Global prices, trade protection, and internal migration: Evidence from Indonesia*

Rizki Nauli Siregar†

University of California, Davis

22 January 2021

Job Market Paper
Please click here for the most recent version.

Abstract

I study how regions respond to price shocks in the presence of internal migration. I examine Indonesia in the 2000s as it faced a commodity boom and initiated its trade protection on rice, a staple food for its large population. I use the variation in the potential shares of palm oil and rice sectors across district economies to measure local exposure to shocks. I find that the commodity boom increased the real expenditure per capita of palm oil-producing districts. These districts also received more migration, providing the evidence that palm oil price shocks were no longer localized. However, these relatively higher levels of real expenditure per capita did not last as the commodity boom ends in 2014, highlighting the short-lived windfall for longer-run cost from well-documented deforestation due to palm oil expansion. Meanwhile, the trade protection on rice did not materialize as higher purchasing power to rice-producing districts, highlighting the ineffectiveness of protection as a second-best policy to structural issues. I estimate that the overall welfare increased by 0.39% in Indonesia between 2005 and 2010. Gains from migration accounts for one third of the these gains.

Acknowledgments: I am very grateful for invaluable guidance and support from my advisors, Rob Feenstra, Giovanni Peri, and Deborah Swenson. I am thankful for valuable comments and suggestions from Anna Ignatenko, Sarah Quincy, Monica Guevara, Claudia Sahm, Matt Curtis, and seminar participants at NEUDC 2020, Urban Economics Association 2020 Meeting, UC Davis International/Macro Brownbags, Asia Pacific Trade Seminar 2019, IRSA Conference 2019, Universitas Indonesia, and Universitas Gajah Mada. I also thank Wisnu Harto, Muhammad Hanri, and Armand Sim for sharing data.

†PhD Candidate, University of California-Davis, Department of Economics. Email: rsiregar@ucdavis.edu.

1 Introduction

Developing economies face two common price shocks. The first type of price shock is external. As many developing economies are primary-commodities producers, they face trade shocks in the form of global price fluctuations. Fernández et al. (2017) show that 30% of domestic output fluctuations are driven by world shocks that stem from commodity prices. The second price shocks is internal. These price shocks stem from trade policy changes. Indeed, Atkin and Khandelwal (2020) show that developing economies put more concerns or use more traditional trade policies, such as tariff and duties, in their policy set.[1] This type of trade policies affect domestic prices directly.[2] In addition, one out of ten people in the world is an internal migrant. In developing countries, the intensity of internal migration ranges from as low as 6% in India and as high as almost 50% in Chile (Lucas, 2015). Therefore, understanding how labor respond through mobility in the face of price shocks in international trade is a relevant question for many developing countries.[3]

The goal of this paper is to study how a multi-region economy responds to price shocks stemming from commodity prices and trade policies in the presence of internal migration. I take the context of Indonesia in the 2000s as it faced a commodity boom and started to ban the import of rice, a staple food for its 260 million population. I fill in the gap in the literature by providing an evidence of trade shocks that are no longer localized, especially when these trade shocks are advantageous to local income.[4] Specifically, I show that internal migration diffuses trade shocks stemmed from the commodity boom as people move to palm-oil producing districts.

This paper also contributes to policy discourse on development, environmental policy, and trade policy. First, I highlight that the windfall from the commodity boom was short-lived. This paper is the first in documenting the impact of commodity boom on welfare indicator overtime. It is important to emphasize that this temporary windfall stands in contrast with potentially long-term social cost from the well-documented deforestation caused by palm oil expansion.[5] This evidence

[1] This fact stands in contrast with the more developed economies which put more concerns on non-traditional trade policies such as intellectual property rights.

[2] I note that whether trade policy is an endogenous outcome or exogenous shocks can be context specific.

[3] Lucas (2015) also mentions that despite many studies on internal migration focusing on urbanization, the actual dominant flows varies across countries. Countries with predominant rural societies, rural-rural flows are more common. While countries like in Latin America, urban-urban flows are more salient. See Lucas (2015) for a survey of studies on internal migration in developing economies and Lagakos (2020) for a survey on studies on the role of internal migration in closing the rural-urban gap.

[4] Many studies on the impact of trade shocks use import shocks that deteriorates income. This observation is also supported by Pavcnik (2017) in her lecture in the Jackson Hole Symposium in 2017. Some important studies using import shocks include Dix-Carneiro and Kovak (2017) for trade liberalization in Brazil, Topalova (2010) in India and Autor et al. (2013) for the surge of imports from China to the US. If there are fixed migration costs or cash-in-advance constraints in migratiom, then we may not see much response through migration in the face of trade shocks that hurt income.

[5] See for example Curtis et al. (2018), Austin et al. (2019), and Seymour and Harris (2019). Hansen et al. (2013) show that Indonesia experienced the world's largest increase in forest loss in 2000-2012. Meanwhile, Austin et al. (2019) show that palm oil plantation was the largest single driver of deforestation in Indonesia for the period of 2001 to 2016. In addition, commodity-driven deforestation has been rampant, which account for an estimated 27% of global forest loss (Curtis et al., 2018).

can inform policymakers including regional leaders who have substantial decision-making power in land concessions, as well as the public. Second, I also show the ineffectiveness of trade protection to solve inherent structural problems as well as the possibility of the trade protection in exacerbating those problems, which requires further studies.

Indonesia is an excellent context for studying the impact of price shocks on developing economies for at least three reasons. First, Indonesia is a large country, in terms of population, size and area, but is mostly a price-taker in the world market. Also, in the context of high trade protection, farmers are individually not large enough to have some market power that they are too price takers. Thus, Indonesia shares the feature of being a small-open economy as with most developing economies. Second, there is a wide heterogeneity in terms of comparative advantage across regions in Indonesia. Hence, it provides the opportunity to study variation in the exposure to shocks in the face of uniform price shocks. Indeed, Indonesia also has data that is regionally representative to allow one to study a multi-region economy. Third, there is no legal-restriction in moving from one region to another in Indonesia. Regions do vary in terms of amenities level and people have heterogeneous preferences in living in certain regions. Nevertheless, it is plausible to regard residential choices as market-driven choices as well.[6]

In order to answer the research question, I perform a set of empirical and quantitative analyses guided by a theoretical framework that matches the context of Indonesia from 2000 to 2015. In particular, I collect three facts that motivate the environment of the model. First, I choose the agriculture sector as the sector of interest as farmers can adjust crop choices as they face changes in crop prices.[7] Districts with high shares of the agriculture sector also tend to be relatively poorer, showing that districts have different starts before the exposure to price shocks. Second, I choose palm oil and rice as the they share around half of the agricultural land in Indonesia. The two crops are also contrasted in terms of their source of shocks. Palm oil price increases were driven by the commodity boom, while rice price increases were driven by import restrictions. Third, gravity equation on migration flows reveals that regions face upward-sloping labor supply. This result implies that labor moves to regions with higher earnings.

Armed with the three motivating facts, I build two theoretical frameworks as the foundation for empirical and quantitative analysis. First, I combine two-sector Specific Factor Model with the multi-region economy as in Redding (2016). I show that the impact of price shocks to regional wages depend on the share of the sector that experiences the increase in relative price. This result guides the measurement of local shocks in the empirical analysis using data. Second, I decompose the welfare changes in the multi-region economy model as in Redding (2016) into gains

[6]According to Artuc et al. (2015), migration costs in Indonesia are approximately close to the average migration costs in developing countries. As a comparison, migration cost is estimated to be 3.46 of annual wage in Indonesia, 5.06 in the Philippines, 3.77 in Korea, 2.75 in China, and 2.21 in the US.

[7]The commodity boom in the 2000s affected both the agriculture sector and the mining sector directly. To take into account exposure of the commodity boom to the mining sector, I control for the shares of mining sector but not necessarily put focus on it.

from migration and gains from trade. This result guides the quantitative analysis in estimating the overall changes in welfare in Indonesia between 2005 to 2010.

Defining districts as unit of regions, I construct a measure of exposure to price shocks for palm oil and rice based on the result of the theoretical framework. I compute local exposure to shocks using potential share of palm oil and rice in district economies using crop suitability data from FAO-GAEZ dataset and harvested area data from the Ministry of Agriculture. Armed with the computed local shocks, I employ the difference-in-difference method to find the impact of exposure to palm oil price shocks and rice price shocks on two main outcome variables: real expenditure per capita as the main proxy for welfare and net-inward migration rate for labor-mobility outcome. I study the impact of the exposure to price shocks on three margins: between exposed and non-exposed, heterogeneity in exposure and spillover to non-exposed districts. In addition, I complement with the discussion on mechanisms that drive the results. Specifically, I analyze the responses of factors of production, i.e labor and land, toward the price shocks. Lastly, applying the framework of asymmetric location and labor mobility as in Redding (2016), I estimate the welfare changes between 2005 and 2010. I decompose the welfare changes into gains from migration and gains from trade.

I present three main findings. First, districts exposed to palm oil shocks had significantly higher real expenditure per capita compared to the non-exposed ones, but there was not much significant difference between districts exposed to rice price shocks and those not exposed. I find that labor respond to the incentives from higher real expenditure per capita in districts exposed to palm oil price shocks. Accordingly, these districts attracted more net-inward migration. Since I follow districts' performance overtime, I find evidence that the impact of the shocks are temporary. As the commodity boom ends, the difference between exposed and non-exposed districts also dissipates.

In an analysis of the mechanisms that drive the result, I find that the growth in palm oil sector was spurred by land expansion (extensification) and not by an increase in actual yield (intensification). In contrast, the rice sector did not grew at all, either through extensification nor intensification. Meanwhile, analyzing district premia using the two-step method introduced by Dix-Carneiro and Kovak (2017), I find contrasting results compared to their results for trade liberalization in Brazil. In the Indonesian context, district premia are relatively equalized across districts. This result implies that frictions to labor mobility may not be significant enough to prevent any shocks to diffuse through internal migration. Indeed, as districts exposed by palm oil price shocks expand the sector by land expansion, they may have increased labor demand in these districts. This increase in labor demand materialized as higher real expenditure per capita and net-inward migration.

Second, I show evidence of spillovers. The nearest non-exposed districts to districts exposed by palm oil shocks also have significantly higher expenditure per capita and migration. This result presents evidence that the shocks are not fully localized. They have an indirect impact on non-exposed districts. As the exposed districts are booming, they demand more goods and services as well as labor from their surrounding.

Lastly, I estimate there was a welfare gain of 0.39% in Indonesia between 2005 to 2010. Gains from migration accounts for one-third of these gains, or 36%. Meanwhile, gains from trade explains the other two-third, or 64%, of the gains.

This paper is related to three strands of literature. First, it relates to broad literature on the impact of international trade to the labor markets in domestic economies. There are two main channels through which the actual trade shocks materialize: the price channel and the quantity channel. In the former, trade shocks can stem from trade liberalization as in Topalova (2010) and Kovak (2013), world price changes as in Adão (2015), trade cost changes such as Donaldson (2018), or their combination such as Sotelo (2015).[8] I complement this literature by studying trade shocks through the price channel. In particular, I use two common sources of price shocks faced by developing economies: changes in world price and protectionist measures. Both of these factors are relevant to developing economies but are rarely compared together even though countries often face them simultaneously. From the contrast results of palm-oil price shocks and rice price shocks in this paper, I show that the impacts are not straightforward.

Second, this paper relates to the relationship between international trade and internal migration. This topic has developed more recently as studies on spatial economics provide frameworks to understand the relationship.[9] I contribute to this literature by showing some evidence on how local labor markets adjust and diffuse trade shocks through internal migration. Recent papers show evidence of the importance of taking into account internal migration. For example, Tombe and Zhu (2019) quantify the welfare impacts of reduction in internal trade cost, international trade cost and internal migration cost in China and show that most of the welfare gain stems from reduction in internal migration costs instead of the more commonly believed reduction in international trade cost as China joined the WTO. Meanwhile, Pellegrina and Sotelo (2020) show that internal migration can shape regions' and ultimately countries' comparative advantage using the case of Brazil.

