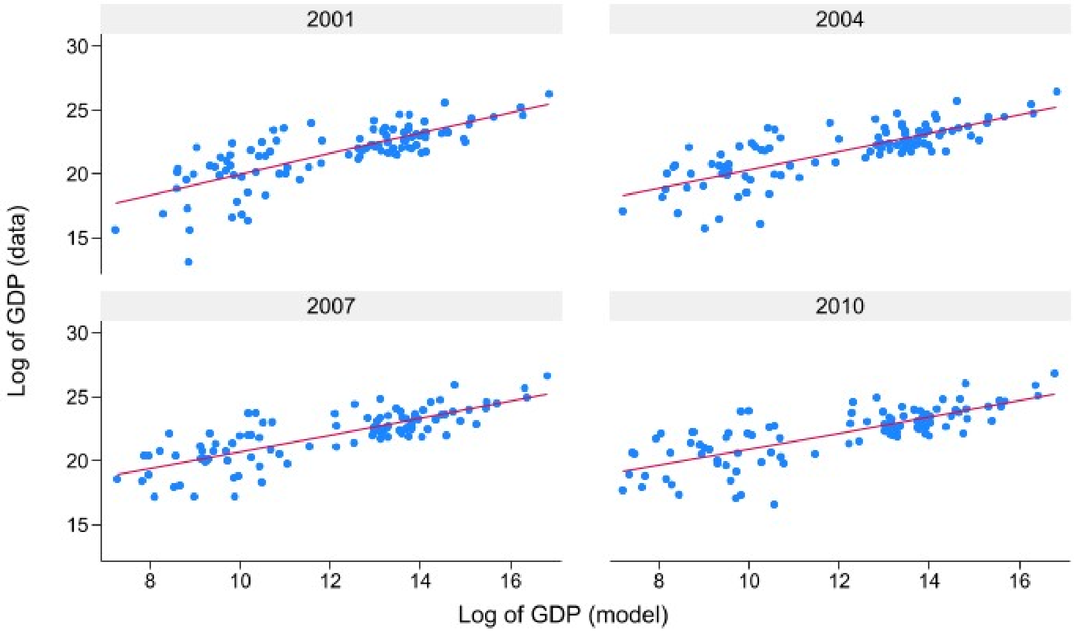


Figure 2.5: Model fit: GDP at the region-sector level

equation using PPML estimator:

$$L(r,s) = exp\Big[\phi_r + \phi_s + \alpha_1\, ln(distance(r,s)) \\ + \alpha_2\, \mathbf{1}\{Contiguity\} + \alpha_3\, ln(pcGDP_r)\Big] \times \epsilon(r,s)$$

where ϕ_s and ϕ_r are the origin and destination fixed effects, respectively. Using the estimates of destination fixed effects for each region, I compute their inverse and normalize them by dividing by the smallest value. Table 2.B.3 reports the resulting destination-specific moving costs for each region.

Model Fit Figure 2.5 presents scatter plots comparing the model's predicted regional-sectoral GDP with observed values for the years 2001, 2004, 2007, and 2010. While the model tends to underpredict GDP levels, it captures the overall variation across regions and sectors reasonably well. When pooling all years, the correlation between predicted and actual GDP is 0.79.

2.4 Quantitative analysis

Using the calibrated model, I conduct several counterfactual analyses. First, I simulate a scenario without the commodity export shocks between 2000 and 2010 to quantify the effects of the commodity boom. Next, I examine how static and dynamic externalities amplify these effects on both aggregate and regional outcomes.

Aggregate and distributional effects of the commodity boom In the baseline economy, commodity export revenues grow by around 10% per year in nominal terms. To quantify the impact of the commodity boom, I consider a counterfactual economy in which there is no export boom in the commodity sector between 2000 and 2010. To do this, I set the productivity growth of the commodity sector in Indonesia to 2-3% per year, which results in commodity export growth of less than 1% per year.

Figure 2.6 shows the difference in GDP levels between the factual economy and a counterfactual scenario without the commodity boom. This difference, defined as GDP in the factual economy minus GDP in the counterfactual, captures the impact of the commodity boom. I focus on year 10, which corresponds to the later stage of the boom period. For aggregate GDP, I report both unweighted and employment-weighted changes, using 2001 employment as the weighting variable.

I find that the commodity boom increased aggregate GDP by 1.48% by the end of the boom period. Although the aggregate effect is relatively small, the boom has considerable effects at the regional level. To illustrate this heterogeneity, I compare the effects of the boom on regions within Java Island, which is relatively more industrialized, and those outside Java. As shown in Figure 2.6, regions outside Java Island experienced a 10.62% increase in GDP relative to the counterfactual, while those on Java Island experienced a 4.61% decline. This highlights the uneven spatial distribution of the commodity boom, as also documented by Benguria et al. (2024), who study Brazil's commodity boom using a spatial equilibrium framework.

The effects of the commodity boom also varied across sectors. As shown in Figure 2.7, by the end of the boom period, the commodity sector's share of GDP increased by 7.86 p.p., and the service sector's share rose by 2.40 p.p. In contrast, the manufacturing sector contracted. The GDP share of food manufacturing declined by 2.59 p.p. and that of non-food manufacturing fell by 7.67 p.p.

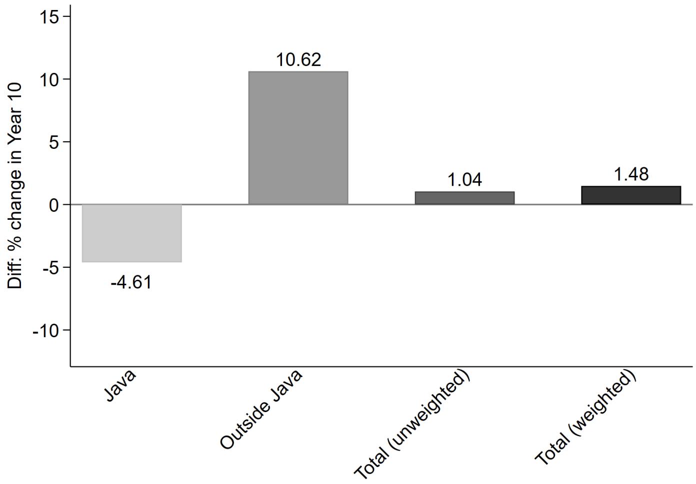


Figure 2.6: Change in GDP level in year 10 relative to the counterfactual (percent change)

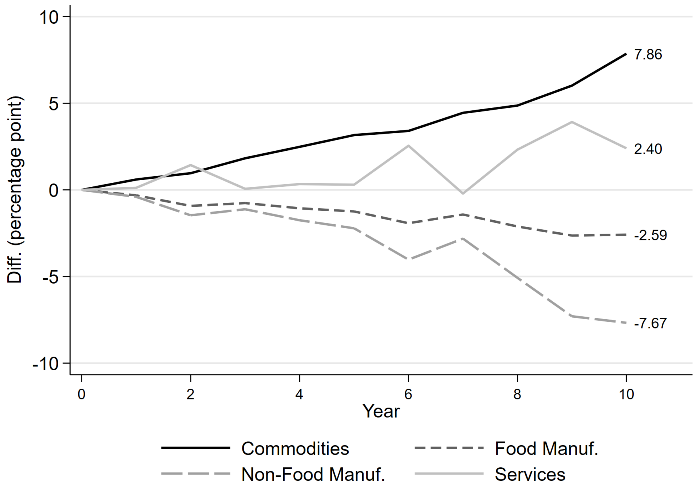


Figure 2.7: Change in sectoral GDP shares in year 10 relative to the counterfactual (percentage points)

The role of agglomeration economies Next, I examine the role of static externalities in amplifying the effects of the commodity boom. Specifically, I assess the impact of the boom in the absence of agglomeration economies in non-commodity sectors by setting $\alpha_j = 0$ in equation (2.21). As shown in Figure 2.8, without agglomeration economies, the economy captures significantly smaller gains from the commodity boom. The weighted change in GDP level in year 10 is approximately 45% lower than in the baseline model.

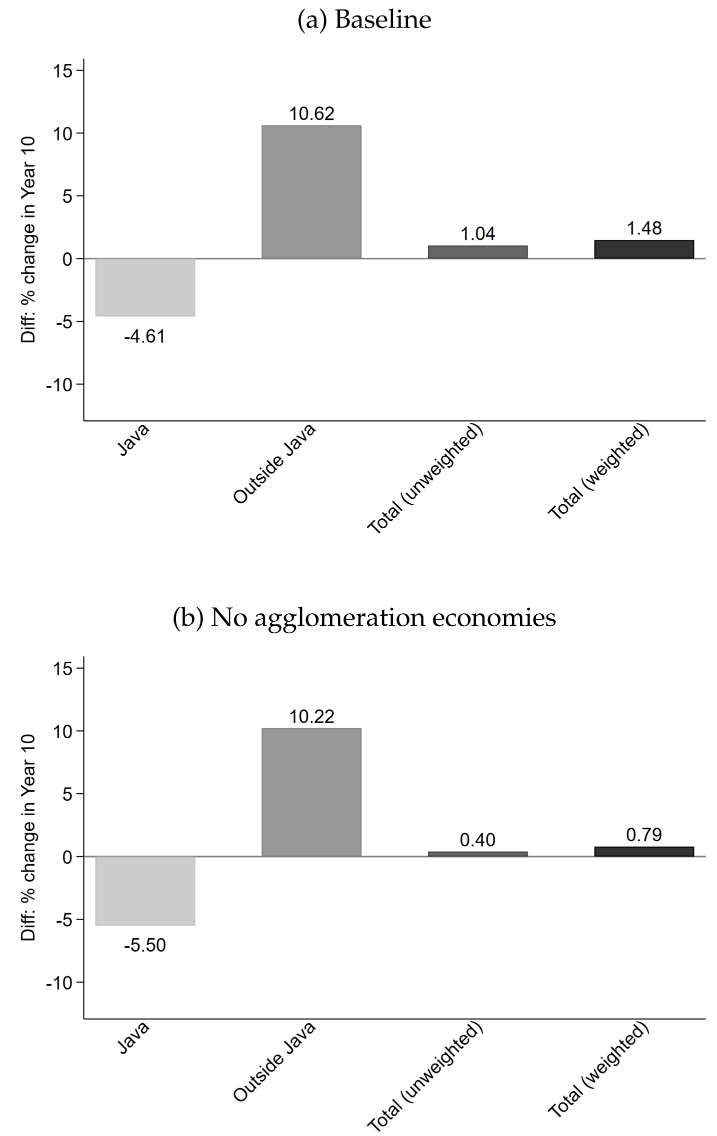


Figure 2.8: Change in GDP level in year 10 relative to the counterfactual (percent change): baseline vs no agglomeration economies

The role of dynamic externalities A key mechanism behind the decline in manufacturing GDP is the slowdown in manufacturing productivity growth induced by the boom. Figures 2.9 and 2.10 show cumulative productivity growth in manufacturing sectors under the baseline and counterfactual scenarios. The results show that the commodity boom negatively affects manufacturing productivity in both Java and non-Java regions. Moreover, the gap between the baseline and counterfactual scenarios widens after the boom period, particularly after 2011, indicating that the adverse effects on productivity persist and intensify over time.

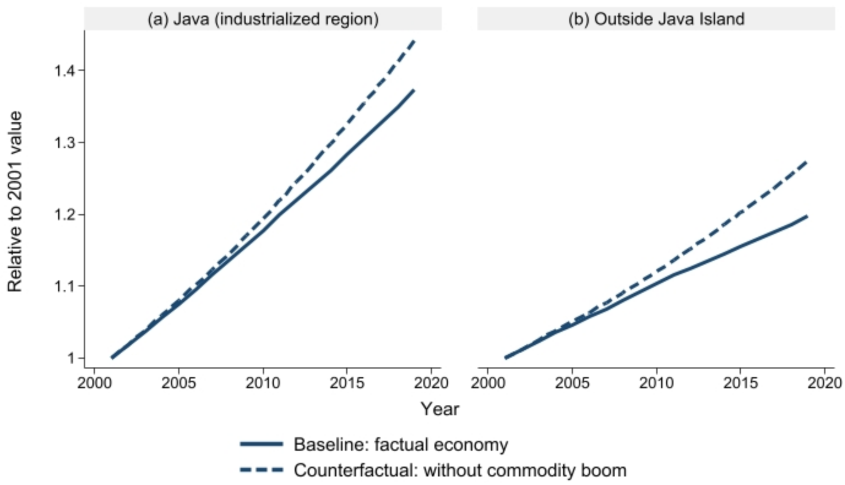


Figure 2.9: Cumulative growth of productivity: food manufacturing

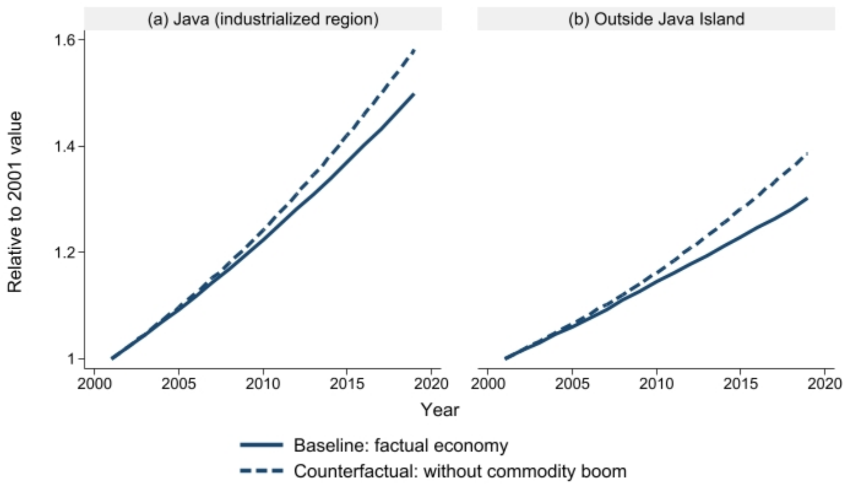
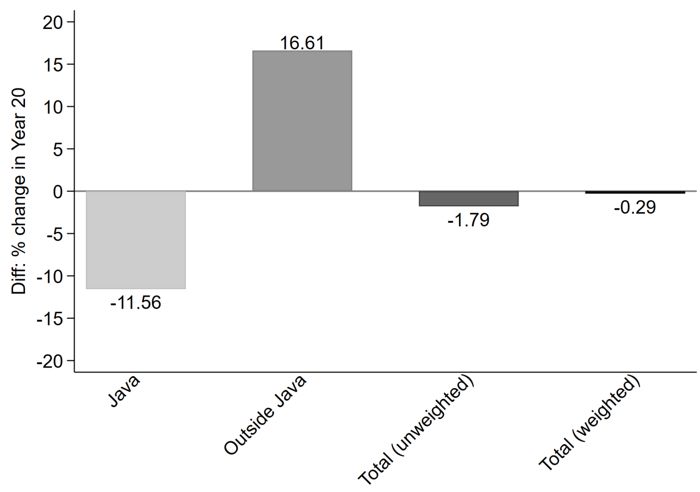


Figure 2.10: Cumulative growth of productivity: non-food manufacturing

To examine the role of dynamic externalities, I set manufacturing productivity in the factual economy (with the commodity boom) equal to manufacturing productivity levels in the counterfactual economy (without the commodity boom). In this scenario, local productivity in manufacturing sectors does not depend on past local innovation. Figure 2.11 compares changes in GDP levels in year 20 between baseline and the scenario without dynamic externalities or learning-by-doing.

As shown in Figure 2.11b, in the absence of learning-by-doing, the weighted change in GDP is positive but relatively small. The regional effects, however, remain substantial. Note that the decline in GDP for Java Island is smaller compared to the baseline scenario with learning-by-doing. These results suggest that dynamic externalities in manufacturing can amplify the adverse effects of commodity booms, particularly in more industrialized regions.