Third, I complement the literature on trade, internal migration and regional dynamics. I contribute in this strand of literature by showing that even for a relatively short period of time, in this case around five years, trade shocks that are advantegous in income can no longer be localized. Second, I show that impact of commodity boom has been short-lived, emphasizing caution to take cyclical factor as a sustainable source of growth for regional development. Meanwhile, using trade liberalization in Brazil, Dix-Carneiro and Kovak (2017) show that regions facing larger liberalization experienced increasingly lower growth in wages and employment. They show that the lack

[8]Meanwhile, the quantity channel can stem from implied technological changes as studied by Autor et al. (2013) for the case of surges of imports from China by the US and by Costa et al. (2016) for the demand and supply shocks faced by Brazil due to the technological shock in China.

[9]These frameworks include Allen and Arkolakis (2014) and Redding (2016).

of internal migration and slow capital adjustment amplify the local effects of trade liberalization. Using the accession of China to the WTO, Fan (2019) shows the importance of taking into account internal migration to better estimate the impact of trade liberalization on interregional inequality and wage inequality. Méndez-Chacón and Van Patten (2019) study the regional dynamics in Costa Rica due to foreign direct investment flows. They show that the ease of internal migration dampens a monopsonist's market power to push down local wages.

The rest of the paper is structured as following. I lay out the context of Indonesia during the commodity boom in the 2000s as well as the trade protection on rice in Section 2. In the same section, I draw three facts that motivate the choice of agriculture sector, the choice of crops and the importance of taking into account internal migration. Guided by these facts, I describe the theoretical frameworks that guide the empirical analysis and the quantitative simulation in Section 3. I describe the main data and the measurement of exposures to price shocks in Section 4. Armed with the computed exposure to shocks, I present and discuss the empirical evidence of the impact of the exposure to the price shocks in Section 5. In Section 6, I describe the quantitative results of welfare changes estimation. In Section 7, I present the conclusions that can be drawn from the analysis.

2 Indonesia in the 2000s

2.1 Overview

Indonesia is the biggest economy in Southeast Asia. It is the largest archipelagic state in the world with more than 16 thousands islands[10], spanning on the equator over 3,100 miles from the west to the east, i.e. approximately the travel distance from Seattle, Washington State to Orlando, Florida. It is an emerging economy and also a home to the fourth largest population in the world with more than 260 million people in 2018.

Indonesia is rich in natural resources. Such natural comparative advantages make Indonesia as an important producer of primary commodities, including agricultural and mining commodities. The contributions of the agriculture sector and mining sector were 9% to 11% and 7% of GDP from 2000 to 2010.[11] Despite the relatively small contribution to the size of the economy, the agriculture sector has the biggest contribution to employment in the economy. It accounted for 45% and 38% of employment in 2000 and 2010, respectively.[12]

At the end of the 1990s, Indonesia experienced a deep economic crisis as part of the Asian Financial Crisis (AFC). In the trough of the crisis in 1998, GDP growth plunged by -13%. The crisis propelled not only economic but also political reform. The economy took some time to

[10] BPS (2019), "Statistical Yearbook of Indonesia 2019".

[11] Ibid.

[12] Calculated by author from the tables of employment by sector and status on BPS' website: www.bps.go.id.

benefit from the reform. It started to recover in 2000. The economy then grew with an average growth of 4.7% in the first half of the 2000s. Given the significant differences in economic and political institutions before and after the AFC, I take the start of the period of interest as 2000 or 2001.

In the second half of the 2000s, the Indonesian economy was characterized by high GDP growth fueled by high export growth. It experienced double-digit export growth with an average of 12.9% in this period. As shown by Table 1 below, the nominal and real expenditure per capita grew fast as well. These indicators are other proxy variables that represent standard of living that I use in this paper.[13] Consecutively, nominal and real expenditure per capita grew 15.8% and 7.4% per year between 2005 to 2010. In general, various economic indicators indicate higher growth in the second half of the 2000s compared to the prior and subsequent periods.

Table 1 also shows statistics on recent migration in Indonesia. Recent migration is defined as changes of residence between survey year and five years prior to the survey year.[14] In addition, as I focus on internal migration, I include changes in residence in district level and exclude international migration. The total recent migration ratio to the nation population may seem quite small, i.e around 3-5%. However, there is high variation of the prevalence of migration across districts.[15]

2.2 A tale of two crops

During the first decade of the 2000s, Indonesia's agriculture sector experienced contrasting dynamics. First, as one of the main producers of primary agriculture commodities in the world market, the country experienced a windfall from the commodity boom that occured in that decade. Meanwhile, as the country grew to be more a democratic nation and as it recovered from the Asian Financial Crisis in 1997 to 1998, the pressure from political groups that claimed to represent farmers also grew. So in contrast to the windfall from immersing in the world market, the Indonesian government enacted a series of protectionist measures for its main food commodity: rice. Starting 2004, Indonesia imposed large import bans on rice, making it virtually cut off from the world rice market.

[13]The government also uses expenditure per capita as the indicator to measure poverty.

[14]I extract figures of recent migration from various rich micro data that capture the condition of the respondents in the year of the survey relative to their residences five years prior. Hence, recent migration figures here are flow variables.

[15]See Table A.4 in Appendix for summary statistics of netmigration rate over the period of this study.

Table 1: Selected economic indicators

Indicator	2000-2005	2005-2010	2010-2015
GDP growth	4.7	5.7	5.5
Export growth	4.5	12.9	-0.1
Growth of expenditure per capita	13.0	15.8	11.1
Growth of real expenditure per capita	3.3	7.4	5.0
	2000	**2010**	**2011-2014**
National recent migration rate	5.2	4.0	3.2
Net-migration rate of the top 10% district	7.4	4.5	
Net-migration rate of the bottom 10% district	-6.6	-3.1	
	Jan 2001 to Dec 2005	**Jan 2006 to Dec 2010**	**Jan 2011 to Dec 2015**
Price of palm oil, world market (USD/ton)	362	701	817
Price of rice, domestic market (IDR/kg)	3,117	5,887	9,292

Sources:World Development Indicator for GDP and exports. Population Census for migration rate in 2000 and 2010, Social-Economic Household Survey (*Susenas*) for the average of recent migration rate in 2011-2014. INDO DAPOER dataset by the World Bank for expenditure per capita. IMF Commodity Price Series for price of palm oil. BPS for price of rice. All growth figures and averages are author's calculation.
Notes: All growth figures are annualized growth rates. Nominal and real expenditure per capita are the median of district-average nominal and real expenditure per capita. Migration is recent migration, i.e. change of residence within five years prior to the survey or census year. Price of palm oil is the simple average of nominal price in the world market in each period. Price of rice is the average of nominal domestic price of rice in each period. Domestic price of rice is the average of provincial prices.

2.2.1 The rising star of the commodity boom in the 2000s: Palm oil

The commodity boom began around 2003-2004 and reached its peak in 2011.[16] During the Global Financial Crisis in 2008 to 2009, commodity prices also plummeted but quickly rose up again in 2010. Indonesia's main export commodities such as palm oil, rubber and coal follow this overall trend in the world commodity market.[17] To provide the extent of the boom for Indonesia as exporters, the world palm oil prices and rubber prices consecutively increased by more than fourfold and ninefold at the peak of the boom compared to their levels in January 2000.

Such extraordinary magnitude and length of the commodity boom provoked two key changes to Indonesia's export profile in that period. First, as shown in Table 1, exports grew faster than the GDP. Second, Indonesia's exports composition transformed during this period. As commodity exports became more valuable, their shares to total exports also increased. Indonesia's main primary commodities for exports gained greater shares in Indonesia's export profile. Meanwhile, the shares of non-commodity exports, such as textiles and electronics, shrank as shown in Figure 1 panel (a).

In addition, Figure 1 panel (b) and Figure A.9 in Appendix show that most of the increase in exports of Indonesia's main export commodities such as palm oil, rubber and coal, were price-driven. For example, exports of palm oil increased by fourfold in quantity but twelvefold in values between 2000 and 2010. This fact helps to justify the assumption used in this paper that world price shocks in this commodity boom period was exogenous to Indonesia.

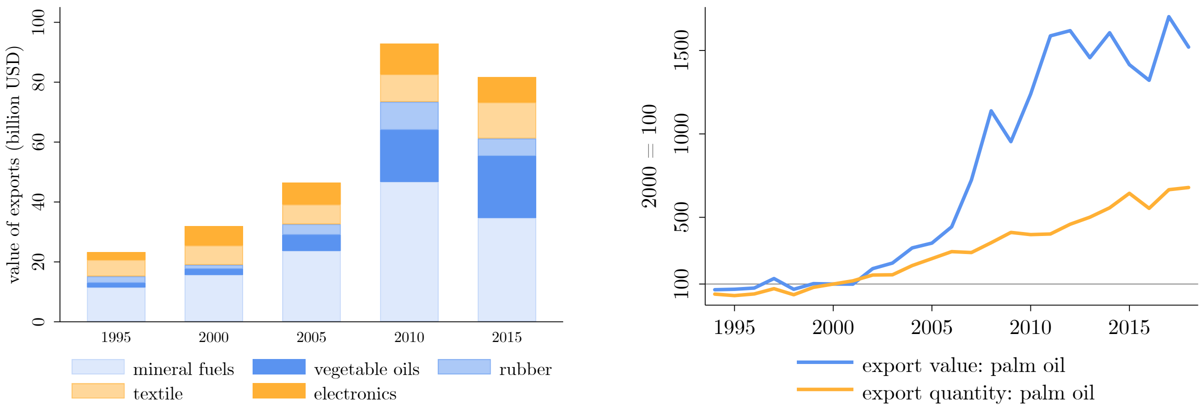
One may argue that as one of the biggest exporters of palm oil, Indonesia is not a price taker in the world market of palm oil.[18] However, various studies on the commodity boom show that determinants of the boom are external factors in the perspective of Indonesian palm oil farmers. Such potential causes, as pointed out by Baffes and Haniotis (2010), include excess liquidity, fiscal expansion and lax monetary policy in many countries. Moreover, they also argue that there is a strong link between energy commodity prices and non-energy commodity prices. Palm oil is used widely in both categories: in biofuel as an energy commodity as well as cooking oil and in numerous consumer goods as a non-energy commodity. Hence, it is plausible to treat Indonesia as a small-open economy in the world market for palm oil.

[16] Fernández et al. (2020) show that the permanent component of the commodity boom peaked in 2008 or 2012 for emerging economies. Meanwhile, Fernández et al. (2017) shows the highest peak occurred in 2008 while the second highest peak occured in 2011. Fernández et al. (2018) estimate that the world-shock component reached its peak in 2008 and 2011. In the case of Indonesia, Sienaert et al. (2015) shows that the peak for Indonesia's commodity basket occurred in February 2011.

[17] See Figure A.6 for the trend of main price indices constructed by the IMF and Figure A.7 and A.8 for the trend of Indonesia's main commodities.

[18] The main exporters of palm oil are Indonesia and Malaysia. Over the period of this study, Indonesia's market share increased from 26% in 2001 to 42% in 2011. Meanwhile, Malaysia's market share decreased from 57% in 2001 to 43% in 2011. In more recent years, Indonesia's market shares reached more than half of the world export market while Malaysia's share takes around one third of the world export market. Figure A.10 shows the trend of world export market for palm oil against Indonesia's and Malaysia's exports.

Figure 1: Indonesia's exports



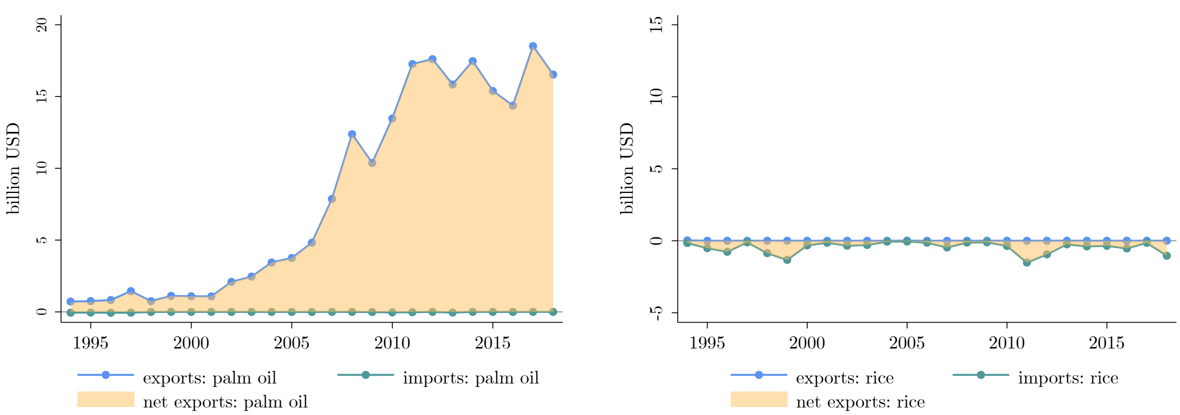
(a) Indonesia's exports transformation

(b) Indonesia's palm oil exports

Source: UNCOMTRADE, author's calculation.
Notes: Mineral fuels refer to HS 27. Vegetable oils refer to HS 15, rubber refers to HS 40, textile refers to HS 61 to HS 64. Electronics refers to HS 85. Panel (a) shows selected exports goods. Bars in blues represent primary-commodity exports, while bars in yellows represent manufacture exports. Panel (b) compares the value and volume of exports of palm oil, defined as HS 1511.

Figure 2 panel (a) below shows the trend of Indonesia's trade of palm oil. Exports have been largely greater than imports, making Indonesia a net-exporter of palm oil. Thus, increases of palm oil price in the world market contribute to improvement in Indonesia's terms-of-trade.

Figure 2: Indonesia's trade of palm oil and rice



(a) palm oil

(b) rice

Source: UNCOMTRADE. Author's calculation for net exports.
Notes: Rice refers to HS 1006. Palm oil refers to HS 1511. Import values are recorded as negative exports. Positive net-exports mean that exports exceed imports, while negative net-exports imply imports exceeds exports.

2.2.2 The political economy of rice

Rice is an, if not the most, important agricultural commodity in Indonesia. It is the main staple food for most Indonesians. The national household survey in 2007 shows that poor households spends on average 22% of their total expenditure on rice, or approximately one-third of their food expenditure (Aldaz-Carroll, 2010). Meanwhile, rice sector is also a major employer. The agriculture census in 2003 reveals that 55% of agriculture households in Indonesia are rice farmers. However, only 6% of those have control over more than 0.5 ha of rice fields (McCulloch, 2008). In addition, in comparison to palm oil, Figure 2 panel (b) also shows that Indonesia tends to be a net-importer of rice even during the import ban period. Since rice is a necessity to most Indonesians, an increase in its prices may reduce purchasing power to net consumers.

Given the strategic position of rice in the economy, rice policy has been closely determined by the political situation as well.[19] Since the early 1970s to late the 1990s, rice price stabilization was achieved through imports. Particularly, the national logistic agency (Bulog) was given a mandate to stabilize rice prices. The government also provided Bulog with import monopoly. Then, in the short period after the AFC, Bulog lost its authority as the sole importer of rice as part of the IMF policy package that Indonesia took. During this time, rice price stabilization was achieved through imports by private traders (McCulloch and Timmer, 2008). Nevertheless, throughout these periods, real rice prices were relatively stable (Fane and Warr, 2008). Due to the trade liberalization in late the 1990s, Indonesia became the world's largest rice importer (Warr, 2011).[20]

Meanwhile in the early 2000s, as Indonesia recovered from the AFC, pressure to protect rice farmers increased as well. Some import restrictions were imposed in the form of import tariffs. Fane and Warr (2008) estimated that the nominal rate of protection on rice increased from 14% in 2000 to 33% in 2003. Finally in 2004, the Indonesian government placed a ban on imports of rice by the private sector. This ban is supposed to be a seasonal ban to avoid flood of imports during harvest seasons. Some imports are allowed with the size of the quota to be determined by the government. The imports can only be conducted by Bulog.[21] Marks (2017) estimates that in 2015 the nominal rate of protection and effective rate of protection in rice sector reached consecutively 67.2% and 204.3%.

Figure 3 shows that since the import ban took place in 2004, domestic rice prices have surged. In addition, discrepancy between domestic prices and the price of imported rice has increased ever since, with some period of reversal during the Food Crisis 2008. Except for the Food Crisis period, the import ban is practically binding as there is lack of incentive to export due to lower prices in export markets. Meanwhile, during the Food Crisis period, the government introduced

[19] McCulloch and Timmer (2008) provide a summary of the political economy of rice in Indonesia from the 1970s to 2008. There is not much changes in terms of policy since 2008 up to the current period.

[20] See Figure 3b for trend of Indonesia's trade flows for rice.

[21] These trade policies on rice are stipulated by Minister of Industry and Trade Regulation No. 9/2004, Minister of Trade Regulation No. 12/2008, and Minister of Trade Regulation No. 19/2014.

an export ban on rice to shield the country from the exorbitant level of world prices fueled by export restrictions from main rice exporters and other trade distortion measures.[22] Despite how the import ban has continued to be binding, leading to a lack of incentive to export, the export bans remain in place.[23]

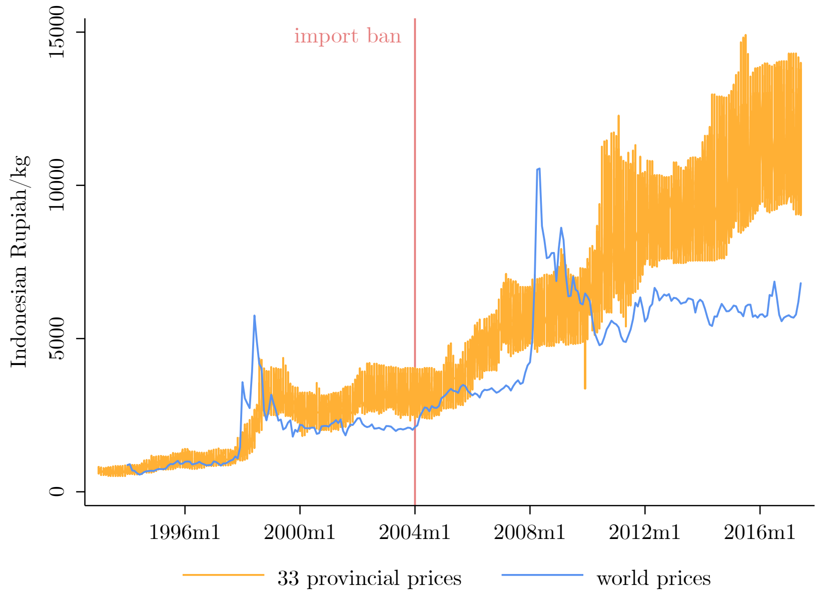
Another observation that we can see in Figure 3 is that price variation across provinces increased after the enactment of the ban. Before the ban, variation of rice prices across provinces are relatively negligible. This fact may indicate lax arbitrage across provinces after the ban started. There are several plausible reasons. First, Bulog may have a weaker role and or resources to stabilize domestic prices (Sim, 2020). Second, there was a disruption of trade relationship between private importers and international source markets that were built during the more liberal period of the late 1990s to 2004 (Bazzi, 2017). Third, Warr (2005) estimates that the elasticity of supply is 0.2 to 0.4. Despite the variation across regions, this elasticity is relatively low, especially compared to the elasticity of demand for rice imported from Thailand that ranges between -2.5 to -5. I also argue that the rice price stabilization policy during the period of import ban may institutionally make it less obvious for the government to tackle price hikes in terms of regional variation. In 2005, the government started to regulate the rice price stabilization mechanism by allowing local governments to propose provisions of stabilization measures in the face of regional price hikes. Once such a proposal is approved by the central government, Bulog performs the stabilization program of open market operation in the concerned region. The general procedure remained in place until 2018.[24] Since price hikes are reported from a local government to the central government, there may be silos in observing provincial rice prices and thus less attention to the price variation across regions.

[22] Various studies show that the price hikes in food commodities during the Food Crisis 2008 were magnified by trade measures. These studies include Giordani et al. (2016), Anderson and Martin (2011) and Bouët and Debucquet (2012). Giordani et al. (2016) in particular document that there were six countries imposing export restrictions or import promotion measures on rice during this period. These trade measures covered 35.72% of world rice trade. For the timeline of enactment of export restrictions and other trade measures on rice see Aldaz-Carroll et al. (2010) and Headey (2011).

[23] In the period of study, export ban on rice is stipulated by Minister of Trade Regulation No. 12/2008 and Minister of Trade Regulation No. 19/2014.

[24] Rice price stabilization with local government alert mechanism is regulated by Minister of Trade Regulation No. 22/2005 and then Minister of Trade Regulation No. 1/2012. The mechanism changed in 2018 under Minister of Trade Regulation No. 127/2018.

Figure 3: Rice prices (Indonesian rupiah/kg)



Sources: Domestic prices are 33 provincial rice prices from BPS. World prices are from IMF Commodity Price Series. Author's calculation.
Notes: I follow Dawe (2008) in estimating retail price for imported rice from world price. In particular, I add 20 USD/ton for shipping and a 10% markup from wholesale to retail. I compute the prices in IDR/kg using exchange rate data from FRED.

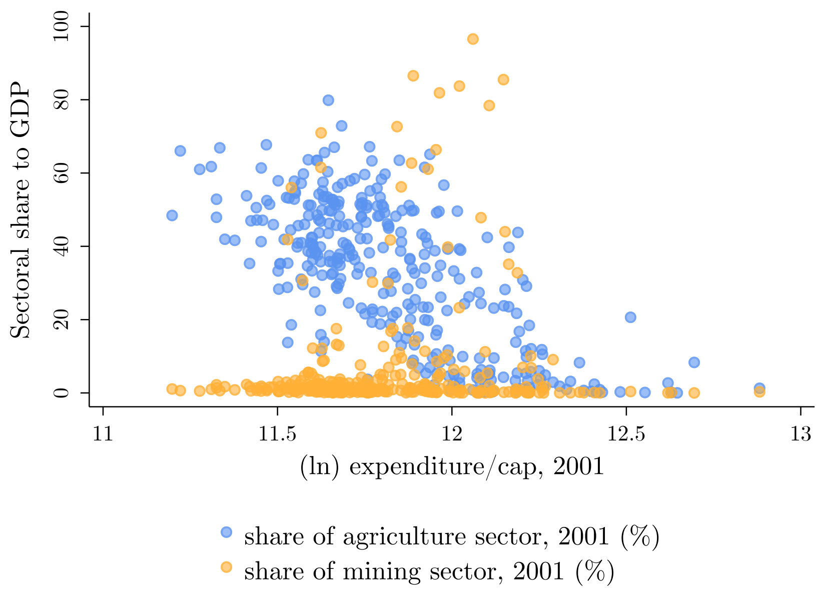
2.3 Three motivating facts

I document three motivating facts that guide me in building the theoretical framework and running empirical exercises to answer what the impacts of the price shocks from the commodity boom and import restrictions to Indonesian economy are. The first fact guides me to understand the variation of the importance of the agriculture sector across districts. The second fact profiles rice and palm oil as the two main crops over the period of study, showing changes in their land shares and the importance of taking into account crop suitability. The third fact motivates the non-short run framework in labor response, i.e. spatial labor mobility as a response to the varying degree of exposure to the commodity boom.

2.3.1 Fact 1: Agriculture sector had higher importance in pre-commodity-boom poorer districts.

Figure 4 compares the shares of the agriculture sector and mining sector in districts' gross domestic products against their level of expenditure per capita in the period prior to the commodity boom and the import restriction on rice. Poorer districts, having lower average expenditure per capita, tend to have a greater share of the agriculture sector. This fact is not surprising given the relatively small share of the agriculture sector's contribution in terms of GDP compared to its large contribution to employment. Meanwhile, there is no clear pattern on whether districts with a higher mining sector are in poorer or richer districts. In addition, the mining sector also depends on natural endowments that are not easily substituted as in the agriculture sector. Given the importance of the agriculture sector to the labor force in the economy, I focus on the exposure of price shocks in that sector. This fact also implies that there may exist some structural differences in less developed districts; hence, it is important to take into account such possible differences. In reduced-form analysis, I include several control variables to capture these potential structural differences.

Figure 4: Importance of the agriculture sector and mining sector across districts



Source: INDO DAPOER, author's calculation.
Notes: Each unit in the scatter plots represents a district. Shares of each sector refers to share in disctrict GDP.