(a) Baseline



(b) No dynamic externalities

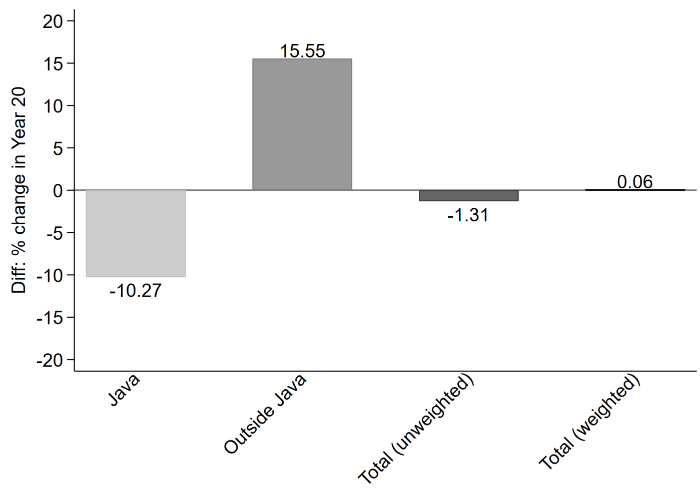


Figure 2.11: Change in GDP level in year 20 relative to the counterfactual (percent change): baseline vs no dynamic externalities

Welfare analysis Lastly, I examine the impact of the commodity boom on welfare. I compute the discounted utility, $\sum \beta^t U^s$ where β is discount factor, t is time period, U is amenity-adjusted real income, and s refers to the scenario. I compute the welfare in the baseline economy relative to the one in the counterfactual economy without the commodity export boom. Table 2.5 shows the results using different values of discount factor. Using $\beta = 0.96$, I find that the commodity boom leads to a decline in welfare by 0.32%. As can be seen from the results, the welfare effect depends on how patient the workers are. It also depends on the magnitude and the length of the boom period.

Table 2.5: Welfare: factual vs counterfactual (without the commodity boom)

Discount factor (β)	Factual	Counterfactual (without the commodity boom)	Difference (%) relative to counterfactual
0.97	100	100.49	-0.49
0.96	100	100.32	-0.32
0.95	100	100.16	-0.16

Notes: Welfare is computed based on simulations from years 1 to 40. Welfare in the baseline (factual) economy is normalized to 100.

2.5 Conclusion

In this chapter, I quantify the aggregate and distributional effects of a commodity boom using a dynamic spatial model. The model incorporates internal migration, sectoral linkages, agglomeration economies, and dynamic externalities in manufacturing sectors. I calibrate the model to the Indonesian economy and conduct counterfactual analysis to examine the effects of commodity export shocks.

The findings provide evidence consistent with the 'Dutch disease' phenomenon, where commodity booms may negatively affect long-term manufacturing outcomes and welfare. While the commodity boom raises aggregate GDP during the boom period, it can reduce welfare and contribute to a decline in manufacturing in the long run, particularly in more industrialized regions. The results also highlight the important roles of static and dynamic externalities. Agglomeration economies amplify short-run gains, while dynamic externalities in manufacturing intensify long-run losses by slowing productivity growth.

Overall, this study has shown that commodity booms have significant impacts on the spatial distribution of economic activities and can potentially hinder industrialization in commodity-exporting countries. While this paper provides valuable insights, one of the limitations is that it abstract from the role of government. A potential extension of the model is to incorporate government responses, such as tax and transfer policies, which can help mitigate adverse effects, particularly in the long term.

In addition, the expansion of resource sectors often comes with environmental costs. In the case of palm oil, for example, the boom has been closely linked to deforestation[8]. The current model does not account for the environmental costs induced by commodity export shocks. Future research could build on this framework to study the welfare effects of commodity booms in the presence of environmental externalities.

[8] For more details, see Naylor et al. (2019), Qaim et al. (2020), Cisneros et al. (2021), Balboni et al. (2021), Busch et al. (2022), Hsiao (2024).

References

Ahlfeldt, G. M. and E. Pietrostefani (2019). The economic effects of density: A synthesis. *Journal of Urban Economics 111*, 93–107.

Allcott, H. and D. Keniston (2018). Dutch disease or agglomeration? The local economic effects of natural resource booms in modern America. *Review of Economic Studies 85*(2), 695–731.

Allen, T. and C. Arkolakis (2014). Trade and the topography of the spatial economy. *Quarterly Journal of Economics 129*(3), 1085–1139.

Allen, T. and D. Donaldson (2020, November). Persistence and path dependence in the spatial economy. Working Paper 28059, National Bureau of Economic Research.

Aragón, F. M. and J. P. Rud (2013). Natural Resources and Local Communities : Evidence from a Peruvian Gold Mine A. *American Economic Journal: Economic Policy 5*(2), 1–25.

Balboni, C., R. Burgess, A. Heil, J. Old, and B. A. Olken (2021). Cycles of fire? politics and forest burning in indonesia. In *AEA Papers and Proceedings*, Volume 111, pp. 415–419. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Baldomero-Quintana, L. (2025). The Geography of Commodity Booms.

Benguria, F., F. Saffie, and S. Urzua (2023). The Transmission of Commodity Price Super-Cycles. *The Review of Economic Studies 00*(0), 1–33.

Benguria, F., F. Saffie, and S. Zhang (2024, December). Spatial linkages and the uneven effects of a commodity boom. Working Paper 33287, National Bureau of Economic Research.

Bjørnland, H. C. and L. A. Thorsrud (2016). Boom or gloom? examining the dutch disease in two-speed economies. *The Economic Journal 126*(598), 2219–2256.

Bjørnland, H. C., L. A. Thorsrud, and R. Torvik (2019). Dutch disease dynamics reconsidered. *European economic review 119*, 411–433.

Bryan, G. and M. Morten (2019). The aggregate productivity effects of internal migration: Evidence from indonesia. *Journal of Political Economy 127*(5), 2229–2268.

Busch, J., O. Amarjargal, F. Taheripour, K. G. Austin, R. N. Siregar, K. Koenig, and T. W. Hertel (2022). Effects of demand-side restrictions on high-deforestation palm oil in europe on deforestation and emissions in indonesia. *Environmental Research Letters 17*(1), 014035.

Cai, S., L. Caliendo, F. Parro, and W. Xiang (2025). Mechanics of spatial growth.

Caliendo, L., M. Dvorkin, and F. Parro (2019). Trade and labor market dynamics: General equilibrium analysis of the china trade shock. *Econometrica 87*(3), 741–835.

Caliendo, L., F. Parro, E. Rossi-Hansberg, and P.-D. Sarte (2018). The Impact of Regional and Sectoral Productivity Changes on the U.S. Economy. *Review of Economic Studies 85*(4), 2042–2096.

Caselli, F. and W. J. Coleman II (2001). The us structural transformation and regional convergence: A reinterpretation. *Journal of political Economy 109*(3), 584–616.

Ciccone, A. and R. E. Hall (1996). Productivity and the density of economic activity. *The American Economic Review 86*(1), 54–70.

Cisneros, E., K. Kis-Katos, and N. Nuryartono (2021). Palm oil and the politics of deforestation in indonesia. *Journal of Environmental Economics and Management 108*, 102453.

Combes, P.-P. and L. Gobillon (2015). The empirics of agglomeration economies. In *Handbook of regional and urban economics*, Volume 5, pp. 247–348. Elsevier.

Conte, B., K. Desmet, D. K. Nagy, and E. Rossi-Hansberg (2021). Local sectoral specialization in a warming world. *Journal of Economic Geography 21*(4), 493–530.

Costa, F., J. Garred, and J. P. Pessoa (2016). Winners and losers from a commodities-for-manufactures trade boom. *Journal of International Economics 102*, 50–69.

Cust, J. and S. Poelhekke (2015). The local economic impacts of natural resource extraction. *Annual Review of Resource Economics 7*(1), 251–268.

Desmet, K. and J. V. Henderson (2015). The geography of development within countries. In *Handbook of regional and urban economics*, Volume 5, pp. 1457–1517. Elsevier.

Desmet, K., D. K. Nagy, and E. Rossi-Hansberg (2018). The geography of development. *Journal of Political Economy 126*(3), 903–983.

Desmet, K. and E. Rossi-Hansberg (2014, April). Spatial development. *American Economic Review 104*(4), 1211–43.

Duranton, G. and D. Puga (2004). Micro-foundations of urban agglomeration economies. In *Handbook of regional and urban economics*, Volume 4, pp. 2063–2117. Elsevier.

Eaton, J. and S. Kortum (2002). Technology, geography, and trade. *Econometrica 70*(5), 1741–1779.

Eaton, J., S. Kortum, B. Neiman, and J. Romalis (2016). Trade and the global recession. *American Economic Review 106*(11), 3401–3438.

Eckert, F. and M. Peters (2018). Spatial Structural Change.

Edwards, R. B. (2024a). Export agriculture and rural poverty: evidence from Indonesian palm oil.

Edwards, R. B. (2024b). Spillovers from agricultural processing.

Ellison, G. and E. L. Glaeser (1997). Geographic Concentration in U.S. Manufacturing Industries: A Dartboard Approach. *Journal of Political Economy 105*(5), 889–927.

Faber, B. and C. Gaubert (2019). Tourism and Economic Development : Evidence from Mexico's Coastline. *American Economic Review 109*(6), 2245–2293.

Fadinger, H., P. Herkenhoff, and J. Schymik (2024). Quantifying the germany shock: Structural labor-market reforms and spillovers in a currency union. *Journal of International Economics*, 103905.

Fan, J. (2019). Internal geography, labor mobility, and the distributional impacts of trade. *American Economic Journal: Macroeconomics 11*(3), 252–288.

Gylfason, T., T. T. Herbertsson, and G. Zoega (1999). A mixed blessing: natural resources and economic growth. *Macroeconomic dynamics 3*(2), 204–225.

Head, K. and J. Ries (2001). Increasing returns versus national product differentiation as an explanation for the pattern of u.s.-canada trade. *American Economic Review 91*(4), 858–876.

Hsiao, A. (2024). Coordination and Commitment in International Climate Action: Evidence from Palm Oil.

Krugman, P. (1987). The narrow moving band, the Dutch disease, and the competitive consequences of Mrs. Thatcher. Notes on trade in the presence of dynamic scale economies. *Journal of Development Economics 27*(1-2), 41–55.

Ma, L. and Y. Tang (2020). Geography, trade, and internal migration in china. *Journal of Urban Economics 115*, 103181.

Matsuyama, K. (1992). Agricultural productivity, comparative advantage, and economic growth. *Journal of economic theory 58*(2), 317–334.

Michaels, G. (2011). The Long Term Consequences of Resource-Based Specialisation. *Economic Journal 121*(551), 31–57.

Nagy, D. K. (2023). Hinterlands, city formation and growth: Evidence from the us westward expansion. *Review of Economic Studies 90*(6), 3238–3281.

Naylor, R. L., M. M. Higgins, R. B. Edwards, and W. P. Falcon (2019). Decentralization and the environment: Assessing smallholder oil palm development in Indonesia. *Ambio 48*(10), 1195–1208.

Qaim, M., K. T. Sibhatu, H. Siregar, and I. Grass (2020). Environmental, Economic, and Social Consequences of the Oil Palm Boom. *Annual Review of Resource Economics 12*(1), 321–344.

Redding, S. J. (2016). Goods trade, factor mobility and welfare. *Journal of International Economics 101*, 148–167.

Redding, S. J. and E. Rossi-Hansberg (2017). Quantitative spatial economics. *Annual Review of Economics 9*(1), 21–58.

Resosudarmo, B. and D. Hartono (2020). Inter-province input output table. Technical report, Tech. rep., ANU.

Rosenthal, S. S. and W. C. Strange (2004). Evidence on the nature and sources of agglomeration economies. In *Handbook of regional and urban economics*, Volume 4, pp. 2119–2171. Elsevier.

Sachs, J. D. and A. M. Warner (1995, December). Natural resource abundance and economic growth. Working Paper 5398, National Bureau of Economic Research.

Simonovska, I. and M. E. Waugh (2014). The elasticity of trade: Estimates and evidence. *Journal of International Economics 92*(1), 34–50.

Tombe, T. and X. Zhu (2019). Trade, migration, and productivity: A quantitative analysis of china. *American Economic Review 109*(5), 1843–72.

Torvik, R. (2001). Learning by doing and the dutch disease. *European economic review 45*(2), 285–306.

Valentinyi, A. and B. Herrendorf (2008). Measuring factor income shares at the sectoral level. *Review of Economic Dynamics 11*(4), 820–835.

van Wijnbergen, S. (1984). The 'Dutch Disease': A Disease After All? *Economic Journal 94*(373), 41–55.

Yotov, Y. V., R. Piermartini, M. Larch, et al. (2016). *An advanced guide to trade policy analysis: The structural gravity model*. WTO iLibrary.

Appendix

2.A Data and descriptive statistics

Table 2.A.1: Real export share by sector, 2000 and 2010

No.	Sector	Sectoral export share (%) 2000	2010	Δ Export share (p.p.)
1	Rice	0.00	0.01	0.01
2	Other food crops	0.05	0.05	0.00
3	Estate crops	0.93	6.05	5.12
4	Animal farming	0.05	0.09	0.04
5	Forestry	0.10	0.05	-0.05
6	Fishery	0.35	0.36	0.01
7	Oil and gas extraction	15.03	12.54	-2.49
8	Mining and quarrying	7.68	17.61	9.93
9	Manufacture of coke, refined petroleum	13.58	2.50	-11.07
10	Manufacture of food, beverages, and tobacco	11.83	16.59	4.75
11	Manufacture of textile, wearing apparel, footwear	13.58	7.53	-6.05
12	Manufacture of wood products, etc	7.17	2.39	-4.78
13	Manufacture of paper and paper products	4.68	4.58	-0.10
14	Manufacture of fertilizers, chemicals, rubber, non-metallic mineral products	8.41	5.02	-3.39
15	Manufacture of cement	0.20	0.05	-0.15
16	Manufacture of basic metals	2.95	6.57	3.62
17	Manufacture of motor vehicles, (electrical) machinery and equipment	11.00	12.30	1.30
18	Manufacture of metal products	1.10	1.98	0.87
19	Other manufacturing sectors	1.30	3.75	2.45
	Total (commodity and manufacturing sectors)	100.00	100.00	

Data sources: Indonesian Inter-regional Input-Output (IRIO), 2000 and 2010.

Table 2.A.2: Real export share by province, 2000 and 2010

No.	Province	Regional export share (%) 2000	2010	Δ Export share (p.p.)
	Sumatera island			
1	Nanggroe Aceh Darussalam	2.63	0.72	-1.91
2	North Sumatra	4.38	5.87	1.49
3	West Sumatra	0.17	1.89	1.73
4	Riau	10.53	19.82	9.30
5	Jambi	0.56	1.01	0.46
6	South Sumatra	2.99	2.19	-0.79
7	Bangka Belitung	0.45	1.19	0.73
8	Bengkulu	0.03	0.08	0.06
9	Lampung	0.84	1.39	0.55
	Java and Bali islands			
10	DKI Jakarta	14.47	23.62	9.16
11	West Java	24.58	0.87	-23.71
12	Banten	3.98	0.88	-3.10
13	Central Java	1.65	2.71	1.06
14	DI Yogyakarta	0.14	0.01	-0.13
15	East Java	8.61	8.68	0.07
16	Bali	0.22	0.27	0.05
	Borneo/Kalimantan island			
17	West Kalimantan	1.34	0.62	-0.71
18	Central Kalimantan	0.21	0.42	0.21
19	South Kalimantan	1.38	4.38	3.01
20	East Kalimantan	13.43	15.12	1.69
	Sulawesi island			
21	North Sulawesi	0.17	0.28	0.11
22	Gorontalo	0.01	0.01	0.00
23	Central Sulawesi	0.27	0.26	-0.01
24	South Sulawesi	0.85	1.47	0.62
25	Southeast Sulawesi	0.24	0.35	0.12
	Nusa Tenggara, Maluku, and Papua regions			
26	West Nusa Tenggara	1.15	1.31	0.17
27	East Nusa Tenggara	0.02	0.02	0.00
28	Maluku and North Maluku	0.23	0.30	0.07
29	Papua	4.52	4.25	-0.27

Data sources: Indonesian Inter-regional Input-Output (IRIO), 2000 and 2010. Regional aggregation is based on the 2000 IRIO, with Maluku and North Maluku merged into a single region.