2.3.2 Fact 2: Rice and palm oil became the two main crops.

Rice has the biggest share of agriculture land in Indonesia. It consistently takes at least one third of aggregate land for crops. There was an added 1 million hectares of rice agricultural land between 2000 to 2010, but its shares reduced from 37% to 33%. Meanwhile, palm oil has grown to be the second biggest share of agricultural land. In the onset of the boom, there were 2 million hectares of palm oil plantation. Over a decade later, its area has increased threefold to 6 million hectares. As a result, its share to land for crops increased from 6% to 14% from 2000 to 2010. In contrast, other main crops have not increased as much and hence, decreased in terms of shares.

Table 2: Land shares of main crops

Crops	Area (million ha.)		Share (%)	
	2000	**2010**	**2000**	**2010**
Rice	12	13	37	33
Palm oil	2	6	6	14
Maize	4	4	11	10
Rubber	2	3	8	9
Coconut	3	3	8	7

Sources: FAO, author's calculation.
Notes: Shares of each crop refers to their shares relative to total land for crops.

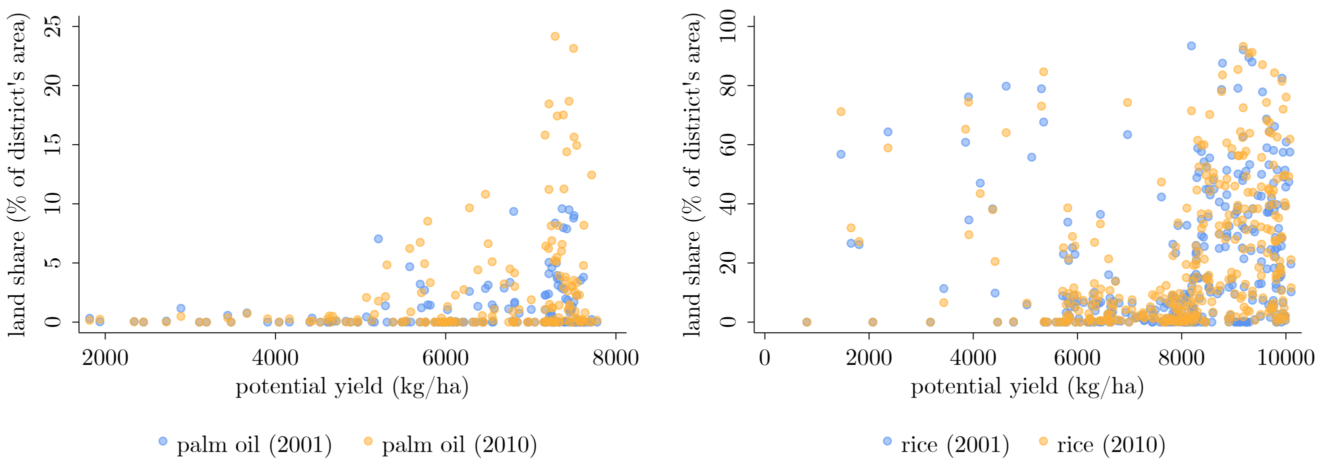
The substantial increase in the land share for palm oil occurred mostly in districts with high potential yield in producing palm oil. Comparing the ratio of palm oil plantations relative to each districts' total area in 2001 and 2011 in Figure 6a, the increase in these shares tends to be larger where potential yield is higher. Meanwhile, Figure 6b shows that land shares for rice have not increased as widely as palm oil. In contrast, some districts have reduced their shares for rice. This pattern goes hand-in-hand with the fact that there has not been much increase in rice fields nationally as shown in Table 2.[25]

The changes in crop mix and in particular the increase of land dedicated for palm oil as a booming crop may imply increases in labor demand in districts suitable for this crop. Figure 6a shows also that suitability, proxied by potential yield estimated by FAO, needs to be taken into account and that there are heterogeneity of these yields across districts.[26] Hence, in this study, I focus on two crops: palm oil and rice. These two crops have also interesting differences as mentioned before, i.e., palm oil is an income crop while rice is a necessity crop.

[25]One may wonder why there are districts with low suitability but high land share for rice. This fact is actually not surprising given that rice is a staple food for most of the Indonesian population. Also, as most farmers have a relatively low area of rice field per households, scaling up may not be easy.

[26]Another crop that could potentially be taken into account is rubber. However, FAO does not estimate the potential yield for rubber.

Figure 5: Land shares of palm oil and rice by potential yield.



(a) palm oil

(b) rice

Source: Area for each crop is from Tree-Crops Statistics, Ministry of Agriculture. District total area is from World Bank's INDO DAPOER. Potential yield data is from FAO GAEZ dataset. Land shares are the author's calculation. District's potential yield is the average of potential yield in the district.
Notes: Each unit represents a district. I exclude districts with land share for each crop of more than 95% of district's area.

2.3.3 Fact 3: Districts face upward-sloping labor supply.

The period of high palm oil and rice price was not only sizable in terms its magnitude but also because it lasted for a relatively substantial period of time. Such circumstances allow people to adjust and maximize their welfare by changing their residency. Starting in 2011, the Indonesian Social and Economic Household surveys (*Susenas*) allows us to observe these movements as the surveys record recent migration, i.e., residence from the five years prior to the survey year. Table 3 shows the results of running gravity equation on these recent migration flows across districts from 2011 to 2014. This period captures precisely internal migration during the high commodity prices period.

The results of running a gravity equation on recent migration flows provides evidence that people move to districts that offer higher expenditure per capita, or the preferred proxy for income in this paper. Specifically, the coefficient for expenditure per capita in destination districts is positive and significant, implying that districts face upward-sloping labor supply. This result also remains if we control for estimated observed amenities level in both destination and origin districts.

Table 3: Gravity on migration flows

	Dependent var.: number of migration from origin to destination	
	(1)	(2)
exp/cap: origin	-0.00302	0.0236
	(0.132)	(0.139)
exp/cap: destination	0.641***	0.564***
	(0.126)	(0.132)
distance	-1.304***	-1.288***
	(0.007)	(0.008)
Control: est. amenities	no	yes
Origin FE	yes	yes
Destination FE	yes	yes
Year FE	yes	yes
N	973210	803736
R2	0.427	0.428

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Gravity equation is estimated using Poisson pseudo-maximum likelihood estimation (PPML) on a panel of origin-destination district pairs in 2011 to 2014. Estimated amenities are predicted first components from running principle component analysis (PCA) on selected variables from the Village Census (PODES) 2005 and 2008.

Table 4: Net-inward migration rates by crop suitability

Year	**palm oil**			**rice**		
	bottom 20%	**median**	**top 20%**	**bottom 20%**	**median**	**top 20%**
2000	-2.1	-0.87	1.2	-1.6	0.0	0.5
2010	-0.05	-0.42	1.3	0.4	0.34	-0.15

Source: Population Census 2000 and 2010 for netmigration rates. FAO GAEZ dataset for potential yield. Author's calculation.
Notes: Migration refers to recent migration, i.e. changes of residence between five years prior to census year and the census year. Potential yield is district averages potential yield.

In order to see the variation of net-inward migration rates across regions, Table 4 above tabulates the net-inward migration rates by the percentiles of potential yield in growing palm oil and rice. Between 2000 and 2010, the median district increased net-inward migration rates. Districts with high suitability in growing palm oil tend to have higher net-inward migration rates in 2010 compared to 2000. Meanwhile, districts with high suitability in growing rice tend to have lower net-inward migration rates in 2010 compared to 2000.[27]

[27]Both claims are true for the 70th, 80th, and 90th percentile, but they are reversed for the top percentile.

3 Theoretical framework

The commodities or the industries of interest in this study are crops. Unlike the manufacture sector, data on employment from crops is rarely available. Hence, we cannot use the exact measurement of exposure to shocks such as in Topalova (2010) or a more general form as in Kovak (2013). Thus the first part of this theoretical framework provides the guide to measure the exposure to price shocks as well as predict how the shocks affect wages in regions. Guided by the motivating facts presented above, I construct a theoretical framework which combines the classsical specific factor model and the spatial economy set-up as in Redding (2016) that allows for the local labor market to face an upward-sloping labor supply. The main difference from Redding (2016) is that I assume a small-open economy which engages in trade with no iceberg trade cost, both for international trade and interregional domestic trade. Meanwhile, labor can move across regions, taking into account asymmetric preference on amenities in these regions.[28] In addition, we simplify the model by assuming a two-sector economy with each sector having a specific factor in its production function.

The second part of the theoretical framework uses the basic spatial model as in Redding (2016) with a continuum of goods instead of only a two-sector economy in order to match more realistically with the actual economy. In this part, I decompose the equation that shows the welfare changes into two parts: gains from migration and gains from trade. This simple decomposition guides the quantitative analysis estimating the welfare changes in the period of the trade shocks.

3.1 Framework for measurement of exposure to price shocks: Two-sector economy

3.1.1 Environment

Consider a small open economy consists of N regions, indexed by $n \in N$. There are two sectors, indexed by $j = 1, 2$. The first sector is the non-commodity sector, labelled as sector 1. The second sector is the commodity sector, labelled as sector 2. Both sector uses labor as inputs and a specific factor. In this set-up, the non-commodity sector uses labor (L) and capital (K), while the commodity sector uses labor and land (T). Total endowment of labor in the economy is fixed at the amount of $\bar{L}$. Meanwhile, goods produced by both sectors are homogeneous and are freely traded internationally and domestically in perfect competition markets. Let us denote the relative price of sector 2 relative to sector 1, p_2.

[28]This setup implicitly assumes that migration frictions are more pronounced than trade frictions. Given that it is for example harder to find information on migration opportunities and there is less means to finance migration compared to trade, I take this assumption is plausible enough.

Consumer Preferences Preferences of each worker ω are defined over consumption on goods produced by the non-commodity sector (C_1), consumption on goods produced by the commodity sector (C_2), and amenities provided by the region n, b_n, where she or he chooses to live:

$$U_n(\omega) = b_n(\omega)\left(\frac{C_1}{\sigma}\right)^{\sigma}\left(\frac{C_2}{1-\sigma}\right)^{1-\sigma}, \tag{1}$$

Elasticity of substitution between goods from sector 1 and sector 2 is α,with $0 < \sigma < 1$. As in Redding (2016), each worker ω takes an independent and idiosyncratic draw on amenities for each region n from the Fréchet distribution:

$$G_n(b) = e^{-B_n b^{-\epsilon}}, \tag{2}$$

where B_n, the scale parameter, determines the average amenities for region n while ϵ, the shape parameter, determines the dispersion of amenities across workers for each region. In this setup, the shape parameter is common to all regions. The higher ϵ, the less dispersed is the distribution.

Price Index Given preferences and the choice of the non-commodity sector 1 as the numeraire, the price index in region n is:

$$P_n = p_2^{1-\sigma}. \tag{3}$$

Note that price index is the same in all regions due to small-open economy assumption and lack of trade cost. Hence we can further define $P \equiv P_n$ for all $n \in N$.

Production and Technology The production functions of both sectors are Cobb-Douglas using labor and the specific factor of each sector. The production function of the non-commodity sector in region n is the following:

$$Y_{n1} = \left(\frac{L_{n1}}{\alpha}\right)^{\alpha}\left(\frac{K_n}{1-\alpha}\right)^{1-\alpha}. \tag{4}$$

Meanwhile, the production function of commodity sector in region n is:

$$Y_{n2} = \left(\frac{L_{n2}}{\beta}\right)^{\beta}\left(\frac{T_n}{1-\beta}\right)^{1-\beta}. \tag{5}$$

Hence, the zero-profit condition implies:

- for sector 1: $1 = w_n^{\alpha} r_{Kn}^{1-\alpha}$
- for sector 2: $p_2 = w_n^{\beta} r_{Tn}^{1-\beta}$

Meanwhile, labor demand for each sector in each region n is:

- for sector 1: $L_{n1}^D = \frac{\alpha Y_{n1}}{w_n}$
- for sector 2: $L_{n2}^D = \frac{\beta p_2 Y_{n2}}{w_n}$

Thus, total labor demand in region n is the sum of labor demand for each sector in the region, i.e:

$$L_n^D = \frac{\alpha Y_{n1} + \beta p_2 Y_{n2}}{w_n}. \tag{6}$$

Income Each worker is endowed with a unit of labor which she or he supplies inelastically. Each worker receives wages for the labor services she or he provided by working in region n. Moreover, I assume that the rent for capital and land in the whole economy is distributed lump-sum to all the population. I use this assumption since the focus on this study is medium-run changes. In this regard, I do not take a stance on how non-labor inputs are endowed. I Hence, for a worker in region n, her or his income equals:

$$v_n = w_n + \varphi, \tag{7}$$

where φ is the lump sum rental income from capital and land distributed to all population in the country, or :

$$\varphi \equiv \frac{\sum_{n=1}^{N} r_{Kn} K_n}{\bar{L}} + \frac{\sum_{n=1}^{N} r_{Tn} T_n}{\bar{L}}.$$

Residential Choice Each worker maximizes her or his utility in (1) by taking into account her or his idiosyncratic preferences on amenities for each region. Using the properties of the Fréchet distribution, the probability that a worker chooses to live in region $n \in N$ is:

$$\frac{L_n}{\bar{L}} = \frac{B_n \left(\frac{v_n}{P_n}\right)^{\epsilon}}{\sum_{k=1}^{N} B_k \left(\frac{v_k}{P_k}\right)^{\epsilon}}. \tag{8}$$

This system of equation represents labor supply in each region $n \in N$. This system allows for an upward-sloping labor supply in which we can expect a higher share of the population will choose to live in regions with relatively higher income and amenity levels. Since each worker supplies one unit of labor in her or his place of residence inelastically, the upward slope of the regional labor supply is only determined by migration.