2.B Quantitative model

Utility maximization As in Desmet et al. (2018), assuming the moving cost as shown in Equation (2.10), the value function of an agent living at r_0 in period 0 after observing a distribution of taste shocks in all locations $(\bar{\varepsilon}_{i1})$ is as follows:

$$V(r_0,\bar{\varepsilon}_{i1}) = \max_{r_1}\left[\frac{a_{r1}\,y_{r1}\,\varepsilon_{ir1}}{m^o_{r_0}\,m^d_{r_1}} + \beta E\Big(\frac{V(r_1,\bar{\varepsilon}_{i2})}{m^o_{r_0}\,m^d_{r_1}}\Big)\right] \tag{2.B.1}$$

$$= \frac{1}{m^o_{r_0}}\max_{r_1}\left[\frac{a_{r1}\,y_{r1}\,\varepsilon_{ir1}}{m^d_{r_1}} + \beta E\Big(\frac{V(r_1,\bar{\varepsilon}_{i2})}{m^d_{r_1}}\Big)\right] \tag{2.B.2}$$

$$= \frac{1}{m^o_{r_0}}\left[\max_{r_1}\left[\frac{a_{r1}\,y_{r1}\,\varepsilon_{ir1}}{m^d_{r_1}}\right] + \beta E\left(\max_{r_2}\left[\frac{a_{r2}\,y_{r2}\,\varepsilon_{ir2}}{m^d_{r_2}} + \frac{V(r_2,\bar{\varepsilon}_{i3})}{m^d_{r_2}}\right]\right)\right] \tag{2.B.3}$$

Sectoral price indices Price index of the commodity sector in region r at time t_0 can be written as:

$$P^{-\theta}_{Crt_0} = (\Lambda\, B_C)^{-\theta}\sum_{u=1}^{N} T^{\theta}_{Cut_0}\, w_{ut_0}^{-\theta(\alpha_C+\mu_C+\vartheta_C)} \times R_{ut_0}^{-\theta(1-\alpha_C-\mu_C-\vartheta_C)}\,\tau(r,u)^{-\theta} \tag{2.B.4}$$

where $\Lambda = \Gamma\Big(1-\frac{\rho}{(1-\rho)\theta}\Big)^{-\frac{1-\rho}{\rho}}$ and

$$B_C = \vartheta_C^{-\vartheta_C}\,\mu_C^{-\mu_C}\,(\vartheta_C+\mu_C)^{-\alpha_C}\,(1-\vartheta_C-\mu_C)^{-1+\alpha_C+\vartheta_C+\mu_C}.$$

Price index of the manufacturing sector $K \in \{F, M\}$ is as follows:

$$P^{-\theta}_{Krt_0} = (\Lambda\, B_K)^{-\theta}\sum_{u=1}^{N} T^{\theta}_{Kut_0}\, w_{ut_0}^{-\theta\gamma_K(\alpha_C+\mu_C+\vartheta_C)} \times R_{ut_0}^{-\theta\gamma_K(1-\alpha_C-\mu_C-\vartheta_C)}\,\tau(r,u)^{-\theta}\prod_{j\in\{C,F,M,S\}} P_{jut_0}^{-\theta\,\gamma_{K,j}} \tag{2.B.5}$$

with

$$B_K = \left[\gamma_K^{-1}\,\vartheta_K^{-\vartheta_K}\,\mu_K^{-\mu_K}\,(\vartheta_K+\mu_K)^{-\alpha_K}\,(1-\vartheta_K-\mu_K)^{-1+\alpha_K+\vartheta_K+\mu_K}\right]^{\gamma_K}\prod_{j=1}^{J}\gamma_{K,j}^{-\gamma_{K,j}}.$$

Service-sector price index simplifies to:

$$P_{Srt_0}^{-\theta} = (\Lambda\, B_S)\; T_{Srt_0}^{-1}\; w_{rt_0}^{\mu_S+\vartheta_S}\; R_{rt_0}^{1-\mu_S-\vartheta_S} \tag{2.B.6}$$

where

$$B_S = \vartheta_S^{-\vartheta_S}\, \mu_S^{-\mu_S}\, (1-\vartheta_S-\mu_S)^{-1+\vartheta_S+\mu_S}$$

Sectoral productivity The fundamental productivity in commodities can be written as:

$$\begin{aligned} T_{Cut_0}^{-\theta} = {} & (\Lambda\, B_C)^{-\theta}\; w_{ut_0}^{-\theta(\alpha_C+\vartheta_C+\mu_C)}\; R_{ut_0}^{-\theta(1-\alpha_C-\vartheta_C-\mu_C)}\; Y_{Cut_0}^{-1} \\ & \times \sum_{r=1}^{N} P_{Crt_0}^{\theta}\, \tau(r,u)^{-\theta} \left[\chi_C\, (w_{rt_0}\, \tilde{L}_{rt_0} + R_{rt_0}\, H_r) + w_{rt_0} \prod_{j\in\{F,M\}} \frac{\gamma_{j,C}}{\mu_j+\vartheta_j}\, \tilde{L}_{jrt_0} \right] \end{aligned} \tag{2.B.7}$$

Similarly, for manufacturing productivity $K \in \{F, M\}$, the corresponding expression is:

$$\begin{aligned} T_{Kut}^{-\theta} = {} & (\Lambda\, B_K)^{-\theta}\; w_{ut_0}^{-\theta\gamma_K(\alpha_K+\vartheta_K+\mu_K)}\; R_{ut_0}^{-\theta\gamma_K(1-\alpha_K-\vartheta_K-\mu_K)}\; Y_{Kut_0}^{-1} \prod_{j\in\{C,F,M,S\}} P_{jut_0}^{-\theta\gamma_{K,j}} \\ & \times \sum_{r=1}^{N} P_{Krt_0}^{\theta}\, \tau(r,u)^{-\theta} \left[\chi_K\, (w_{rt_0}\, \tilde{L}_{rt_0} + R_{rt_0}\, H_r) + w_{rt_0} \prod_{j\in\{F,M\}} \frac{\gamma_{j,K}}{\mu_j+\vartheta_j}\, \tilde{L}_{jrt_0} \right] \end{aligned} \tag{2.B.8}$$

Table 2.B.3: Destination-specific moving costs (normalized)

No	Region	Moving Cost
1	Nanggroe Aceh Darussalam	1.299
2	North Sumatra	1.252
3	West Sumatra	1.196
4	Riau and Riau Islands	1.538
5	Jambi	1.146
6	South Sumatra and Bangka Belitung Islands	1.244
7	Bengkulu	1.112
8	Lampung	1.109
9	DKI Jakarta, West Java, and Banten	1.275
10	Central Java	1.125
11	DI Yogyakarta	1.144
12	East Java	1.169
13	West Kalimantan	1.188
14	Central Kalimantan	1.250
15	South Kalimantan	1.199
16	East Kalimantan	1.741
17	North Sulawesi and Gorontalo	1.194
18	Central Sulawesi	1.222
19	South Sulawesi	1.112
20	Southeast Sulawesi	1.131
21	Bali	1.210
22	West Nusa Tenggara	1.111
23	East Nusa Tenggara	1.000
24	Maluku and North Maluku	1.246
25	Papua and West Papua	1.246

Table 2.B.4: Parameter values: input-output coefficient (IRIO 2000) ($\gamma_{j,k}$)

Ouput j:	Food manufacturing ($j = F$)	Non-Food manufacturing ($j = M$)
Input $k \in C, F, M, S$		
$\gamma_{j,C}$	0.54	0.08
$\gamma_{j,F}$	0.27	0.01
$\gamma_{j,M}$	0.02	0.43
$\gamma_{j,S}$	0.17	0.48

Table 2.B.5: Summary of parameter values

Parameter	Values [sector $j \in C, F, M, S$]	Notes (source)
Technology		
ϑ_j	$\vartheta_C = 0.001$, $\vartheta_F = 0.0036$, $\vartheta_M = \vartheta_S = 0.014$,	innovation labor share (Sakernas 2002) and Conte et al. (2021)
μ_j	$\mu_C = 0.68$, $\mu_F = 0.63$, $\mu_M = 0.62$, $\mu_S = 0.62$,	production labor share
$1 - \mu_j - \vartheta_j$	0.3 for $j = \{C, F\}$, 0.23 for $j = \{M, S\}$	land share (Nagy (2023), Caselli and Coleman II (2001))
γ_j	$\gamma_C = 1$, $\gamma_F = 0.3$, $\gamma_M = 0.33$, $\gamma_S = 1$	value-added share in gross output for $j \in \{F, M\}$ (IRIO 2000)
$\gamma_{j,k}$	Table 2.B.4	material share: input from sector k used in sector j's production
θ	4	trade elasticity (Simonovska and Waugh (2014))
δ	0.993	one minus strength of technology diffusion (Desmet et al. (2018))
α_j	$\alpha_C = 0$, $\alpha_F = \alpha_M = \alpha_S = 0.02$	elasticity of productivity w.r.t local employment density (Ahlfeldt and Pietrostefani (2019))
κ_j	$\kappa_F = \kappa_M = 0.003$	elasticity of productivity w.r.t. local sectoral innovation (Table 2.1)
Preference		
χ_j	$\chi_C = 0.14$, $\chi_F = 0.22$, $\chi_M = 0.22$, $\chi_S = 0.42$	sectoral shares of final consumption (IRIO 2000)
ρ	0.75	CES parameter within sector (elasticity of substitution $\sigma = 4$)
υ	0.32	congestion externalities (Desmet et al. (2018))
η	2.7	location taste heterogeneity parameter (Bryan and Morten (2019), Tombe and Zhu (2019))
β	0.96	annual discount rate
Spatial frictions		
$\tau(r, s)$		bilateral trade cost (estimated using the 2000 IRIO and WIOD data)
m_r^d		destination-specific migration cost (Table 2.B.3)

Chapter 3

Firm Responses to Industrial Policy: Evidence from Local Content Requirement (LCR) Policy

3.1 Introduction

Governments in both developing and developed countries increasingly use industrial policy to promote domestic production and technological upgrading. One of the policy instruments is the local content requirement (LCR), which mandates that targeted sectors or firms source a certain proportion of inputs from domestic suppliers. LCRs have been used in various sectors and countries to promote domestic production, support local industries, and encourage technological upgrading (Deringer et al. (2018), Deringer et al. 2018, (Deringer et al., 2018)). However, this policy remains controversial due to concerns about its economic efficiency (Grossman (1981), Richardson (1991), Krishna and Itoh (1988), Ing and Grossman (2023)) and potential conflicts with international trade agreements (Bown (2024), Limenta and Ing (2022), Fernando and Ing (2022)).

A potential downside of the local content requirements (LCR) policy is highlighted by Grossman (1981). He argues that increases in LCRs have an ambiguous effect on industry value added. The overall impact depends on how responsive intermediate goods production is to changes in output prices, and how sensitive final goods production is to changes in input prices. One possible outcome is that higher LCRs raise the price of domestic inputs, increasing production costs for downstream firms. This can lead to higher final goods prices, which may reduce consumer demand and, in turn, lower the demand for intermediate inputs.

This paper studies how firms respond to local content requirements, focusing on both the intended and unintended consequences of the policy. Using detailed plant-level data from Indonesia, I study the effects of LCR policy in the telecommunications sector. First, I investigate how the LCR policy affect firms' input composition and cost structure. Second, I estimate the impacts of the policy on firm-level outcomes, such as sales, employment, and value-added. Lastly, I examine whether firms in upstream sectors benefit from the policy through production linkages.

Previous studies have documented the economic impact of LCR policies in various sectors and countries. However, there is limited evidence on how firms respond to LCR policies, particularly in the context of developing economies where policy implementation and firm compliance are often less predictable. Indonesia provides an excellent setting, as manufacturing product-level data allow the construction of plant-level exposure to the policy, which varies across plants.

Indonesia has imposed LCR policies in various sectors, including telecommunications, energy, electricity, and the automotive industry. The LCR regulations in the telecommunications sector were issued in 2009, while LCR regulations in other industries were mostly imposed after 2011. Since the manufacturing data in this study are only available until 2015, I focus on the telecommunications sector to investigate how firms' responses evolve over time.

To identify causal effects, I exploit cross-plant variation in exposure to the LCR policies in the telecommunications sector. I measure plant-level exposure based on the share of LCR-targeted products in each plant's output[1]. I use pre-policy data from 2006 to mitigate endogeneity concerns, as firms may adjust their product mix in response to the LCR policy. In terms of timing, I set the treatment year to 2007—two years before the LCR regulations were issued—to account for the legal process that took place prior to the policy's implementation.

To estimate the effects of the LCR policy on firm outcomes, I use a difference-in-differences approach. Specifically, I use Two-Way Fixed Effects (TWFE) and a dynamic extension of the TWFE model to examine both static and dynamic effects. The identifying assumption is that, in the ab-

[1]The manufacturing survey data cannot be aggregated to the firm level. In this paper, I use the terms 'plant' and 'firm' interchangeably.

sence of the LCR policy, firms with different levels of exposure would have followed similar trends over time. I test the plausibility of this assumption using the dynamic specification. The LCR policy may affect not only firms that produce the targeted products but also firms in upstream sectors that supply inputs to them. To isolate the policy's effect from potential shocks in upstream sectors, I extend the baseline model by including a control for upstream exposure.

I find that the local content requirement (LCR) policy in Indonesia's telecommunications sector induced firms producing targeted products to substitute away from imported inputs toward domestic sources. Firms producing LCR-targeted products increased their domestic content share, primarily through a higher wage bill share, while the share of imported materials in total material expenditures declined. Looking at the effects on output and employment, I find no significant effects on firm-level sales, employment, or value added. The findings also suggest that labor productivity tends to decline and unit labor costs tend to increase over time.

I also find evidence of indirect effects on upstream firms. Firms more exposed to the policy through their production linkages increased their use of domestic inputs, but not through labor cost channels as observed in the targeted industry. While the average effects on output and productivity were muted, there is evidence of short-run employment gains between 2008 and 2011 among upstream suppliers. This suggests that the LCR policy propagated upstream mainly through employment, with limited impact on output. Overall, the results highlight how firms in the targeted industry and those in upstream sectors respond differently after the implementation of the policy.

This paper contributes to the growing body of research on industrial policy (Evenett and Fritz (2020), Juhász et al. (2023), Juhász and Steinwender (2024), Juhász and Lane (2024), Bown (2024)), with a particular focus on local content requirements (LCRs) (Grossman (1981), Vousden (1987), Richardson (1991), Krishna and Itoh (1988), Deringer et al. (2018), Ing and Grossman (2023)). Ing and Grossman (2023) provide a general overview of LCR policies and discuss recent developments in both theoretical and empirical research on their economic impacts across various settings. Aswicahyono et al. (2023) present a related review focused on Indonesia, and examine the effects of LCR policies using both econometric analysis and a computable general equilibrium (CGE) model. Within this growing literature, Vadila and Christian (2023) analyze the trade effects of LCRs using product-level data, while Ing and Zhang (2023) estimate the impact of LCRs on manufacturing firms linked to the oil and gas sector using a structural model. Both Negara (2017) and Aswicahyono et al. (2023) study the effects of LCRs on manufacturing firms, using different methods to identify treated firms. Negara (2017) uses imported input shares as a proxy for LCR exposure, while Aswicahyono et al. (2023) use the actual share of local content certificates in each sector as a proxy for LCR policy intensity.

I contribute to this literature in three main ways. First, compared to Aswicahyono et al. (2023) and Negara (2017), I construct firm-level exposure using detailed product-level data and rely on pre-policy information to mitigate endogeneity concerns. Second, I compare firms with different levels of exposure within ICT-related sectors, which improves the comparability between treated and control firms. Third, building on Vadila and Christian (2023) that examine the propagation of LCR effects to upstream sectors using trade data, I provide evidence on the indirect impact of LCR policies on upstream firms using manufacturing plant-level data.

The remainder of this chapter is structured as follows. Section 3.2 provides background on LCR regulations in Indonesia's telecommunications sector and describes the data used in the analysis. Section 3.3 presents the empirical strategy, and Section 3.4 presents the results. Section 3.5 concludes.

3.2 Background and data

3.2.1 LCR policies in the telecommunications sector

Indonesia has implemented local content requirement (LCR) policies across several sectors, including telecommunications, pharmaceuticals, oil and gas, and energy infrastructure. Aswicahyono et al. (2023) provide a comprehensive review of LCR policy implementation in Indonesia. In this section I provide a brief overview of the LCR regulations introduced in the telecommunications sector in 2009.

In telecommunications sector, LCR policy has been introduced since 2009 through the Ministry of Communication and Information Technology (MCI) regulations: MCI Regulation No. 7/2009, MCI Regulation No. 30/2009, and MCI Regulation No. 41/2009. The first regulation is MCI Regulation No. 7/2009, issued in January 2009. It outlines how radio frequency bands should be managed and allocated for wireless broadband services in Indonesia. The main goal of this regulation is to ensure the radio frequency spectrum is used efficiently and effectively to support the growth and delivery of wireless broadband across the country. Although this regulation mainly deals with managing radio frequencies, it also highlights the need to support local industries. It encourages the use of telecommunication equipment that includes a certain amount of locally made components.

The second regulation is MCI Regulation No. 30/2009, issued in August 2009. It sets the rules for offering IPTV (Internet Protocol Television) services in Indonesia and explains the licensing process, technical requirements, and how IPTV providers should operate. One important part of this regulation is that it also encourages providers to use equipment and services that include a certain amount of local content.

The third relevant regulation is MCI Regulation No. 41/2009, which outlines the procedures for assessing the achievement of the Domestic Component Level (*Tingkat Komponen Dalam Negeri*, or TKDN) in telecommunications infrastructure development in Indonesia. Operators are required to conduct annual self-assessments of their TKDN attainment, based on verifiable data, and submit these reports to the Ministry of Communication and Information Technology. The regulation also allows for verification by independent survey institutions accredited by the government. Non-compliance with the TKDN requirements can result in administrative sanctions, including fines or revocation of telecommunications operation licenses.

One of the required documents in the reporting and verification process is the Local Content Requirement (LCR) certificate for products. Firms must obtain certification if they claim their products use local resources. To receive a Local Content (TKDN) certificate, a firm must first calculate the share of domestic components in its product, covering materials, labor, and services, using a standardized formula provided by the Ministry of Industry. After completing this self-assessment, the firm must prepare supporting documents such as production data, invoices for locally sourced inputs, and technical specifications, and submit them through the official e-TKDN platform. Verification is conducted by accredited agencies, such as Sucofindo or Surveyor Indonesia, which may include audits and factory inspections. If the review is successful, the Ministry of Industry issues a TKDN certificate, valid for three years. This certification is mandatory for firms that participate in government procurement or sell regulated products, including those covered by MCI Regulation No. 7/2009 and MCI Regulation No. 30/2009.

Aswicahyono et al. (2023) document the distribution of LCR certificates across two-digit industries using data from the Ministry of Industry's LCR database. They find that around half of the LCR certificates issued to manufacturing firms report a local content score between 30% and 50%. Most of these firms are in the pharmaceutical and computer, electronics, and optical sectors. They also highlight that these sectors account for approximately 85% of all LCR certificates with local content ratios in the 30–50% range.

Products directly-affected by the LCR policies I compile a list of LCR-targeted products, including CPC and HS codes, using information from the relevant regulations, the Global Trade Alert database, and Vadila and Christian (2023). I then merge this dataset with product-level data from the Annual Manufacturing Survey to identify firm-level exposure to LCR policies among firms in ICT-related industries. The Global Trade Alert database identifies products that are potentially affected by the regulation on wireless broadband, but not by the one on IPTV. To address this, I complement the product list from the Global Trade Alert database with information from Partnership on Measuring ICT for Development (2022). Table 3.A.5 shows a selection of products that are directly affected by MCI Regulation No. 7/2009 and No. 30/2009.

3.2.2 Data and variables

Manufacturing plant-level data To construct the plant-level panel dataset, I use the Indonesian Annual Survey of Manufacturing Plants that consists of medium and large firms with 20 or more employees. It covers all manufacturing sectors in Indonesia. In 2006, the survey was conducted as a census which was also part of the economic census that is conducted every 10 year. The economic census covers all sectors including agriculture and services, but the data used in this paper only covers manufacturing sectors. The dataset provides detailed industry information (up to five-digit ISIC codes) and the location of each plant at the district level.

Since I focus on telecommunications sector, I use firms that are classified within these two-digit industry, according to ISIC Rev 3 classification: (29) Manufacture of machinery and equipment n.e.c.; (30) Manufacture of office, accounting and computing machinery; (31) Manufacture of electrical machinery and apparatus n.e.c.; (32) Manufacture of radio, television and communication equipment and apparatus.

I construct annual plant-level data from 2003 to 2015. I use information on sales, employment, and value-added as the main dependent variables. To investigate firm responses, I use information on firm's expenditures on employment, intermediate inputs, electricity, fuel, and other items. Specifically, expenditures on intermediate inputs are disaggregated into domestic and imported materials. I construct proxies for domestic content in each plant using information on wage bill and other expenditures. I define two proxies for domestic content shares which are shown in the following equations:

$$DomContent^{WB}_{ist} = \frac{DomesticInputs_{ist} + WageBill_{ist}}{TotalExpenditures_{ist}} \tag{3.1}$$

$$DomContent_{ist} = \frac{DomesticInputs_{ist}}{TotalExpenditures_{ist}} \tag{3.2}$$

where i indexes a plant (or firm), s denotes a two-digit industry, and t denotes the year. It is important to note that the information on expenditures on imported items are only available for materials. Therefore, I assume that, apart from imported materials, all other inputs are purchased domestically.

Plant-level Input-Output data In addition to the main dataset, the Statistical Office also provides data on products used by plants as inputs and products produced as outputs. Note that the inputs mostly include only tradable goods (agriculture, mining, and manufacturing). Detailed inputs from service sectors are not available. The product-level datasets are crucial for this paper, as they allow me to construct a measure of plant-level exposure to the LCR policy based on the targeted products. Product-level data provide information on domestic and imported inputs, as well as domestic sales and exports. Products are classified using the nine-digit *Klasifikasi Komoditi Indonesia (KKI)*, which can be matched with the *Klasifikasi Baku Komoditas Indonesia (KBKI)* concordance published by the Central Statistics Agency (BPS). The KBKI is the national adaptation of the CPC product classification, which can be matched to the HS code system. The product-level dataset is matched with LCR-targeted products based on information from regulations and from the Global Trade Alert database.

Plant exposure to LCR policy Regarding timing, I set the treatment year to 2007, two years before the LCR regulations in the telecommunications sector were issued in 2009. The time required for legal approval varies widely depending on the type of regulation and the issuing institution. The process typically involves drafting by the relevant ministry directorate, public consultation, inter-ministerial coordination (if needed), legal harmonization by the Ministry of Law and Human Rights, and dissemination through the State Gazette or relevant government website. No detailed timeline is available for these two regulations prior to their publication. In general, ministerial, government, or presidential regulations can take several months to two years to be finalized, assuming no major disputes arise.

I measure plant-level exposure based on the share of LCR-targeted products in each plant's output. According to the 2006 Manufacturing Census, around 33.63% of manufacturing plants in Indonesia produce multiple products, as shown in Table 3.A.4. Because firms may adjust their product mix in response to the LCR policy, I use pre-policy data in 2006 to mitigate endogeneity concerns. Specifically, I use the detailed output data at the plant-level as shown in the following equation:

$$LCR\_exposure_{is,2006} = \sum_{d \in D} \frac{sales_{dis,2006}}{\sum_p sales_{pis,2006}} \tag{3.3}$$

where p is an index for a nine-digit KKI product produced by a plant or firm i in sector s, d is an index for the LCR-affected products, D indicates the set of products affected by the LCR policy, and s refers to a sector (at the two-digit industry level).

Plants in the Upstream sectors In this study I do not have information on which plants or firms that supply inputs to those producing the LCR-targeted products. In the absence of firm-to-firm transaction data, I use plant-level input and output data to identify upstream firms. Using the measure of LCR exposure defined in equation (3.3), I identify firms that produce the LCR-targeted products. Using the plant-level input data, I construct a dataset of nine-digit product-level inputs used by firms producing the LCR-targeted products. I then merge this dataset with the plant-level output data to identify firms that produce inputs to firms in the targeted industry. I measure a plant's exposure to upstream sectors as follows:

$$Upstream\_LCR_{is,2006} = \sum_{q \in I} \frac{sales_{qis,2006}}{\sum_p sales_{pis,2006}} \tag{3.4}$$

where p indexes a product produced by plant or firm i in sector s, q is an index for products used as inputs by firms producing the LCR-targeted products, I denotes the set of inputs used by the LCR-targeted firms, and s

refers to the two-digit industry classification.

3.3 Empirical strategy

To estimate the effects of local content requirements on firm outcomes, I use Two-Way Fixed Effects (TWFE) and a dynamic extension of TWFE estimations. Each method is applied using two specifications: a baseline model and an extended model that accounts for upstream sector measure. Across all specifications, the identifying assumption is that, in the absence of the LCR policy, firms with different levels of exposure to the policy would have followed similar trends over time. I test the plausibility of this assumption using the dynamic specification. As a robustness check, I also estimate the effects using a long-difference approach.

Baseline specification: Two-Way Fixed Effects (TWFE) estimation To examine the impact of the LCR policy on firms producing the targeted products, I estimate the following equation:

$$y_{ist} = \lambda_i + \lambda_t + \beta \, Post \times LCR\_exposure_{is,2006} + \gamma_s + \Phi^{'}_{ist_0} \delta + \varepsilon_{ist} \quad (3.5)$$

where y_{ist} is the outcome of plant or firm i in industry s and year t. The term λ_i captures plant or firm fixed effects, controlling for time-invariant firm characteristics. λ_t denotes year fixed effects, accounting for aggregate shocks common to all firms in a given year. $Post$ is a dummy variable equal to one in the post-policy period 2007–2015. $LCR\_exposure_{is,2006}$ measures the pre-policy exposure to the LCR policy, as defined in equation (3.3). I also control for the two-digit industry fixed effects (γ_s) that capture differential trends in outcomes across industries. $\Phi^{'}_{ist_0}$ includes initial firm characteristics such as number of employment, exporter status, and importer status. In addition, I control for exposure to LCR policies in the energy and automotive sectors, defined using 2006 data. ϵ_{ist} is the error term.

Dynamic Two-Way Fixed Effects (TWFE) estimation To examine the dynamic effects of the LCR policy on firms producing targeted products, I estimate the following model:

$$y_{ist} = \lambda_i + \lambda_t + \sum_{k \neq -1} \beta_k \, \mathbf{1}\{k = t - 2007\} \times LCR\_exposure_{is,2006} + \gamma_{st} + \nu_{ist} \quad (3.6)$$

The coefficients β_k are the main interest as they capture the marginal effect of the LCR policy in year $t = 2007 + k$, relative to the omitted base year 2006. Assuming parallel trends, the post-2007 β_k coefficients can be interpreted as the differential impact of the LCR policy on more-exposed versus less-exposed firms over time. This specification also allows me to test for differential pre-policy trends by exposure level. I include industry $\times$ year fixed effects γ_{st} (at the two-digit industry level) to control for any industry-specific shocks in a given year, such as technological changes, other policy reforms, or demand fluctuations, that may be correlated with the LCR-exposure measures. ν_{ist} is the error term.

Extended specification with upstream sectors The LCR policy may affect not only firms that produce the targeted products but also firms in upstream sectors that supply inputs to them. To isolate the policy's effect from potential shocks in upstream sectors, I extend the baseline model in equation (3.5) by adding a control for upstream exposure:

$$\begin{aligned} y_{ist} = \lambda_i + \lambda_t + \beta_l \, Post \times LCR\_exposure_{is,2006} \\ + \beta_u \, Post \times Upstream\_LCR_{is,2006} + \gamma_s + \Phi'_{ist_0} \, \delta + \varepsilon_{ist} \end{aligned} \tag{3.7}$$

where $Upstream\_LCR_{is,2006}$ is defined in equation (3.4). I also modify the dynamic specification in equation (3.6) to include the upstream exposure:

$$\begin{aligned} y_{ist} = \alpha_i + \lambda_t + \sum_{k \neq -1} \beta_k \, \mathbf{1}\{k = t - 2007\} \cdot LCR\_exposure_{is,2006} \\ + \sum_{m \neq -1} \beta_m \, \mathbf{1}\{m = t - 2007\} \cdot Upstream\_LCR_{is,2006} + \gamma_{st} + \epsilon_{ist} \end{aligned} \tag{3.8}$$

The coefficients β_m capture the indirect effects of the LCR policy on firms in upstream sectors in year $t = 2007 + m$, relative to the omitted base year 2006.

Long-difference estimation As a robustness check, I also estimate a long-difference specification to capture the cumulative impact of local content requirements (LCRs) on firms producing the regulated products. This approach complements the main Two-Way Fixed Effects (TWFE) estimates by reducing concerns about serial correlation. To estimate the medium or long-run effects of the LCR policy, I estimate the following equation:

$$\Delta y_{is} = \gamma_s + \alpha \, LCR\_exposure_{is,2006} + \Phi'_{ist_0} \, \delta + \varepsilon_{is} \tag{3.9}$$

where Δy_{is} is the annualized change in the plant or firm i's outcomes between the baseline year (2007) and the last year the firm is observed in the sample. ε_{is} is an error term. To focus on the medium or long-run effects, the sample is restricted to plants or firms that are observed in the baseline year and survive after 2009. As in the TWFE specification, I also examine the indirect effects on the upstream firms in the long-difference specification as follows:

$$\Delta y_{is} = \gamma_s + \alpha_l \ LCR\_exposure_{is,2006} + \alpha_u \ Upstream\_LCR_{is,2006} + \Phi_{ist_0}^{'} \ \delta + \varepsilon_{is} \tag{3.10}$$

3.4 Results

In this section, I present the estimation results on the effects of the local content requirement (LCR) policy on firms that produce the targeted products as well as on upstream firms. I examine the policy's impact on: (1) input composition and cost structure, (2) output and employment, and (3) labor costs and productivity.

3.4.1 Effects of the LCR policy on firms producing the targeted products

Input composition and cost structure Panel A of Table 3.1 reports the main regression estimates. Column (1) shows that a one standard deviation increase in exposure to the policy tends to increase domestic content share by 2.2 p.p. The coefficient implies a post-policy effect of around 3% (0.022/0.737) relative to the pre-policy mean for firms at average exposure. This increase is mostly driven by an increase in wage bill as there is no significant effect on domestic content share when I exclude wage bill as shown in Column (2).

I find that after the implementation of the LCR policy, firms producing the targeted products tend to allocate a greater share of their total expenditures to labor. Column (3) shows that a one standard deviation increase in exposure to the LCR policy is associated with an increase in wage bill share by 1.9 p.p. This is equivalent to about a 9% (0.019/0.211) increase relative to the pre-policy mean.

For intermediate inputs, Column (4) in Panel A of Table 3.1 shows that the share of imported materials in total material expenditures also declined. The estimated effect corresponds to a 5.1% (-0.027/0.525) reduction in import share relative to the baseline level of 52.5%. These effects are statistically significant at 1% level and remain robust to the inclusion of firms' initial characteristics and exposure to LCR policies in energy and car industries. The results indicate that firms producing the LCR-targeted products tend to respond to the policy by shifting toward local inputs and labor-intensive production.

Figures 3.1 and 3.2 show the evolution of treatment effects over time. Although the increase in domestic content share is not statistically significant in individual years, the point estimates show an upward trajectory over time (Figure 3.1a). The wage bill share was significantly higher in 2011 and 2015 (Figure 3.2b), while the imported materials share was significantly lower in 2010 (Figure 3.2a). These findings suggest that the policy induced an increase in labor cost and a reduction in import.