Equilibrium Equilibrium in the economy is defined as $\{w_{n,} L_n, L_{n2}, r_{Kn}, r_{Tn}\}$ for each region $n \in N$, which solves the following system of equations:

$$p = w_n^{\beta-\alpha} r_{Tn}^{1-\beta} r_{Kn}^{\alpha-1}, \tag{9}$$

$$L_n = L_{n1} + L_{n2} \tag{10}$$

$$\frac{L_n^D}{\bar{L}} \equiv \frac{\frac{\alpha\left(\frac{L_{n1}}{\alpha}\right)^{\alpha}\left(\frac{K_n}{1-\alpha}\right)^{1-\alpha}}{w_n} + \frac{p_2\beta\left(\frac{L_{n2}}{\beta}\right)^{\beta}\left(\frac{T_n}{1-\beta}\right)^{1-\beta}}{w_n}}{\bar{L}} = \frac{B_n\left(\frac{v_n}{P_n}\right)^{\epsilon}}{\sum_{k=1}^{N} B_k\left(\frac{v_k}{P_k}\right)^{\epsilon}} \equiv \frac{L_n^S}{\bar{L}}, \tag{11}$$

$$p_2 = \left(\frac{\alpha}{1-\alpha}\right)^{1-\alpha}\left(\frac{1-\beta}{\beta}\right)^{1-\beta}\frac{K_n^{1-\alpha}}{T_n^{1-\beta}}\frac{L_{n2}^{1-\beta}}{L_{n1}^{1-\alpha}}, \tag{12}$$

$$\sum_{n=1}^{N} L_n = \bar{L}. \tag{13}$$

3.1.2 Exogenous Price Shock

I will analyze the impact of an exogeneous price shocks to wages in different regions. If labor had full labor mobility and homogeneous preferences across regions, wages across regions will equalize. Conversely, if regions as local labor market have fixed amounts of labor, i.e. no labor mobility across regions, then the exogeneous price shock would be localized and the impact in the short run would be as predicted in the classic specific-factor model. That is, the exogeneous increase in price would be followed by an increase in wages of a lower percentage change.

Allowing for full labor mobility, but with heterogeneous preference across regions, I provide a framework between the two extreme cases explained above. From the labor-supply side, each worker will consider all regions and maximize her or his expected utility. Meanwhile, since each region may differ in their endowments of specific-factors in each sector, the exposure to the shock will vary across regions despite all of them facing the same price shock. This variation in exposure to shocks leads to variation in labor demand responses in each region. Hence, we can expect to see variation in the responses of wages in different regions from a universal price shock.

A Simple Case: $\alpha = \beta$ In order to derive the intuition above, consider a simple case when labor intensity in sector 1 and sector 2 are assumed to be equal, i.e. $\alpha = \beta$. Suppose there is an exogenous change in the relative price of sector 2. In order to see the changes in labor demand in region n, totally differentiate (6) and use the Envelope Theorem to obtain:

$$\hat{L_n^D} = \gamma_{n2}\hat{p_2} - \hat{w}, \tag{14}$$

where $\hat{x} \equiv {}^{dx}/_{x}$ and $\gamma_{n2} \equiv \frac{\alpha p_2 Y_{n2}}{\alpha(Y_{n1}+p_2Y_{n2})}$, which is the share of sector 2 in the total output of region n.

Meanwhile, we totally differentiate (8) to see the changes in labor supply in region n:

$$\hat{L_n^S}\frac{L_n^S}{\bar{L}} = \epsilon B_n(w_n+\varphi)^{\epsilon-1}w_n\hat{w_n} - \left[\sum_{k=1}^{N}\frac{w_k\hat{w}_k}{\epsilon B_k(w_k+\varphi)^{\epsilon-1}}\right]. \tag{15}$$

Let us define $\hat{D} \equiv \sum_{k=1}^{N}\frac{w_k\hat{w}_k}{\epsilon B_k(w_k+\varphi)^{\epsilon-1}}$. Hence,

$$\hat{L_n^S}\frac{L_n^S}{\bar{L}} = \epsilon B_n(w_n+\varphi)^{\epsilon-1}w_n\hat{w_n} - \hat{D}. \tag{16}$$

Armed with the change in labor demand in (14) and the change in labor supply in (16), we can use the population-mobility condition in (13) to solve fo the changes in wages due to changes in price. From the population mobility condition we have:

$$\sum_{n=1}^{N}\hat{L_n^S}\frac{L_n^S}{\bar{L}} = 0. \tag{17}$$

Using 16, we can get:

$$\sum_{n=1}^{N}\left[\theta_n\hat{w_n} - \hat{D}\right]\frac{L_n^S}{\bar{L}} = 0 \tag{18}$$

$$\Leftrightarrow \hat{D} = \sum_{n=1}^{N}\theta_n\frac{L_n^S}{\bar{L}}\hat{w_n} \tag{19}$$

where we define $\theta_n \equiv \epsilon B_n(w_n+\varphi)^{\epsilon-1}w_n$.

Furthermore, using the labor-market clearing condition in each region $n \in N$ as in (11),

$$\hat{L_n^D} = \hat{L_n^S} \tag{20}$$

$$\Leftrightarrow \gamma_{n2}\hat{p} - \hat{w_n} = \theta_n\hat{w_n}\frac{\bar{L}}{L_n^S} - \hat{D}\frac{\bar{L}}{L_n^S} \tag{21}$$

$$\Leftrightarrow \hat{w_n} = \left(\frac{\lambda_n}{\lambda_n+\theta_n}\right)\left[\gamma_{n2}\hat{p} + \frac{\hat{D}}{\lambda_n}\right] \tag{22}$$

where we define $\lambda_n \equiv \frac{L_n}{\bar{L}}$.

Proposition 1. *For a given change in relative price, $\hat{p}$, the impact on wages between region n and m :*

$$\frac{\lambda_n}{\lambda_n+\theta_n}\gamma_{n2} > \frac{\lambda_m}{\lambda_m+\theta_m}\gamma_{m2} \Rightarrow \hat{w_n} > \hat{w_m},$$

where $\lambda_n \equiv \frac{L_n}{\bar{L}}$, $\theta_n \equiv \epsilon B_n(w_n+\varphi)^{\epsilon-1}w_n$, $\gamma_{n2} \equiv \frac{\alpha p_2 Y_{n2}}{\alpha(Y_{n1}+p_2Y_{n2})}$.

Facing a uniform price shock, the impacts on wages across regions differ. The changes in wages in each region depends on the region's share of the population, amenity level, and sectoral composition. Intuitively, an increase in relative price of sector 2, i.e., the commodity sector, increases the demand for labor in sector 2. This mechanism allows a uniform price shock to be exposed to regions differently. Meanwhile, the increase in demand for labor in sector 2 in each region pushes up the wages in the region, which simultaneously attracts workers to move to the region with the booming sector. The movement of workers, then, affects changes in wages as more workers move to the region in the form of higher supply of labor faced by the region. This is when the upward-supply of labor kicks in. The magnitude of changes in wages then depends also on labor share and amenity level as these two factors affect labor supply. A region with the relatively higher amenity level attracts more workers or likewise, retains more workers. Thus, for a given price shock and sectoral composition, the higher the amenity level of a region, the less the impact of price shocks on changes in the region's wages.

3.2 Decomposition of welfare changes: Multi-sector multi-region economy

The goal in the quantitative analysis is to estimate the welfare changes for the set of the whole economy. Thus, I use the general framework as in Redding (2016). The main environment of the multi-region economy includes: preferences over amenities provided by location of residence, a set of tradable goods with share α and housing with share $1-\alpha$. Agents draw idiosyncratic amenities from the Fréchet distribution with shape parameter ϵ. Meanwhile, production for tradeable goods are performed in monopolistic competition with many firms. Each region has productivity drawn from the Fréchet distribution with shape parameter θ.

The welfare gains from trade in this setup is shown by Equation 23. The equation shows the proportional changes in welfare of people living in region n when the economy changes from state 0 to state 1. The welfare gains depend on not only the changes in domestic trade shares, π_{nn}, but also on changes in population shares. Parameters include α as share of tradeable goods and services, θ, as the shape parameter of the distribution of productivity and ϵ as the shape parameter of the distribution of amenities across districts.

$$\frac{U_n^1}{U_n^0} = \frac{U^1}{U^0} = \left(\frac{\pi_{nn}^0}{\pi_{nn}^1}\right)^{\frac{\alpha}{\theta}} \left(\frac{L_n^0}{L_n^1}\right)^{\frac{1}{\epsilon}+(1-\alpha)} \tag{23}$$

3.3 Decomposition

Consider the formula for the welfare gains from trade shown in Equation 23. Take the relative changes for each region n, where $\hat{x} \equiv \frac{dx}{x}$.

$$\hat{\pi}_{nn} = \frac{\theta}{\alpha}\left[\left(\frac{1}{\epsilon} + (1-\alpha)\right)\hat{L_n}\right] - \frac{\theta}{\alpha}\hat{U} \tag{24}$$

Multiply by regional weights φ_n that sum up to 1, and sum over all region n. These regional weights are the share of expenditure by region n, i.e. $\varphi_n = \frac{w_n}{\sum_i w_i} = \frac{w_n}{E}$.

$$\sum_n \hat{\pi}_{nn}\varphi_n = \sum_n \left[\frac{\theta}{\alpha}\left(\frac{1}{\epsilon} + (1-\alpha)\right)\hat{L_n}\right]\varphi_n - \sum_n \frac{\theta}{\alpha}\hat{U}\varphi_n$$

Since the aggregate domestic trade share is the weighted sum of the regional trade shares,[29] i.e. $\hat{\pi} = \sum_n \hat{\pi}_{nn}\varphi_n$, hence the changes in the aggregate domestic trade shares, $\hat{\pi}$:

$$\hat{\pi} = \sum_n \left[\frac{\theta}{\alpha}\left(\frac{1}{\epsilon} + (1-\alpha)\right)\hat{L_n}\right]\varphi_n - \sum_n \frac{\theta}{\alpha}\hat{U}\varphi_n$$

Since $\sum_n \varphi_n = 1$,

$$\frac{\theta}{\alpha}\hat{U} = \sum_n \left[\frac{\theta}{\alpha}\left(\frac{1}{\epsilon} + (1-\alpha)\right)\hat{L_n}\right]\varphi_n - \hat{\pi} \tag{25}$$

Meanwhile with $\bar{L}$ as the total population of the whole economy, we also know that:

$$\sum_n L_n = \bar{L}$$

Take the total differentials:

$$\sum_n dL_n = d\bar{L}$$

Divide and multiply by L_n:

[29] The total expenditure of the economy is the sum of the regional expenditures, w_n.

$$\sum_n w_n = E$$

We can also express it in terms of shares of regional expenditures as below.

$$\sum_n \frac{w_n}{E} = 1$$

$$\sum_n \varphi_n = 1$$

With domestic trade shares, π_{nn}, as how much region n buys from its own relative to its total expenditures, the weighted sum of regional domestic trade shares using these regional expenditure shares is the aggregate domestic trade shares.

$$\sum_n \pi_{nn}\varphi_n = \sum_n \frac{x_{nn}}{w_n}\frac{w_n}{E} = \frac{1}{E}\sum_n x_{nn} = \pi$$

$$\sum_n \frac{dL_n}{L_n} L_n = d\bar{L}$$

divide by $\bar{L}$:

$$\sum_n \frac{dL_n}{L_n} \frac{L_n}{\bar{L}} = \frac{d\bar{L}}{\bar{L}}$$

$$\sum_n \hat{L}_n \frac{L_n}{\bar{L}} = \frac{d\bar{L}}{\bar{L}} \tag{26}$$

where $\frac{d\bar{L}}{\bar{L}}$ is the aggregate growth of the population. We can set it as zero if there is no population growth or generalize it shown above.