Sales, employment, and value added Panel A of Table 3.2 presents the main regression results. Columns (1) and (2) show that a one unit increase in exposure to the LCR policy is associated with an an 8.5% reduction in firm sales and a 6.4% reduction in value-added. However, these effects are not statistically significant once I control for firms' initial characteristics and exposure to LCR policies in energy and car industries. In terms of employment, I find no significant impact. Figure 3.3 also shows that no significant changes in sales, employment, or value added over time.

Labor costs and productivity In terms of labor productivity, measured by VA per worker, Column (4) in Panel A of Table 3.2 shows that a one unit increase in exposure to the policy tends to decrease labor productivity by 5.6%. This effect remains statistically significant at 10% level after including control variables in Panel B. I also explore how the policy affects labor cost per worker. Table 3.3 shows that there is no significant effect on labor cost per worker, but dynamic TWFE estimation results indicate that labor cost per worker increased significantly in 2009 (Figure 3.4b). Once I control for the interaction between firms' initial characteristics and year fixed effects, labor costs are also significantly higher in 2007 and 2009 (Figure 3.B.7b). In addition, Figure 3.4c shows that unit labor costs increase significantly in 2015. These patterns suggest that the LCR policy may lead to higher labor costs in both the short and long run.

3.4.2 Indirect effects of the LCR policy on upstream firms

Input composition and cost structure Similar to firms in the targeted industry, I also find evidence of adjustments in input sourcing among upstream firms. The domestic content share among upstream firms also increased after the implementation of the LCR policy, but this does not appear to be driven by an increase in the wage bill. Column (2) in Panel B of Table 3.1 shows that a one standard deviation increase in upstream exposure is associated with a 1.9 p.p. increase in local content shares, excluding the wage bill. Meanwhile, greater exposure to upstream sectors is associated with a lower share of the wage bill in total expenditures, although this effect is only significant at the 10% level (Column (3)). Similarly, I find that after the policy implementation, firms with higher upstream exposure tend to have a lower share of imported materials in total material inputs, but this effect is only statistically significant at the 10% level (Column (4)).

Figures 3.B.1 and 3.B.2 show how the indirect effects on input composition among upstream firms evolve over time. In Figure 3.B.1a, the domestic content share (including the wage bill) was significantly higher in 2007 and 2010. However, once I control for interactions between initial firm characteristics and year fixed effects (Figure 3.B.8b), the effects are no longer statistically significant. For imports, the point estimates in Figure 3.B.2a are lower in the post-2006 period, suggesting evidence of changes in input sourcing among upstream firms.

Sales, employment, and value added Panel B of Table 3.2 shows that there are no statistically significant effects of the LCR policy on sales, employment, or value added among upstream firms. However, the estimates from the dynamic model show several important patterns. Most notably, employment was significantly higher between 2008 and 2011 (Figure 3.5c). These effects are statistically significant at the 5% level and remain robust even after accounting for firms' initial characteristics and exposure to LCR policies in the energy and car industries (Figure 3.B.10c). A one standard deviation increase in upstream exposure is associated with a 4.2% increase in employment between 2008 and 2011. This finding suggests a possible short-run employment gain among upstream firms during the initial phase of the LCR policy.

Labor costs and productivity Lastly, I examine the effects of the LCR policy on labor productivity and labor costs among upstream firms. In contrast to firms in directly targeted industries, I find no evidence of significant changes in value added per worker or in labor costs among upstream firms (Figure 3.B.3). This findings suggests that although the LCR policy may have increased employment temporarily, it did not result in significant changes in labor productivity or unit labor costs among upstream firms.

Table 3.1: Effects of the LCR policy on domestic content measures

	Domestic Content (incl. Wage Bill)	Domestic Content (excl. Wage Bill)	Wage Bill/ Total Exp.	Imported/Total Material Exp.
	(1)	(2)	(3)	(4)
Panel A: Baseline regressions				
Firm exposure to LCR in telecomm × Post	0.022***	0.003	0.019***	-0.027**
	(0.008)	(0.008)	(0.006)	(0.011)
Firms in upstream sectors × Post	0.009	0.010	-0.001	-0.018*
	(0.008)	(0.008)	(0.005)	(0.010)
Observations	9257	9257	9257	9257
R^2	0.720	0.602	0.377	0.779
Panel B: Control for firms' initial characteristics and exposures to LCR in other industries				
Firm exposure to LCR in telecomm × Post	0.018**	-0.002	0.020***	-0.019*
	(0.008)	(0.008)	(0.006)	(0.011)
Firms in upstream sectors × Post	0.009	0.019**	-0.010*	-0.020*
	(0.008)	(0.008)	(0.006)	(0.011)
Observations	9257	9257	9257	9257
R^2	0.724	0.605	0.380	0.787
Panel C: Control for industry-by-year fixed effects				
Firm exposure to LCR in telecomm × Post	0.017**	-0.004	0.022***	-0.018
	(0.008)	(0.009)	(0.007)	(0.011)
Firms in upstream sectors × Post	0.009	0.018**	-0.009	-0.020*
	(0.008)	(0.008)	(0.006)	(0.011)
Observations	9257	9257	9257	9257
R^2	0.726	0.608	0.388	0.787

Notes: Post is an indicator for the period after policy implementation, covering 2007-2015. Column (1) defines domestic content as in equation (3.1), measured by $\frac{\text{Domestic Inputs}+\text{Wage Bill}}{\text{Total Expenditures}}$. Column (2) uses the definition in equation (3.2), which excludes the wage bill: $\frac{\text{Domestic Inputs}}{\text{Total Expenditures}}$. Domestic inputs cover expenditures on domestic materials, electricity, fuel, and other items. Regressions in Panel B control for firms' initial characteristics (exporter, importer, and log number of workers) and exposures to LCR policies in car and electricity or energy industries. All regressions in Panels A and B include firm, year, and two-digit industry fixed effects. Panel C includes firm, year, and industry-by-year fixed effects, along with the control variables from Panel B. Standard errors in parentheses are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.2: Effects of the LCR policy on employment, sales, and value-added

	Log sales	Log VA	Log Number of workers	Log VA per worker
	(1)	(2)	(3)	(4)
Panel A: Baseline regressions				
Firm exposure to LCR in telecomm × Post	-0.085**	-0.064*	-0.008	-0.056**
	(0.039)	(0.035)	(0.022)	(0.027)
Firms in upstream sectors × Post	-0.013	-0.007	0.015	-0.022
	(0.041)	(0.035)	(0.026)	(0.027)
Observations	9257	9257	9257	9257
R^2	0.760	0.787	0.869	0.514
Panel B: Control for firms' initial characteristics and exposures to LCR in other industries				
Firm exposure to LCR in telecomm × Post	-0.056	-0.033	0.015	-0.048*
	(0.039)	(0.035)	(0.021)	(0.028)
Firms in upstream sectors × Post	0.046	0.032	0.014	0.018
	(0.043)	(0.038)	(0.026)	(0.030)
Observations	9257	9257	9257	9257
R^2	0.762	0.788	0.871	0.517
Panel C: Control for industry-by-year fixed effects				
Firm exposure to LCR in telecomm × Post	-0.028	0.015	0.020	-0.006
	(0.040)	(0.034)	(0.023)	(0.027)
Firms in upstream sectors × Post	0.056	0.050	0.017	0.032
	(0.043)	(0.037)	(0.026)	(0.029)
Observations	9257	9257	9257	9257
R^2	0.766	0.793	0.872	0.529

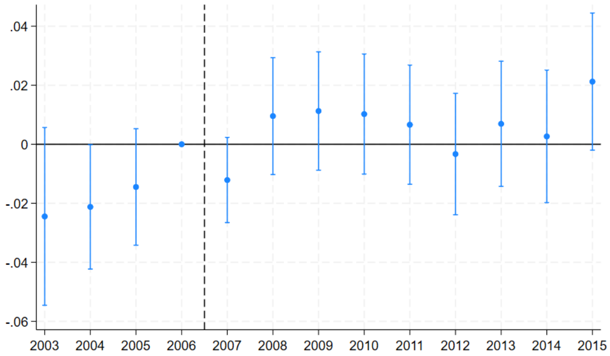
Notes: Post is an indicator for the period after policy implementation, covering 2007-2015. Sales and value added are expressed in real terms, deflated using sector-specific producer price indices. Regressions in Panel B control for firms' initial characteristics (exporter, importer, and log number of workers) and exposures to LCR policies in car and electricity or energy industries. All regressions in Panels A and B include firm, year, and two-digit industry fixed effects. Panel C includes firm, year, and industry-by-year fixed effects, along with the control variables from Panel B. Standard errors in parentheses are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3: Effects of the LCR policy on wage bill and labor cost per worker

	Log Wage bill	Log Labor cost per worker: all workers	Log Labor cost per worker: production	Log Labor cost per worker: non-production
	(1)	(2)	(3)	(4)
Panel A: Baseline regressions				
Firm exposure to LCR in telecomm × Post	-0.016	-0.008	-0.002	-0.133
	(0.028)	(0.016)	(0.017)	(0.084)
Firms in upstream sectors × Post	0.013	-0.001	0.000	-0.039
	(0.029)	(0.014)	(0.016)	(0.088)
Observations	9257	9257	9257	9257
R^2	0.776	0.463	0.442	0.481
Panel B: Control for firms' initial characteristics and exposures to LCR in other industries				
Firm exposure to LCR in telecomm × Post	0.014	-0.001	0.002	-0.095
	(0.027)	(0.016)	(0.017)	(0.086)
Firms in upstream sectors × Post	0.009	-0.005	-0.002	-0.031
	(0.029)	(0.015)	(0.018)	(0.093)
Observations	9257	9257	9257	9257
R^2	0.779	0.464	0.443	0.482
Panel C: Control for industry-by-year fixed effects				
Firm exposure to LCR in telecomm × Post	0.046*	0.025	0.021	-0.066
	(0.028)	(0.016)	(0.017)	(0.092)
Firms in upstream sectors × Post	0.021	0.004	0.005	-0.021
	(0.029)	(0.015)	(0.018)	(0.092)
Observations	9257	9257	9257	9257
R^2	0.781	0.474	0.452	0.485

Notes: Post is an indicator for the period after policy implementation, covering 2007-2015. Wage bill and labor cost per worker are expressed in nominal terms. Regressions in Panel B control for firms' initial characteristics (exporter, importer, and log number of workers) and exposures to LCR policies in car and electricity or energy industries. All regressions in Panels A and B include firm, year, and two-digit industry fixed effects. Panel C includes firm, year, and industry-by-year fixed effects, along with the control variables from Panel B. Standard errors in parentheses are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(a) Domestic Content Share (incl. Wage Bill)



(b) Domestic Content Share (excl. Wage Bill)

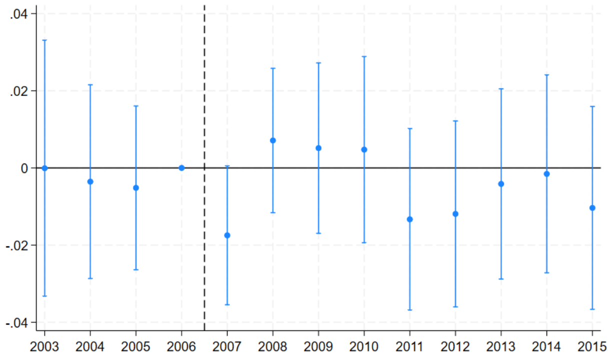
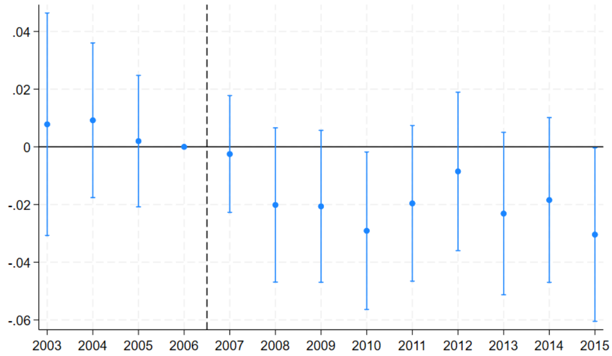


Figure 3.1: Effects of the LCR policy on firms producing the targeted products: domestic content

(a) Imported Share of Materials



(b) Wage Bill Share of Total Expenditure

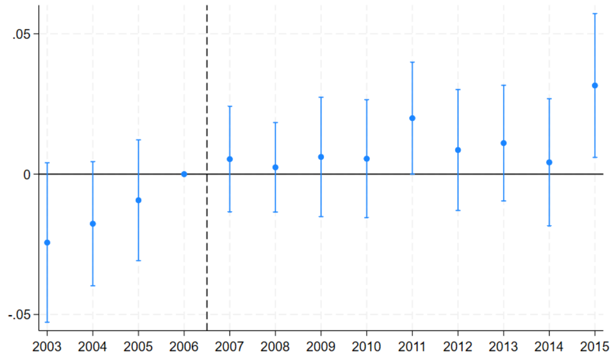
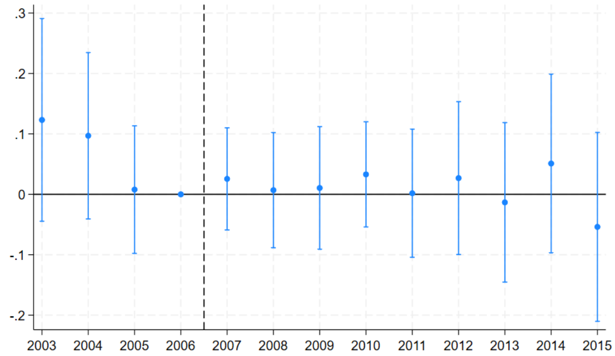
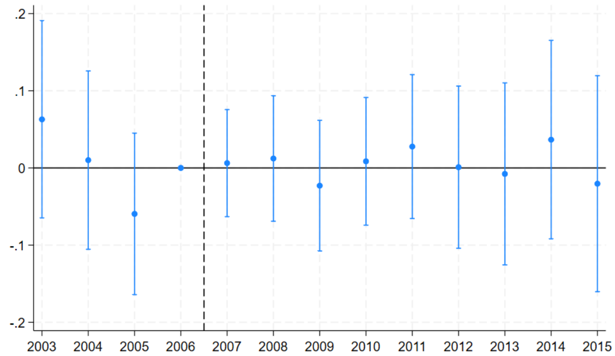


Figure 3.2: Effects of the LCR policy on firms producing the targeted products: imports and wage bill

(a) Log Sales



(b) Log Value Added



(c) Log Number of Workers

Figure 3.3: Effects of the LCR policy on firms producing the targeted products: sales and employment

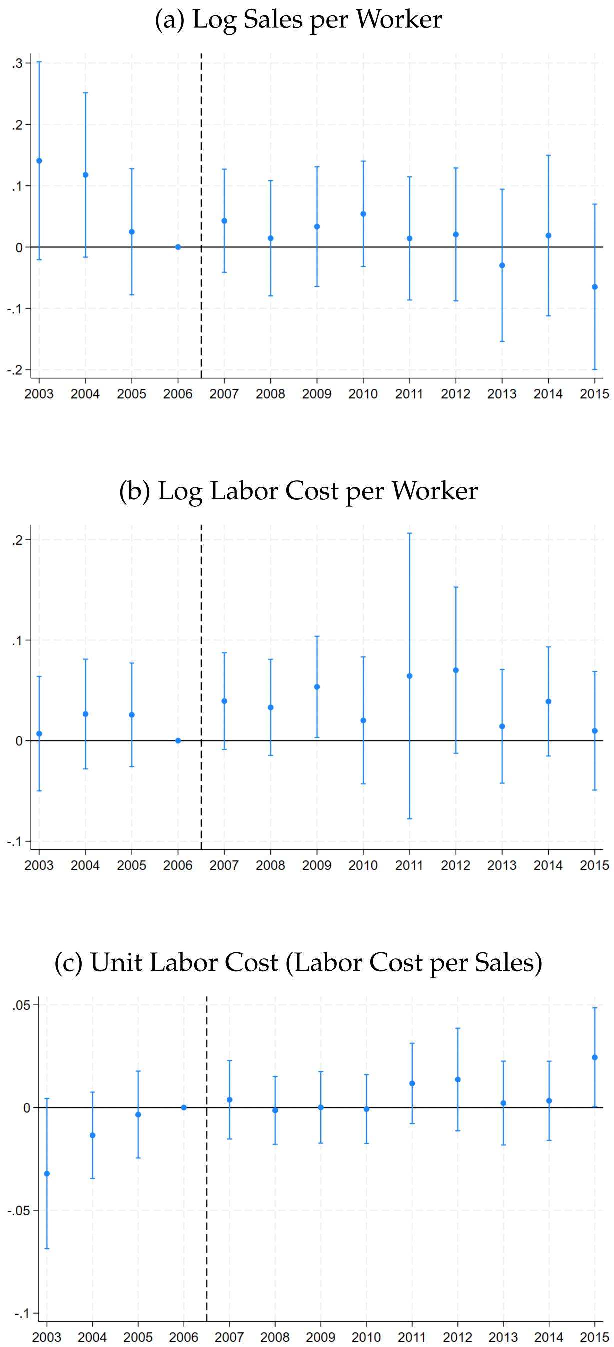


Figure 3.4: Effects of the LCR policy on firms producing the targeted products: labor costs and productivity