Assume that there is change in total labor endowment in the whole economy, i.e. $\frac{d\bar{L}}{\bar{L}} = 0$, and substract Equation 25 with the right-hand side of Equation 26:

$$\hat{U} = \underbrace{\left(\frac{1}{\epsilon} + (1-\alpha)\right) \sum_n \hat{L}_n \left(\varphi_n - \frac{L_n}{\bar{L}}\right)}_{\text{gains from migration}} - \underbrace{\frac{\alpha}{\theta} \sum_n \hat{\pi}_{nn} \varphi_n}_{\text{gains from trade}} \tag{27}$$

Proposition 2. *Assumming there is no change in total labor endowment in the whole economy, i.e.* $\frac{d\bar{L}}{\bar{L}} = 0$ *and using* φ_n *as district's share of expenditure in national expenditure and* λ_n *as district's population share, the welfare change can be decomposed as the following equation. The first term represents gains from migration while the second term represents gains from trade.*

$$\hat{U} = \underbrace{\left(\frac{1}{\epsilon} + (1-\alpha)\right) \sum_n \hat{L}_n \left(\varphi_n - \lambda_n\right)}_{\textit{gains from migration}} - \underbrace{\frac{\alpha}{\theta} \sum_n \hat{\pi}_{nn} \varphi_n}_{\textit{gains from trade}} \tag{28}$$

Equation 27 shows that the welfare gains have two components. The first one is gains from migration. The intuition is straightforward. The economy gains if people move to richer districts, i.e. districts with higher expenditure shares, φ_n , compared to their population shares, λ_n. The second component is the changes in aggregate domestic trade shares. The economy also gains if domestic trade shares, π_{nn}, decrease.

4 Data and measurement of exposure to shocks

Armed with the guidance in measuring regional exposure to price shocks as shown by Proposition 1, I compute the exposure of palm oil price shocks due to the commodity boom and the rice price shocks due to the trade protection at the district level. Modeling Indonesia as a multi-region small open economy, I use districts as the unit of observation for regions. Districts are the second-level administrative unit in Indonesia.[30] The heads of districts, as well as parliamentary memberships at the district-level, are elected directly by residents of the districts every five years. Local governments have some income from local taxes but also receive transfers from the central government. In addition, minimum wage is set at the district-level.[31] Over the course of the period studied here, there have been numerous district and province proliferations. I use the administrative district definition in 2000 to maintain the same set of districts over time of 321 districts.[32]

4.1 Data

In most of empirical exercises I focus on datasets that are representative up to the district level. I combine several sources of data that can capture the determinants of regional welfare and regional exposure to price shocks as guided by the theoretical framework. I describe the main variables and datasets I use in this subsection. Appendix A provides more detailed description on data.

Real expenditure per capita The main outcome variable is real expenditure per capita. I use expenditure per capita because in the case for Indonesia, data on expenditure has been better recorded than data on income. Expenditure can better capture well-being compared to labor income as we want to also take into account any income from land rent.[33] Furthermore, households savings rate is relatively small. Vibrianti (2014) tabulates the Indonesian Family Life Survey (IFLS) 2007 and shows that only 26% households have savings. Hence, households expenditure data is a good representation to income.[34]

I obtain data on households expenditure per capita from the Social and Economic Household Survey (*Susenas*) directly and the one published on World Bank's INDO DAPOER database computed from *Susenas*. I use several district-averages of expenditure per capita. First, I use the total district average, which includes the whole sample for each district. Second, I compute district-average expenditure per capita by sector of employment of the head of households. I

[30] Indonesia has a central government and two levels of local governments. The first level of local government is at the province level. The second level of local government is at the district level. The central government has the sole authority on several subjects, including trade policy.

[31] There is an exception for the capital city of Jakarta which is granted autonomy up until province level only. Hence, minimum wage is set in the province level for Jakarta province.

[32] The complete set has 342 districts. In most empirical exercises I use a panel of 321 districts. Data availability was the reason the full dataset was not obtained.

[33] Deaton (1997) discusses the advantages in using expenditures to capture lifetime well-being. As summarized by Goldberg and Pavcnik (2007), these advantages include (1) conditions on whether agents can shift inter-temporal resources, current expenditure better captures lifetime well-being, (2) if there is less problem in reporting for consumption data than income data, and (3) changes in relative prices affect consumers not only through income but also purchasing power of their current income.

[34] IFLS is nationally representative. Its survey sample represent 83% of Indonesian population living in 13 out of 26 provinces. IFLS in 2007 is the fourth wave of the survey. Given the representation, it is fair to take the estimates on households savings rate tabulated from IFLS as an upper bound for Indonesia. More information on IFLS, see: RAND Corporation, https://www.rand.org/well-being/social-and-behavioral-policy/data/FLS/IFLS/study.html.

categorize sectors of employment into 2 groups: agriculture and non-agriculture.[35] I also extract district premia from mincerian regression on expenditure per capita reported in *Susenas* as another outcome variable. Furthermore, in order to get real expenditure per capita, I deflate expenditure per capita with Indonesia's CPI obtained from the BPS-Statistics Indonesia (*BPS*).

Recent migration I use recent migration as the outcome variable that represents labor mobility. Recent migration is defined as a change of residential location between survey years and five years prior to the survey years. For the years 2011 to 2016, I extract data on migration flows across districts from *Susenas*. Meanwhile, for earlier years, I obtain migration flow data from a sample of the Population Census and Inter-Census Population Surveys provided by IPUMS. From the constructed matrix of migration flows, I compute net-migration rate.

Crop data In order to estimate the potential production of each crop in each district, I use the agro-climatically attainable yield provided in 5-grid level raster data for palm oil and rice from the FAO - GAEZ dataset. This estimated yield depends on climate, soil condition and rainfall, which are exogenous factors in the production of each crop. This variable is constructed using certain assumption on climate, a long-term variable. Specifically, the estimated yield is a single-measure that represents the period of 1960 to 1990. I argue that the use of such a single-measure yield is a plausible stance as farmers care more about long-run cycles instead of high-frequency variables such as daily rainfall in non-horticulture crop mix decisions such as rice and palm oil. Furthermore, I choose assumptions on the most relevant use of technology for each crop. I then take the district average of the yield for each crop.

I obtain data for harvested areas by district and by crop from the Ministry of Agriculture's statistics website.[36] The data of harvested area include all types of plantation, i.e., both large and small plantation holders. For national aggregate crop area, I use the FAO database. The total area for each district is obtained from the World Bank's INDO DAPOER.

Prices All data on prices are converted into rupiah. World palm oil price data is obtained from IMF Commodity Price Series. These price series are in US dollars. In order to take into account rupiah's depreciation over the same period, I calculate the rupiah prices using exchange rate data from the FRED Database. As a small open economy, the rupiah-prices are the relevant prices. Hence, the price shocks measured in this paper is inclusive of this depreciation. Meanwhile, retail domestic rice price data by province is obtained from *BPS*. Rice price data is in Indonesian rupiah. For both crops, I deflate the nominal prices with Indonesia's CPI from the *BPS* to get real prices.

[35] I include "rice crop", "horticulture", "tree crops or plantation", "forestry and other agriculture" as agriculture sector. I define the rest of the sectors as nonagriculture sector. See Appendix A for more details on the construction of district-average expenditure per capita by agriculture and non-agriculture households.

[36] Data can be downloaded on the following link: https://aplikasi2.pertanian.go.id/bdsp/en/commodity.

Ideally, one would use the farm-gate prices instead. For the case of palm oil, since Indonesia is a price taker in the world market, and if we assume trade costs faced by each producing districts do not vary over the period of interest, the changes in real world prices suffice to represent the changes in prices received by palm oil farmers as these trade costs cancel out. Meanwhile for the case of rice, I assume that the pass-through margin and the trade costs that make up the wedges between provincial retail price and farm gate price do not vary over the period of interest. Hence, the changes in real provincial prices also represent the changes in real farm-gate prices faced by rice farmers.

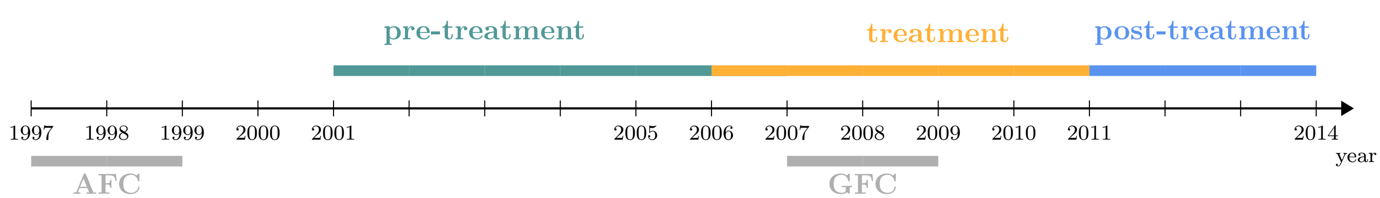
4.2 Exposure to price shocks

As we learn from Fact 1 and Fact 2, districts vary in their comparative advantage on agriculture products, especially in growing palm oil and rice. Hence, districts are not uniformly exposed to the increase in rice price and palm oil prices. In order to capture this exposure heterogeneity, I construct a measure of exposure to price shocks for each district and crop based on Proposition 1.

First, in order to capture the price changes, it is useful to define the timeline that I am using. I illustrate this timeline on Figure 6. Figure 7 shows the trend of real palm oil prices and real rice prices that I use as the basis in constructing the timeline. I define treatment period as the onset of the commodity boom for palm oil price and as the import ban started to take impact on rice prices. For palm oil prices, I take 2010 as the end of the treatment period as prices started to decline in 2011 even though the average price was still quite high. Meanwhile, as we can see from the figure below, real prices of rices have been quite stagnant since 2011. Hence, I also take 2010 as the end of the treatment period for rice price shocks. The post-treatment period of interest is then the subsequent three to five years after the treatment period, i.e. from 2011 to 2014 or longer when data is available.

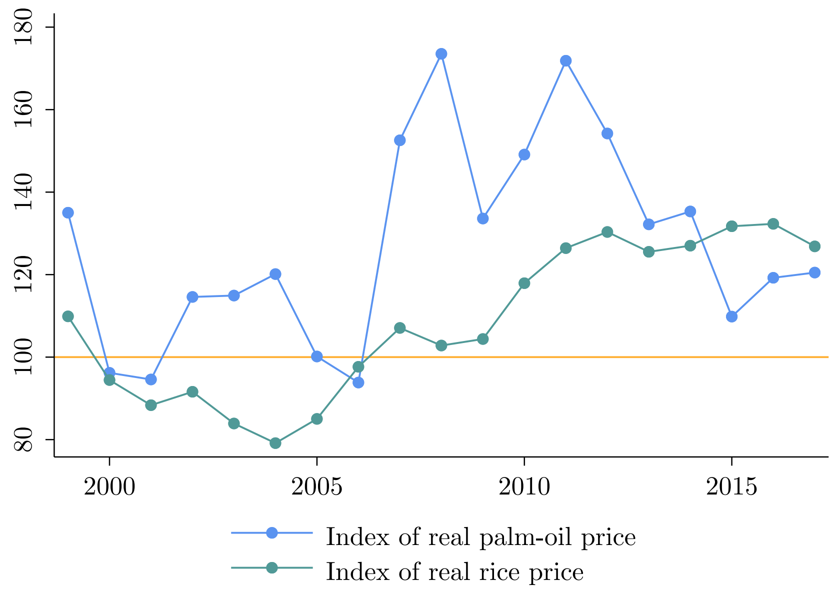
I define the pre-treatment period price as the average price between January 2001 to December 2005. Meanwhile, I define the treatment period price as the average price of the period that starts in January 2006 and ends in December 2010. In order to measure price changes, I take the long difference in log between the treatment period and the pre-treatment period.

Figure 6: Timeline



Notes: AFC stands for Asian Financial Crisis. GFC stands for Global Financial Crisis.

Figure 7: Real palm oil price and real rice price (Jan 2000 = 100)



Source: IMF Commodity price series for world palm oil prices, FRED Database for exchange rates, BPS for provincial rice prices and Indonesian CPI. Author's calculation.
Notes: National rice prices are the simple average of provincial rice prices.

Applying the results shown by Proposition 1 in the theoretical framework that the impact of exogeneous price changes to income depends on the output share of the sector whose price changes, I construct a measure of exposure to price shocks of palm oil and rice for each district, S_{id}. Equation 29 below shows the construction of this measure. The measure allows districts to be exposed differently to uniform price shocks. The price of palm oil is exogeneously determined in the world market. Hence, all districts in the sample face the same prices and price changes for palm oil. Meanwhile prices of rice clear in the provincial-level. I assume that farmers in each districts are price takers to these provincial rice prices. Such an assumption is plausible given the relative size of each farmer to the province aggregate.

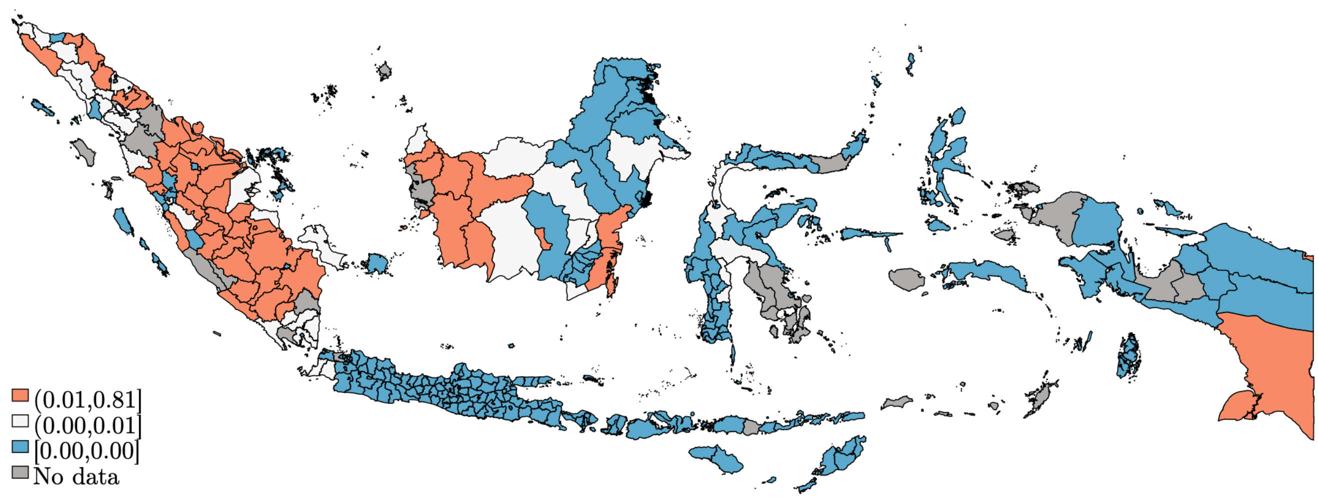
$$S_{id} = \hat{p}_i \frac{Y_{id0}}{GDP_{d0}} = \hat{p}_i \frac{p_{i0} \cdot T_{id0} \cdot \psi_{id}}{GDP_{d0}} \tag{29}$$

Crop i refers to palm oil and rice. Meanwhile, the sub-index d represents districts. The price change of crop i, $\hat{p}_i$, is the long difference of log price of crop i. The pre-treatment estimated production value of crop i in district d, Y_{di0}, is computed using the pre-treatment average price of crop i, p_{i0}; pre-treatment harvested area of crop i in district d, T_{id0}; and the district-average potential yield of crop i in district d, ψ_{id}. Meanwhile GDP_{d0} is the district GDP excluding the oil and gas sector in pre-treatment period.

Variation across districts on estimated production of palm oil and rice are determined by variation in harvested area in the pre-treatment period and variation in estimated potential yield from the FAO GAEZ data. In the pre-boom period, there was no indication that farmers would have predicted the commodity boom to occur. As Fact 2 suggests, even in districts that are very suitable to palm oil, the harvested areas were relatively similarly low as in districts that are less suitable. Meanwhile, the import ban on rice was enacted in 2004. I assume that rice farmers could not have predicted such protection to happen. Furthermore, the importance of each crop across districts is also determined by the size of the economy of the district. I use district GDP excluding the oil and gas sector as I assume that this measure better represents the pie of the economy that are distributed locally in each district.

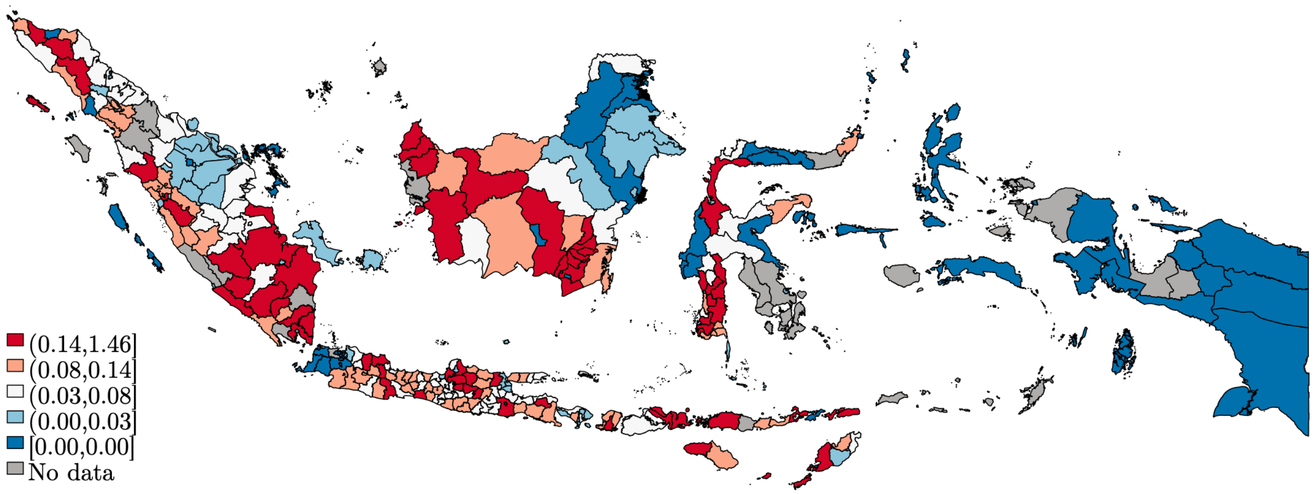
Figure 8 and 9 display the computed exposures of palm oil price shocks and rice price shocks across districts. Districts with the highest exposure to palm oil price shocks are concentrated in Sumatra, the main island on the west end of the country, and Borneo, the main island east to Sumatra. Meanwhile, districts with the highest exposure to rice price shocks are more spread out in all main islands of Indonesia. Table A.3 exhibits the summary statistic of the computed exposure to price shocks.

Figure 8: Exposure to palm oil price shocks



Notes: Districts definition use district boundaries in 2000. Exposure to price shocks is calculated using Equation (29).

Figure 9: Exposure to rice price shocks



Notes: Districts definition use district boundaries in 2000. Exposure to price shocks is calculated using Equation (29).

Defining exposed districts

I group districts into a set of exposed districts and a set of non-exposed districts for each crop. As we can observe from the distribution of exposure to shocks in Figure 8, Figure 9 and Table A.3, more than half of the districts are not exposed to palm oil price shocks. Meanwhile, most districts have some degree of exposure to rice price shocks. The latter fact is not surprising because rice is the staple food for most of Indonesia's population. Many districts produce some amount of rice even if they are not net-producers.

For palm oil, I define exposed districts as districts with positive values of exposure to shocks and non-exposed districts as those with zero exposure to palm oil price shocks. On the other hand, for rice, I define exposed districts as districts with an exposure value of higher than 40 percentile. Meanwhile, I define districts with value of exposure to rice price shocks in the bottom 60% as non-exposed districts for rice. The final set of these exposed and non-exposed districts are summarized in the table below and illustrated in Figure A.12 and A.13.

Table 5: Number of exposed and non-exposed districts

Group	**palm oil**	**rice**
exposed districts	81	129
non-exposed districts	240	192

5 Empirical evidence

I use the constructed exposure to price shocks to study how it affects districts in two fronts: comparison between exposed districts and non-exposed districts and spillovers to non-exposed districts. I further show some mechanisms that can explain the results by analysing the impact of the price shocks on district premium and land share for crops.

5.1 Specification

I use difference-in-difference method for econometrics specification to study the impact of palm oil price shocks and rice price shocks on districts economies. Specifically, I use Equation 30 to show the average differences between exposed and non-exposed districts over time. Meanwhile, I use Equation 31 to show any heterogeneity in the impact of the shocks.

$$y_{dt} = \alpha + \sum_{i} \sum_{r \neq 2005} \beta_{ir} \left(I_{di} \cdot \mathbb{1} \left(year_r = t \right) \right) + \boldsymbol{\gamma} \boldsymbol{X_d} + \delta_d + \delta_t + \epsilon_{dt} \tag{30}$$

$$y_{dt} = \alpha + \sum_{r \neq 2005} \beta_{igr} \left(I_{idg} \cdot \mathbb{1} \left(year_r = t \right) \right) + \boldsymbol{\gamma} \boldsymbol{X_d} + \delta_d + \delta_t + \epsilon_{dt} \tag{31}$$

The outcome variables, y_{dt}, are average real expenditure per capita and net-inward migration. Our coefficient of interest is β_{ir}s, i.e., the coefficient for the indicator variable for exposure status for crop $i \in \{palm, rice\}$ in year r, or coefficient β_{igr}s, i.e., the coefficient for tercile g in exposure to shocks of crop i in year r. These coefficients show the difference between districts exposed to price shocks in crop i and the non-exposed districts in year r relative to the base year. I use 2005 as the base year.

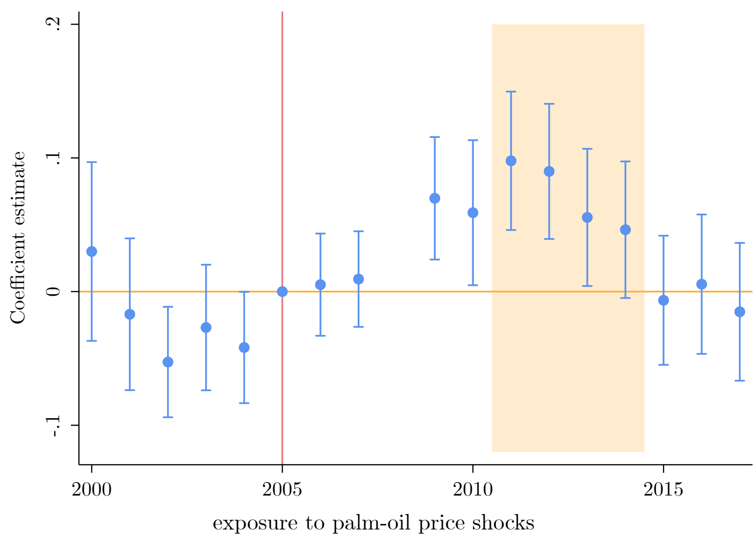
Furthermore, as Fact 3 in Section 2 reveals, districts with a high share of the agriculture sector in their economies can be structurally different because they tend to be poorer compared to those that rely less on the agriculture sector. Hence, I include a matrix of control variables to take this fact into account. These controls include the percentage of rural population in 2000, the share of villages with asphalt road in 2000 and the length of district roads in bad condition. I also include the size of a district's output in the mining sector in 2000 to control for any difference across districts due to the exposure of the commodity boom on mining commodities. In addition, I include year and district fixed-effects. Thus the coefficients of interest capture the within-district changes in the outcome variables.