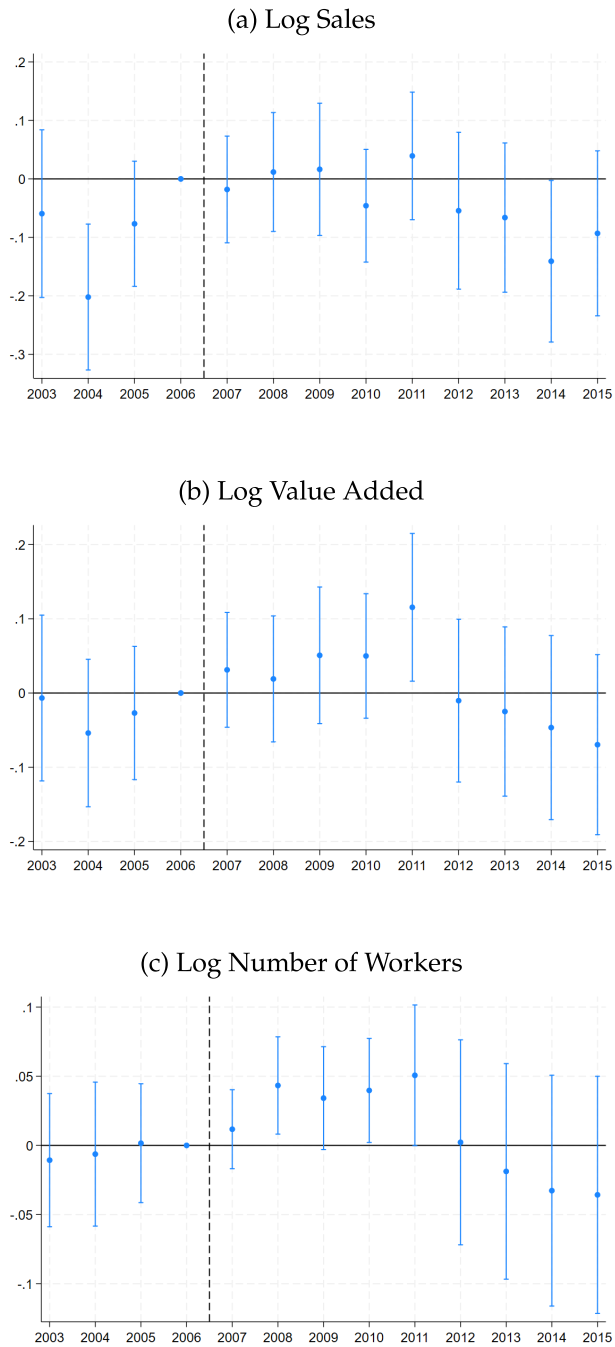


Figure 3.5: Effects of the LCR policy on upstream firms: sales and employment

3.5 Conclusion

This chapter examines how firms respond to local content requirement (LCR) policies, using detailed plant-level data from Indonesia's telecommunications sector. I find that firms affected by the policy reduced their use of imported inputs and relied more on domestic sources, mainly by increasing their use of labor. However, these changes did not lead to improvements in output or employment. Instead, firms faced higher labor costs and a decline in productivity over time. I also find some evidence that the policy affected upstream firms. While there was little impact on their output or productivity, these firms experienced short-term increases in employment, suggesting that the policy had spillover effects along the supply chain.

While this chapter focuses on firms' responses along the intensive margin, further work is needed to assess adjustments along the extensive margin. One possible next step is to use product-level data following the policy implementation to study market dynamics in greater detail. Using this information would make it possible to track changes in market shares between incumbent firms and new entrants, and to examine whether producers of LCR-targeted products have expanded into related input products. This additional analysis would provide a more comprehensive understanding of how the LCR policy influences competition and product specialization.

References

Aswicahyono, H., A. Fauri, D. Friawan, I. Setiati, J. S. Ngadiman, C. Mangunsong, and Y. R. Damuri (2023). Economic impacts of local content requirements in indonesia. CSIS Research Report.

Bown, C. P. (2024). Modern industrial policy and the world trade organization. *Annual Review of Economics 16*.

Deringer, H., F. Erixon, and P. Lamprecht (2018). The economic impact of local content requirements: A case study of heavy vehicles. Technical report, ECIPE.

Evenett, S. J. and J. Fritz (2020). The global trade alert database handbook.

Fernando, O. and L. Y. Ing (2022). Indonesia's local content requirements: An assessment on consistency with Free Trade Agreement commitments. Technical report, Economic Research Institute for ASEAN and East Asia.

Grossman, G. M. (1981, November). The Theory of Domestic Content Protection and Content Preference. *The Quarterly Journal of Economics 96*(4), 583.

Ing, L. Y. and G. Grossman (2023). *Local Content Requirements: Promises and Pitfalls*. Routledge.

Ing, L. Y. and R. Zhang (2023). Quantifying the impacts of local content requirements: An analysis on indonesia. In *Local Content Requirements*, pp. 212–245. Routledge.

Juhász, R. and N. Lane (2024). The political economy of industrial policy. *Journal of Economic Perspectives 38*(4), 27–54.

Juhász, R., N. Lane, and D. Rodrik (2023). The new economics of industrial policy. *Annual Review of Economics 16*.

Juhász, R. and C. Steinwender (2024). Industrial policy and the great divergence. *Annual Review of Economics 16*.

Krishna, K. and M. Itoh (1988). Content protection and oligopolistic interactions. *The Review of Economic Studies 55*(1), 107–125.

Limenta, M. and L. Y. Ing (2022). Indonesia's Local Content Requirements: Assessment with WTO Rules.

Negara, S. D. (2017). Assessing the impact of local content requirements on Indonesia's manufacturing. In *The Indonesian Economy* (1 ed.)., pp. 213–237. London: Routledge.

Partnership on Measuring ICT for Development (2022). Core List of ICT indicators. Technical report, Partnership on Measuring ICT for Development.

Richardson, M. (1991). The effects of a content requirement on a foreign duopsonist. *Journal of International Economics 31*(1-2), 143–155.

Vadila, Y. and D. Christian (2023). The effects of local content requirements on trade: The case of Indonesia. In *Local Content Requirements*, pp. 174–211. Routledge.

Vousden, N. (1987, November). Content protection and tariffs under monopoly and competition. *Journal of International Economics 23*(3-4), 263–282.

Appendix

3.A Additional tables

Table 3.A.1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Firm exposure to LCR in telecomm	-0.008	0.986	-0.392	2.985	9257
Firms exposure to upstream sectors (telecomm)	-0.005	0.993	-0.447	2.603	9257
Log sales (total) (real)	17.111	2.042	8.217	24.127	9257
Log VA (total) (real)	16.583	1.857	11.517	23.565	9257
(Domestic Inputs+Wage Bill)/Total Exp.	0.819	0.267	0.001	1	9257
Domestic Inputs/Total Exp.	0.562	0.289	0	1	9257
Wage Bill/Total Exp.	0.257	0.217	0	1	9257
Imported Materials/Total Exp. on Materials	0.292	0.39	0	1	9257
Log Wage Bill (nom)	14.805	1.619	8.096	20.916	9257
Log labor cost per worker (nom)	9.996	0.835	3.559	13.063	9257
Log Number of workers	4.825	1.287	2.708	9.113	9257
Log Number of production workers	4.565	1.335	0	8.973	9257
Log Number of non-production workers	2.939	1.498	0	8.447	9257
Log VA (total) per worker (real)	11.773	1.083	4.798	18.519	9257
Log Sales per worker (real)	12.302	1.311	4.858	18.519	9257
Unit labor cost (wage bill/sales)	0.195	0.218	0.003	1.726	9257
=1, exporter (initial)	0.194	0.395	0	1	9257
=1, importer (initial)	0.494	0.5	0	1	9257
Log of number of workers (initial)	4.797	1.235	2.944	8.931	9257
Firm exposure to LCR in car industry	0.015	0.995	-1.378	0.811	9257
Firm exposure to LCR in electricity/energy	0.013	1.005	-0.696	1.568	9257

Table 3.A.2: Initial firms' characteristics in 2006

	Other firms			Firms with high exposure (>75%)			
	N	Mean	sd	N	Mean	sd	Diff
Log Number of workers	704	4.76	1.24	75	5.42	1.26	0.653***
Log sales (total) (real)	704	16.86	1.96	75	17.72	1.89	0.859***
Log VA (total) (real)	704	16.29	1.78	75	17.16	1.81	0.867***
Log VA (total) per worker (real)	704	11.54	1.03	75	11.75	1.11	0.208
Log labor cost/worker (nom)	704	9.67	0.61	75	9.66	0.65	-0.013
Log labor cost/worker: production (nom)	704	9.54	0.63	75	9.51	0.64	-0.026
Log labor cost/worker: non-production (nom)	704	9.09	3.08	75	9.45	2.70	0.360
Wage Bill/Total Exp.	704	0.26	0.21	75	0.24	0.21	-0.016
Imported Materials/Total Exp. on Materials	704	0.28	0.38	75	0.52	0.44	0.243***
=1, exporter	704	0.22	0.42	75	0.39	0.49	0.164***
=1, importer	704	0.44	0.50	75	0.67	0.47	0.231***

Table 3.A.3: Summary statistics: mean exposure

Variable	Mean	Std. Dev.	Min.	Max.	N
Firm exposure to LCR in telecomm	0.005	0.144	-0.225	0.245	20
(Domestic Inputs+Wage Bill)/Total Exp.	0.737	0.234	0.287	1	20
Domestic Inputs/Total Exp.	0.526	0.3	0.13	0.99	20
Wage Bill/Total Exp.	0.211	0.159	0.007	0.58	20
Imported Materials/Total Exp. on Materials	0.525	0.412	0	0.993	20
Log sales (real)	18.089	2.002	14.734	23.384	20
Log value-added (real)	17.407	1.831	13.724	21.247	20
Log wage bill (nom)	15.371	1.492	12.656	18.224	20
Log labor cost per worker (nom)	9.983	0.511	9.013	11.016	20
Log number of workers	5.396	1.169	3.497	7.482	20
Log number of production workers	5.195	1.137	3.296	7.327	20
Log number of non-production workers	3.569	1.332	1.792	5.69	20
Log VA (total) per worker (real)	12.019	1.211	10.035	14.403	20
Log sales per worker (real)	12.701	1.479	9.818	15.902	20
Unit labor cost (wage bill/sales)	0.168	0.216	0.005	0.992	20

Notes: Mean dependent variables are calculated for firms with exposure levels within $\pm$ 0.25 SD of the sample mean.

Table 3.A.4: Shares of single- and multi-product manufacturing plants

Number of products	Freq.	Percent
1	19,521	66.37
2	5,111	17.38
3	2,183	7.42
4	1,112	3.78
5	633	2.15
6	376	1.28
7	200	0.68
8	112	0.38
≥ 9	163	0.55
Total	**29,411**	**100.00**

Data source: Annual Manufacturing Census, 2006 (all plants)

Table 3.A.5: Examples of products directly-targeted by the LCR policies in telecommunications

HS2012 code	Product description
8471.30	Automatic data processing machines
8471.60	Units of automatic data processing machines
8517.62	Communication apparatus (excluding telephone sets or base stations)
8517.70	Telephone sets and other apparatus
8525.50	Transmission apparatus for radio-broadcasting or TV
8525.80	Television cameras, digital cameras and video camera recorders
8528.72	Reception apparatus for television
8529.10	Reception and transmission apparatus
8529.90	Reception and transmission apparatus (excluding aerials and aerial reflectors)
8544.70	Insulated electric conductors; optical fibre cables

TWFE specification: Additional results

Table 3.A.6: Effects of the LCR policy on employment

	Log Number of workers (1)	Log Number of production workers (2)	Log Number of non-production workers (3)
Panel A: Baseline regressions			
Firm exposure to LCR in telecomm × Post	-0.008	-0.003	-0.027
	(0.022)	(0.024)	(0.034)
Firms in upstream sectors × Post	0.015	0.002	0.027
	(0.026)	(0.026)	(0.045)
Observations	9257	9257	9257
R^2	0.869	0.864	0.720
Panel B: Control for firms' initial characteristics and exposures to LCR in other industries			
Firm exposure to LCR in telecomm × Post	0.015	0.021	-0.017
	(0.021)	(0.023)	(0.033)
Firms in upstream sectors × Post	0.014	0.002	0.019
	(0.026)	(0.027)	(0.049)
Observations	9257	9257	9257
R^2	0.871	0.866	0.721
Panel C: Control for industry-by-year fixed effects			
Firm exposure to LCR in telecomm × Post	0.020	0.026	-0.017
	(0.023)	(0.025)	(0.036)
Firms in upstream sectors × Post	0.017	0.004	0.018
	(0.026)	(0.026)	(0.050)
Observations	9257	9257	9257
R^2	0.872	0.867	0.722

Notes: Post is an indicator for the period after policy implementation, covering 2007-2015. Regressions in Panel B control for firms' initial characteristics (exporter, importer, and log number of workers) and exposures to LCR policies in car and electricity or energy industries. All regressions in Panels A and B include firm, year, and two-digit industry fixed effects. Panel C includes firm, year, and industry-by-year fixed effects, along with the control variables from Panel B. Standard errors in parentheses are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Long-difference specification: Main results

Table 3.A.7: Medium- and long-run effects of the LCR policy on domestic content measures

	Δ Domestic Content (incl. Wage Bill) (1)	Δ Domestic Content (excl. Wage Bill) (2)	Δ Wage Bill/ Total Exp. (3)	Δ Import-ed/Total Material Exp. (4)
Panel A: Baseline regressions				
Firm exposure to LCR in telecomm	0.004***	0.001	0.003*	-0.003**
	(0.001)	(0.001)	(0.001)	(0.002)
Firms in upstream sectors	-0.002*	0.000	-0.002*	0.003*
	(0.001)	(0.001)	(0.001)	(0.002)
Observations	779	779	779	779
R^2	0.020	0.001	0.007	0.009
Panel B: Control for firms' initial characteristics and exposures to LCR in other industries				
Firm exposure to LCR in telecomm	0.004***	0.000	0.003**	-0.003
	(0.001)	(0.002)	(0.002)	(0.002)
Firms in upstream sectors	-0.003*	0.000	-0.003**	0.003
	(0.001)	(0.002)	(0.001)	(0.002)
Industry FE	✓	✓	✓	✓
Observations	779	779	779	779
R^2	0.053	0.022	0.030	0.036
Panel C: Control for region fixed effects				
Firm exposure to LCR in telecomm	0.004***	0.000	0.003**	-0.003
	(0.001)	(0.002)	(0.002)	(0.002)
Firms in upstream sectors	-0.003*	0.000	-0.003**	0.003*
	(0.001)	(0.002)	(0.001)	(0.002)
Industry FE	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
Observations	779	779	779	779
R^2	0.053	0.024	0.030	0.038

Notes: The dependent variables are annualized changes measured between 2007 and the last year each firm is observed in the sample, with 2015 being the latest year. Column (1) defines domestic content as in equation (3.1), measured by $\frac{\text{Domestic Inputs+Wage Bill}}{\text{Total Expenditures}}$. Column (2) uses the definition in equation (3.2), which excludes the wage bill: $\frac{\text{Domestic Inputs}}{\text{Total Expenditures}}$. Domestic inputs cover expenditures on domestic materials, electricity, fuel, and other items. Regressions in Panels B and C control for firms' initial characteristics (exporter, importer, and log number of workers) and exposures to LCR policies in car and electricity or energy industries. Panel C includes industry and region fixed effects. The region variable shows whether a firm is located on Java island. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A.8: Medium- and long-run effects of the LCR policy on sales, value-added, and employment

	Δ Log Sales	Δ Log Value Added	Δ Log Number of workers	Δ Log VA/worker
	(1)	(2)	(3)	(4)
Panel A: Baseline regressions				
Firm exposure to LCR in telecomm	-0.010	-0.009	-0.003	-0.006
	(0.009)	(0.009)	(0.005)	(0.008)
Firms in upstream sectors	-0.011	-0.016**	-0.005	-0.011*
	(0.008)	(0.008)	(0.005)	(0.006)
Observations	779	779	779	779
R^2	0.005	0.008	0.003	0.005
Panel B: Control for firms' initial characteristics and exposures to LCR in other industries				
Firm exposure to LCR in telecomm	-0.011	-0.006	0.004	-0.010
	(0.009)	(0.009)	(0.005)	(0.008)
Firms in upstream sectors	-0.006	-0.013	-0.003	-0.010
	(0.009)	(0.009)	(0.006)	(0.007)
Industry FE	✓	✓	✓	✓
Observations	779	779	779	779
R^2	0.032	0.037	0.066	0.033
Panel C: Control for region fixed effects				
Firm exposure to LCR in telecomm	-0.012	-0.006	0.004	-0.010
	(0.009)	(0.009)	(0.005)	(0.008)
Firms in upstream sectors	-0.006	-0.013	-0.003	-0.010
	(0.009)	(0.009)	(0.006)	(0.007)
Industry FE	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
Observations	779	779	779	779
R^2	0.034	0.041	0.069	0.035

Notes: The dependent variables are annualized changes measured between 2007 and the last year each firm is observed in the sample, with 2015 being the latest year. Regressions in Panels B and C control for firms' initial characteristics (exporter, importer, and log number of workers) and exposures to LCR policies in car and electricity or energy industries. Panel C includes industry and region fixed effects. The region variable shows whether a firm is located on Java island. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A.9: Medium- and long-run effects of the LCR policy on wage bill

	Δ Log Wage bill	Δ Log Labor cost per worker	Δ Log Labor cost per worker: Production	Δ Log Labor cost per worker: Non-production
	(1)	(2)	(3)	(4)
Panel A: Baseline regressions				
Firm exposure to LCR in telecomm	-0.002	0.000	0.002	-0.010
	(0.005)	(0.003)	(0.003)	(0.028)
Firm in upstream sectors	-0.004	0.001	0.001	-0.027
	(0.006)	(0.003)	(0.003)	(0.022)
Observations	779	779	779	779
R^2	0.001	0.000	0.000	0.003
Panel B: Control for firms' initial characteristics and exposures to LCR in other industries				
Firm exposure to LCR in telecomm	0.000	-0.004	-0.004	0.011
	(0.006)	(0.003)	(0.004)	(0.028)
Firm in upstream sectors	-0.001	0.002	0.001	-0.002
	(0.007)	(0.004)	(0.005)	(0.022)
Industry FE	✓	✓	✓	✓
Observations	779	779	779	779
R^2	0.029	0.019	0.021	0.020
Panel C: Control for region fixed effects				
Firm exposure to LCR in telecomm	0.000	-0.004	-0.004	0.011
	(0.006)	(0.003)	(0.004)	(0.028)
Firm in upstream sectors	-0.001	0.002	0.000	-0.002
	(0.007)	(0.004)	(0.005)	(0.022)
Industry FE	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
Observations	779	779	779	779
R^2	0.031	0.019	0.021	0.022

Notes: The dependent variables are annualized changes measured between 2007 and the last year each firm is observed in the sample, with 2015 being the latest year. Regressions in Panels B and C control for firms' initial characteristics (exporter, importer, and log number of workers) and exposures to LCR policies in car and electricity or energy industries. Panel C includes industry and region fixed effects. The region variable shows whether a firm is located on Java island. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A.10: Medium- and long-run effects of the LCR policy on employment

	Δ Log number of workers	Δ Log number of production workers	Δ Log number of non-production workers
	(1)	(2)	(3)
Panel A: Baseline regressions			
Firm exposure to LCR in telecomm	-0.003	-0.003	-0.001
	(0.005)	(0.005)	(0.009)
Firms in upstream sectors	-0.005	-0.005	-0.012
	(0.005)	(0.005)	(0.008)
Observations	779	779	779
R^2	0.003	0.003	0.003
Panel B: Control for firms' initial characteristics and exposures to LCR in other industries			
Firm exposure to LCR in telecomm	0.004	0.003	0.009
	(0.005)	(0.005)	(0.010)
Firms in upstream sectors	-0.003	-0.003	-0.005
	(0.006)	(0.006)	(0.009)
Industry FE	✓	✓	✓
Observations	779	779	779
R^2	0.066	0.063	0.027
Panel C: Control for region fixed effects			
Firm exposure to LCR in telecomm	0.004	0.003	0.009
	(0.005)	(0.005)	(0.010)
Firms in upstream sectors	-0.003	-0.003	-0.006
	(0.006)	(0.006)	(0.009)
Industry FE	✓	✓	✓
Region FE	✓	✓	✓
Observations	779	779	779
R^2	0.069	0.065	0.027

Notes: The dependent variables are annualized changes measured between 2007 and the last year each firm is observed in the sample, with 2015 being the latest year. Regressions in Panels B and C control for firms' initial characteristics (exporter, importer, and log number of workers) and exposures to LCR policies in car and electricity or energy industries. Panel C includes industry and region fixed effects. The region variable shows whether a firm is located on Java island. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Long-difference specification: Alternative sample (including firms that re-entered after 2007)

Table 3.A.11: Medium- and long-run effects of the LCR policy on domestic content measures (alternative sample)

	Δ Domestic Content (incl. Wage Bill)	Δ Domestic Content (excl. Wage Bill)	Δ Wage Bill/ Total Exp.	Δ Import-ed/Total Material Exp.
	(1)	(2)	(3)	(4)
Panel A: Baseline regressions				
Firm exposure to LCR in telecommunications	0.004*	0.000	0.003*	-0.002
	(0.001)	(0.002)	(0.001)	(0.003)
Firms in upstream sectors	-0.003***	-0.001	-0.002**	0.003**
	(0.000)	(0.001)	(0.000)	(0.000)
Observations	789	789	789	789
R^2	0.061	0.037	0.043	0.047
Panel B: Control for firm exposures to LCR in other sectors				
Firm exposure to LCR in telecommunications	0.004**	0.000	0.003*	-0.002
	(0.001)	(0.002)	(0.001)	(0.002)
Firms in upstream sectors	-0.003	-0.000	-0.003*	0.003
	(0.002)	(0.001)	(0.001)	(0.002)
Observations	789	789	789	789
R^2	0.061	0.037	0.043	0.047

The dependent variables are annualized changes. In column (1), domestic content is defined as $\frac{DomesticInputs+WageBill}{TotalExpenditures}$. In column (2), domestic content is defined as $\frac{DomesticInputs}{TotalExpenditures}$. Domestic inputs cover expenditures on domestic materials, electricity, fuel, and other items. Regressions in Panel B control for firm exposures to LCR in car and electricity or energy industries. All regressions control for province and two-digit industry fixed effects, and firms' initial characteristics (exporter, importer, and log number of workers). Standard errors in parentheses are clustered at the two-digit industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A.12: Medium- and long-run effects of the LCR policy on sales, value-added, and employment (alternative sample)

	Δ Log Sales	Δ Log Value Added	Δ Log Number of workers	Δ Log VA/worker
	(1)	(2)	(3)	(4)
Panel A: Baseline regressions				
Firm exposure to LCR in telecommunications	-0.012	-0.006	0.003	-0.009
	(0.010)	(0.014)	(0.009)	(0.005)
Firms in upstream sectors	-0.006***	-0.010	-0.004	-0.006
	(0.000)	(0.005)	(0.003)	(0.005)
Observations	789	789	789	789
R^2	0.059	0.063	0.074	0.054
Panel B: Control for firm exposures to LCR in other sectors				
Firm exposure to LCR in telecommunications	-0.012	-0.007	0.003	-0.010
	(0.009)	(0.012)	(0.009)	(0.004)
Firms in upstream sectors	-0.006	-0.013	-0.003	-0.011
	(0.006)	(0.012)	(0.004)	(0.012)
Observations	789	789	789	789
R^2	0.059	0.064	0.075	0.058

The dependent variables are annualized changes in firm-level outcomes. Regression in Panel B control for firm exposures to LCR in car and electricity or energy industries. All regressions control for province and two-digit industry fixed effects, and firms' initial characteristics (exporter, importer, and log number of workers). Standard errors in parentheses are clustered at the two-digit industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A.13: Medium- and long-run effects of the LCR policy on wage bill (alternative sample)

	Δ Log Wage bill	Δ Log Avg. wage	Δ Log Avg. wage: Production	Δ Log Avg. wage: Non-production
	(1)	(2)	(3)	(4)
Panel A: Baseline regressions				
Firm exposure to LCR in telecommunications	-0.001	-0.004	-0.004	0.009
	(0.005)	(0.004)	(0.005)	(0.025)
Firms in upstream sectors	-0.004	0.000	-0.000	-0.009
	(0.002)	(0.003)	(0.005)	(0.011)
Observations	789	789	789	789
R^2	0.065	0.078	0.070	0.031
Panel B: Control for firm exposures to LCR in other sectors				
Firm exposure to LCR in telecommunications	-0.000	-0.004	-0.005	0.011
	(0.004)	(0.005)	(0.006)	(0.026)
Firms in upstream sectors	-0.003	-0.000	-0.002	0.002
	(0.006)	(0.006)	(0.007)	(0.007)
Observations	789	789	789	789
R^2	0.065	0.078	0.072	0.032

The dependent variables are annualized changes in firm-level outcomes. Regression in Panel B control for firm exposures to LCR in car and electricity or energy industries. All regressions control for province and two-digit industry fixed effects, and firms' initial characteristics (exporter, importer, and log number of workers). Standard errors in parentheses are clustered at the two-digit industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A.14: Medium- and long-run effects of the LCR policy on employment (alternative sample)

	Δ Log number of workers	Δ Log number of production workers	Δ Log number of non-production workers
	(1)	(2)	(3)
Panel A: Baseline regressions			
Firm exposure to LCR in telecommunications	0.003	0.003	0.006
	(0.009)	(0.009)	(0.006)
Firms in upstream sectors	-0.004	-0.005	-0.010
	(0.003)	(0.004)	(0.004)
Observations	789	789	789
R^2	0.074	0.069	0.030
Panel B: Control for firm exposures to LCR in other sectors			
Firm exposure to LCR in telecommunications	0.003	0.003	0.007
	(0.009)	(0.009)	(0.006)
Firms in upstream sectors	-0.003	-0.003	-0.005
	(0.004)	(0.004)	(0.006)
Observations	789	789	789
R^2	0.075	0.070	0.033

The dependent variables are annualized changes in firm-level outcomes. Regression in Panel B control for firm exposures to LCR in car and electricity or energy industries. All regressions control for province and two-digit industry fixed effects, and firms' initial characteristics (exporter, importer, and log number of workers). Standard errors in parentheses are clustered at the two-digit industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.A.15: Medium- and long-run effects of the LCR policy on materials (alternative sample)

	Δ Log (nom) exp on domestic mat.	Δ Log (nom) exp on imported mat.	Δ Log (nom) exp on total mat.
	(1)	(2)	(3)
Panel A: Baseline regressions			
Firm exposure to LCR in telecommunications	0.018	-0.025	-0.005
	(0.019)	(0.043)	(0.027)
Firm in the upstream sectors	-0.048*	0.023**	-0.007
	(0.016)	(0.004)	(0.008)
Observations	789	789	789
R^2	0.025	0.049	0.019
Panel B: Control for firm exposures to LCR in other sectors			
Firm exposure to LCR in telecommunications	0.020	-0.024	-0.000
	(0.021)	(0.033)	(0.025)
Firm in the upstream sectors	-0.031	0.028	0.013
	(0.021)	(0.043)	(0.019)
Observations	789	789	789
R^2	0.028	0.049	0.023

The dependent variables are annualized changes in firm-level outcomes. Regression in Panel B control for firm exposures to LCR in car and electricity or energy industries. All regressions control for province and two-digit industry fixed effects, and firms' initial characteristics (exporter, importer, and log number of workers). Standard errors in parentheses are clustered at the two-digit industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.B Additional figures

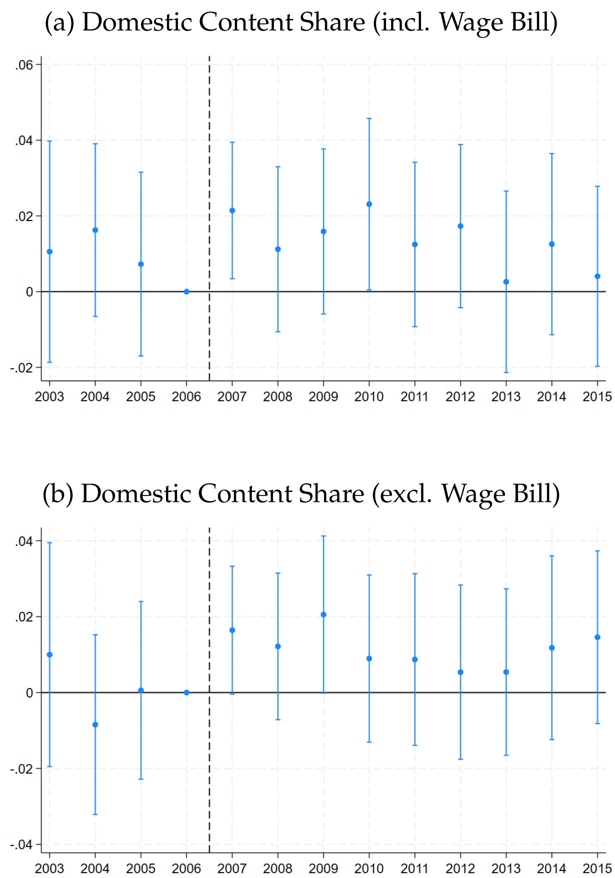


Figure 3.B.1: Effects of the LCR policy on upstream firms: domestic content

Figure 3.B.2: Effects of the LCR policy on upstream firms: imports and wage bill

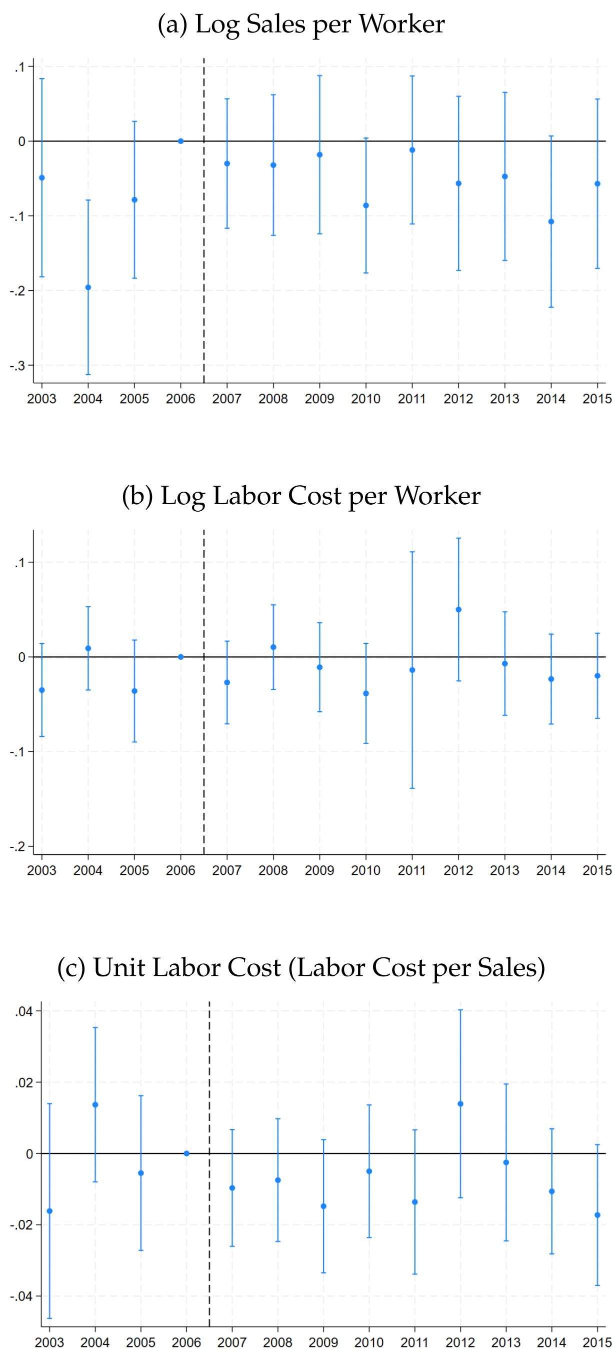
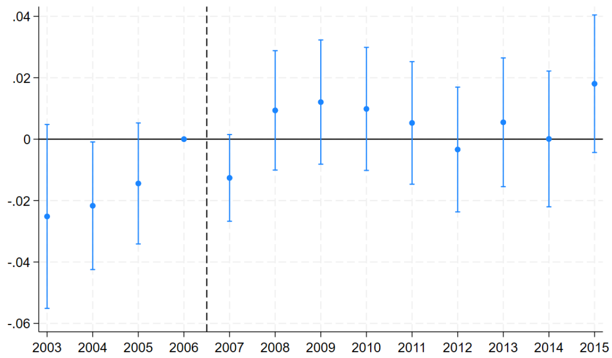


Figure 3.B.3: Effects of the LCR policy on upstream firms: labor costs and productivity

Dynamic TWFE: Robustness checks (including control variables × year FEs)

(a) Domestic Content Share (incl. Wage Bill)



(b) Domestic Content Share (excl. Wage Bill)

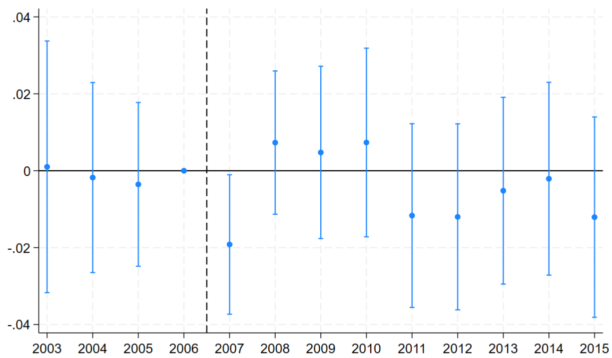
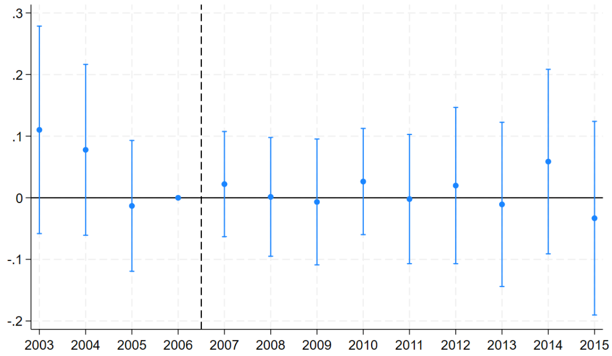


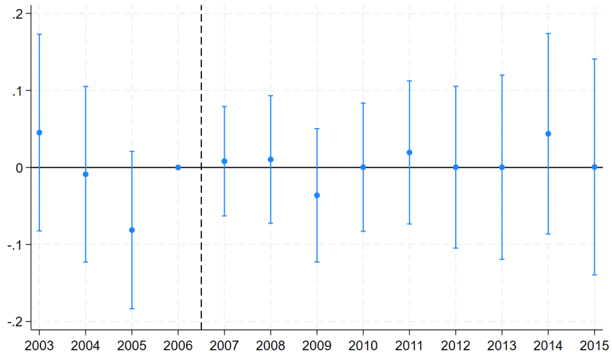
Figure 3.B.4: Effects of the LCR policy on firms producing the targeted products: domestic content (robustness checks)

Figure 3.B.5: Effects of the LCR policy on firms producing the targeted products: imports and wage bill (robustness checks)

(a) Log Sales



(b) Log Value Added



(c) Log Number of Workers

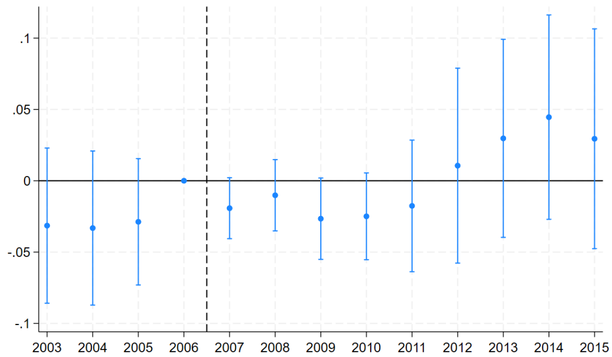
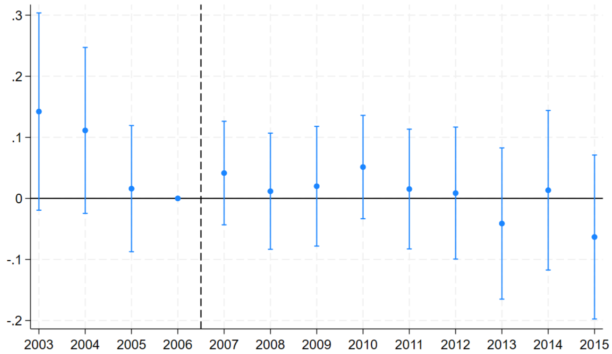
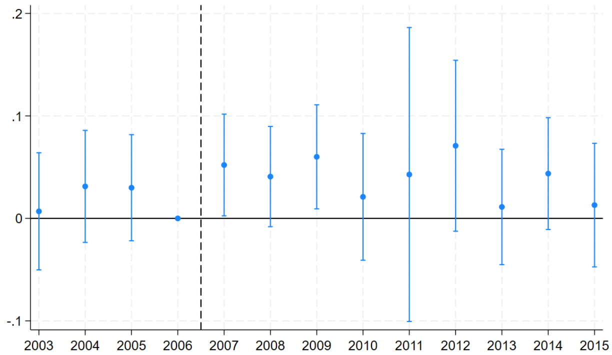


Figure 3.B.6: Effects of the LCR policy on firms producing the targeted products: sales and employment (robustness checks)

(a) Log Sales per Worker



(b) Log Labor Cost per Worker



(c) Unit Labor Cost (Labor Cost per Sales)

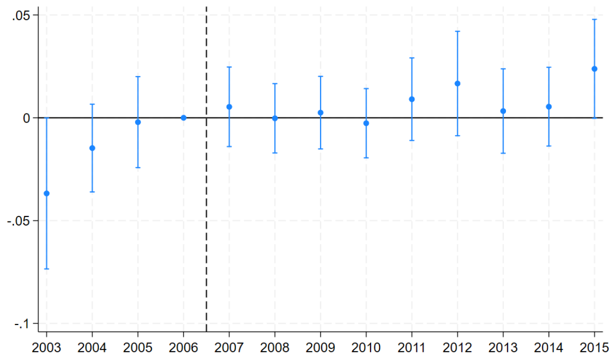


Figure 3.B.7: Effects of the LCR policy on firms producing the targeted products: labor costs and productivity (robustness checks)

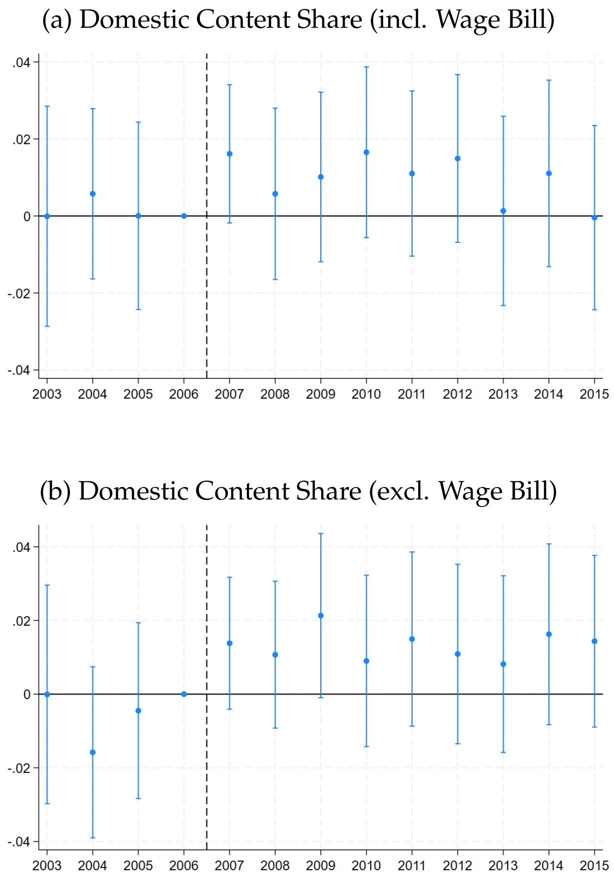
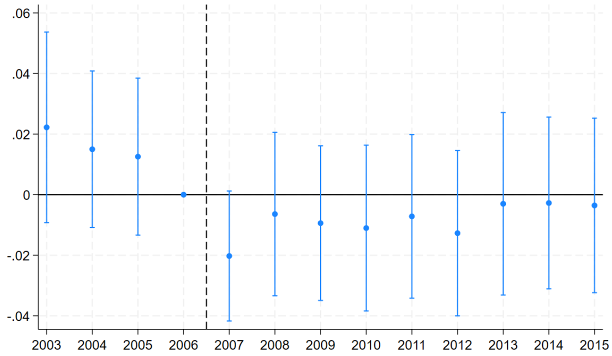


Figure 3.B.8: Effects of the LCR policy on upstream firms: domestic content (robustness checks)

(a) Imported Share of Materials



(b) Wage Bill Share of Total Expenditure

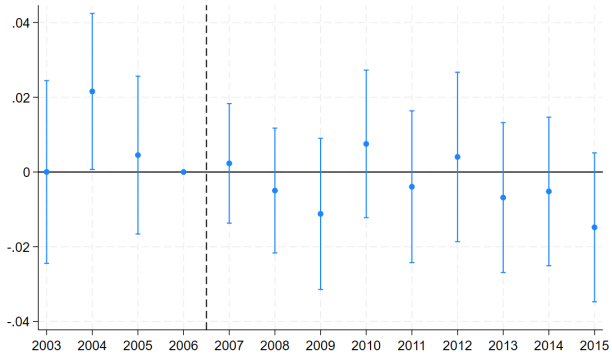
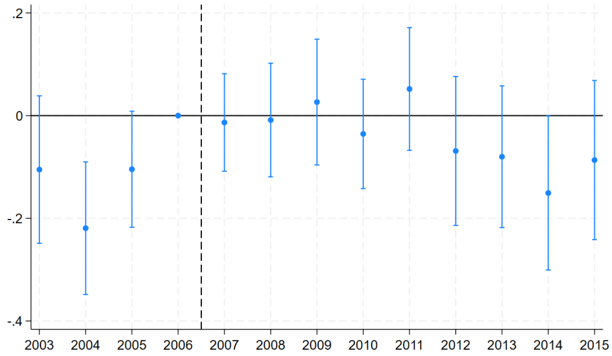
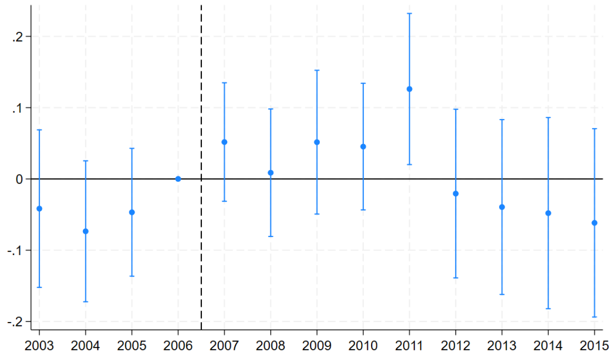


Figure 3.B.9: Effects of the LCR policy on upstream firms: imports and wage bill (robustness checks)

(a) Log Sales



(b) Log Value Added



(c) Log Number of Workers

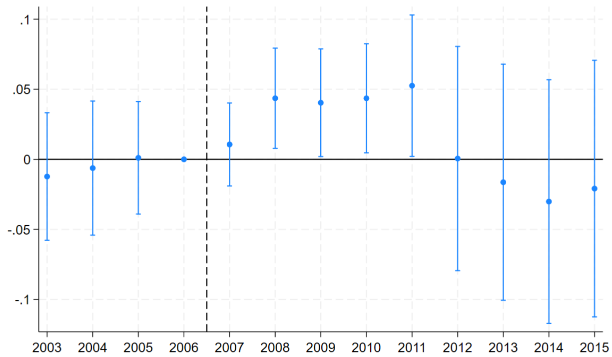
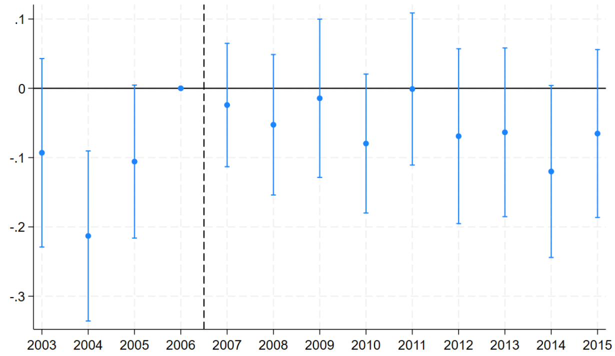
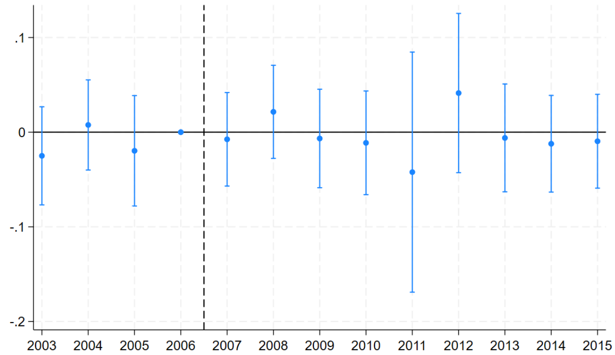


Figure 3.B.10: Effects of the LCR policy on upstream firms: sales and employment (robustness checks)

(a) Log Sales per Worker



(b) Log Labor Cost per Worker



(c) Unit Labor Cost (Labor Cost per Sales)

Figure 3.B.11: Effects of the LCR policy on upstream firms: labor costs and productivity (robustness checks)

This dissertation is the result of my own work, and no other sources or means, except the ones listed, have been employed.

Mannheim, May 27, 2025

Sandra Kurniawati

Curriculum Vitae

2019–2025	University of Mannheim (Germany) Ph.D. in Economics
2016	The Australian National University (Australia) Master of International and Development Economics
2015	The Australian National University (Australia) Graduate Diploma of International and Development Economics
2012	Bandung Institute of Technology (Indonesia) Bachelor of Science in Regional and City Planning