The difference-in-difference specification can establish the causal impact of exposure to the price shocks if it fulfills three assumptions. First, there is a parallel trend between the exposed districts and the non-exposed districts. Second, the price shocks are exogenous shocks to districts. In addition to using exogenous components in constructing the exposure to shocks, exogeneity is fulfilled as there is no uptick in the coefficients of interest during pre-treatment period. The following plots of the coefficients of interest confirm that the first and second assumption are fulfilled. Third, there is no changes in crop productivity. If crop productivity increased due to the price shocks, then the coefficients are biased since they also capture the impact of the increase in crop productivity. Table A.7 and A.8 confirm that there is no changes in actual yield for both palm oil and rice in the period of study, i.e. the third assumption is also fulfilled. Thus, the coefficients of interest reflect the impact of exposure to palm oil price shocks and exposure to rice price shocks.

5.2 Impact of the exposure to palm oil price shocks

Districts exposed to palm oil price shocks had higher expenditure per capita for several years, with a peak in 2011. Figure 10 plots the estimated β_{ir}s for palm oil price shocks and their respective 95% confidence obtained from running Equation 30. Exposed districts had significantly higher real expenditure per capita on average compared to the non-exposed ones in throughout 2009 to 2013. This result shows that income shocks from palm oil price were translated as an increase in purchasing power.

Figure 10: Impact of exposure to palm oil price shocks on real expenditure per capita

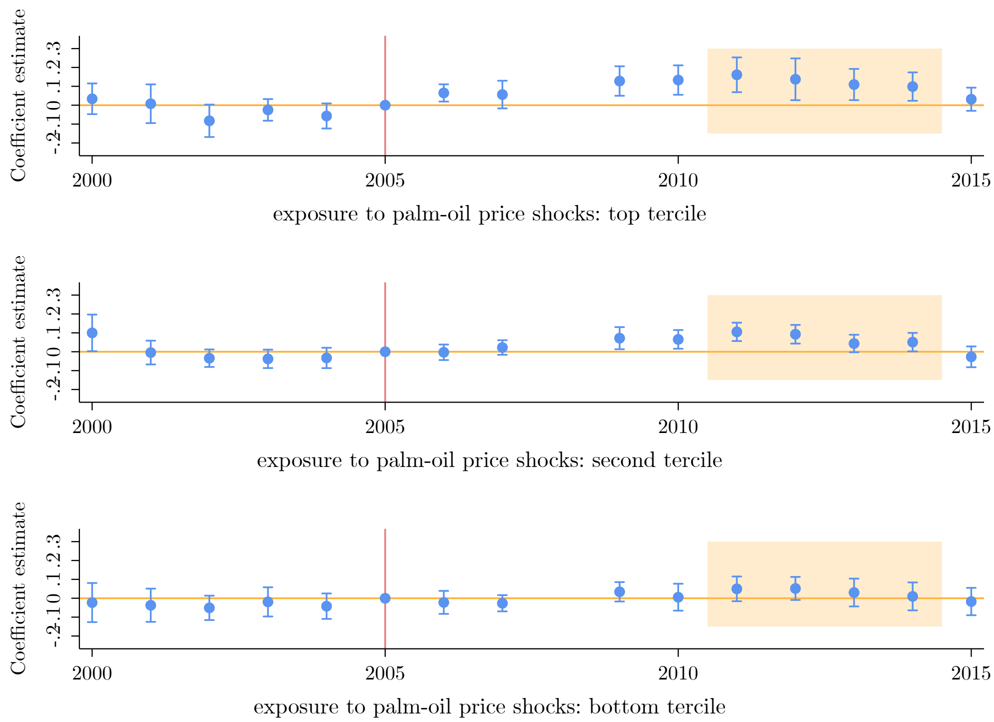


Notes: The dependent variable is the log of (district average) real expenditure per capita. The model includes control variables, districts and year fixed-effects. Regression is run on panel of districts over year with population in 2011 as weights. Standard errors are clustered at the district-level. Point estimates are relative to year 2005, the omitted category. The 95% confidence intervals for coefficients are shown by the range plots. Shaded area shows post-treatment period.

Figure 10 also shows that the exposed and non-exposed districts were not significantly different in the pre-treatment period of 2000 to 2004 relative to the base year 2005. One exception is that districts exposed by palm oil price shocks had significantly lower (ln) real expenditure per capita in 2002. However, the difference is negligible in other years. Hence, the results establish the valid causal impact of the palm oil price shocks.

The palm oil price shocks increased the real expenditure per capita in the exposed districts by 10 log points or approximately 10% relative to the base year at its peak in 2011. This effect corresponds to 63% of one standard deviation in the proportional change of real expenditure per capita in 2011 relative to 2005. The impact of the commodity boom decays afterwards with a lower coefficient overtime until 2013. The cycle seems to follow directly the global commodity prices as they started to decline in 2013 to 2014 as well. This result fills in the gap in the literature by providing the first evidence that the commodity boom affects subnational regions differently and that these regions did not gain permanently from the boom.

Figure 11: Impact of palm oil price shocks to real expenditure per capita across terciles



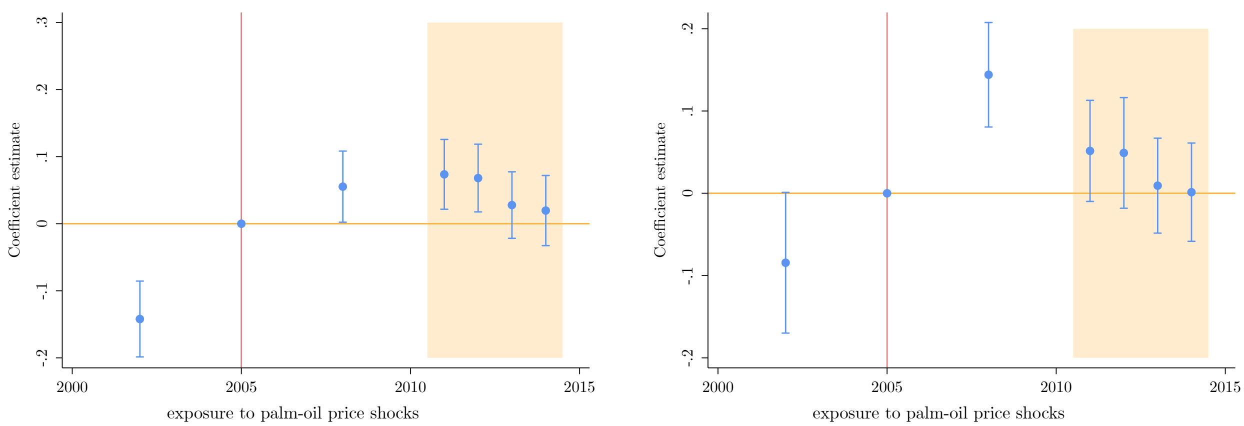
Notes: The dependent variable is (ln) real expenditure per capita. The model includes control variables, districts and year fixed-effects. Regression is run on panel of districts over year with population in 2011 as weights. Standard errors are clustered in district-level. Point estimates are relative to year 2005, the omitted category. The 95% confidence intervals for coefficients are shown by the range plots. Shaded area shows post-treatment period.

Among districts exposed by palm oil price shocks, I find heteregeneity in the impact of palm oil price shocks. Higher exposure to palm oil price shocks create larger impact. Figure 11 plots the estimated coefficient for three terciles of palm oil price shocks over time. Districts in the top two terciles of palm oil price shocks a significantly had higher (ln) real expenditure per capita during the post-treatment period compared to the non-exposed districts. For the top tercile, the difference reached 16 log points or around 17% higher in 2011 relative to the base year 2005. This difference corresponds to one standard deviation of the growth of real expenditure per capita in 2011 relative to 2005. The impact for the second tercile is lower. It reached 10 log points or 10% higher in 2011 relative to 2005. Following the trend in the overall impact of palm oil price shocks, the impact shrinks over time. By 2014 to 2015, the impact is no longer significantly different from zero with 95% confidence level.

In order to analyze whether the the price shocks affect the agriculture sector more, I run Equation 30 on the district-average expenditure per capita of agriculture households and non-agriculture households. An agriculture household is a household whose household head works in the agriculture sector. Figure 12 shows the estimated β_{ir}s for agriculture households and the estimated β_{ir} for non-agriculture households for exposure to palm oil price shocks.[37]

I find that agriculture households in districts exposed to palm oil shocks have on average higher real expenditure per capita in the first two years of the peak of the boom. Specifically, agriculture households in districts exposed to palm oil shocks have 7 log points higher real expenditure per capita in 2011 and 2012 relative to the base year 2005. Meanwhile, the coefficients of interest for non-agriculture households are positive but do not have strong statistical significance during the outcome period of 2011 to 2014, despite showing significance during the treatment period in 2008. The results for agriculture households may capture a positive structural trend due to the negative coefficient in the period before the base year, but overall these results provide the indication that the impact of the palm oil price shocks benefitted the agriculture households more.

Figure 12: Impact of palm oil price shocks: agriculture households and nonagriculture households



(a) agriculture households (b) non-agriculture households

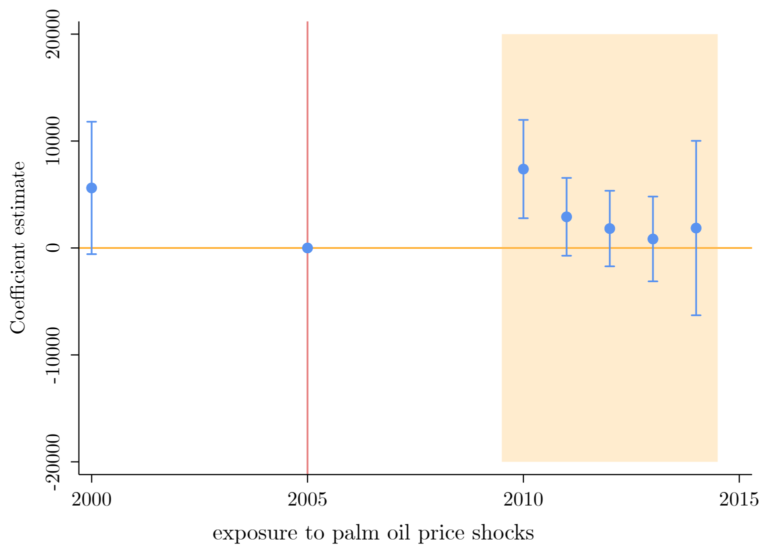
Notes: The dependent variable is the log of (district average) expenditure per capita of agriculture households and non-agriculture households. The model includes control variables, districts and year fixed-effects. Regression is run on panel of districts over year with population in 2011 as weights. Standard errors are clustered in district-level. Point estimates are relative to year 2005, the omitted category. The 95% confidence intervals for coefficients are shown by the range plots. Shaded area shows post-treatment period.

As districts exposed with palm oil price shocks had higher expenditure per capita, they might attract labor to move to these exposed districts. To test whether districts exposed with the shocks

[37]Unfortunately, I only have one year period before the base year. Hence, I encourage readers to take into account this limitation in analysing Figure 12.

receive more migration, I run Equation 30 on net-inward migration. Figure 13 below plots the estimated β_{ir}s for net-inward migration as the outcome variable. Before I continue with the analysis of the result, I would like to describe some of its limitations. Since recent migration data was not collected annually before 2011, I combine several datasets to construct recent migration flows data over time. For years 2000 and 2010, I use Census Population that is provided by IPUMS. While for year 2005, I extract recent migration flows from the Inter-Census Population Survey provided by IPUMS. For the years 2011 to 2014, I use the Socio-Economic Household Survey(*Susenas*) datasets. Hence, there may exist some structural differences in the sampling of these datasets.[38] In this regard, in analysis on migration as the outcome variable, I loosely also include the year 2010 as part of post-treatment period.

Figure 13: Impact of palm oil price shocks on net-inward migration



Notes: The dependent variable is the net-inward migration. The model includes control variables, districts and year fixed-effects. Regression is run on panel of districts over year. Standard errors are clustered in district-level. Point estimates are relative to year 2005, the omitted category. The 95% confidence intervals for coefficients are shown by the range plots. Shaded area shows post-treatment period.

Figure 13 shows that districts exposed to palm oil price shocks receive more net-inward migration compared to the non-exposed ones in 2010 relative to the base year 2005, despite no significant difference in the years after. The result on net-inward migration as the outcome variable supports previous results that districts exposed to palm oil price shocks become more attractive for labor to move to these regions. Since we find that labor respond to incentives to move to booming regions, the price shocks were also no longer fully localized. Similar results prevail if we use the net-inward

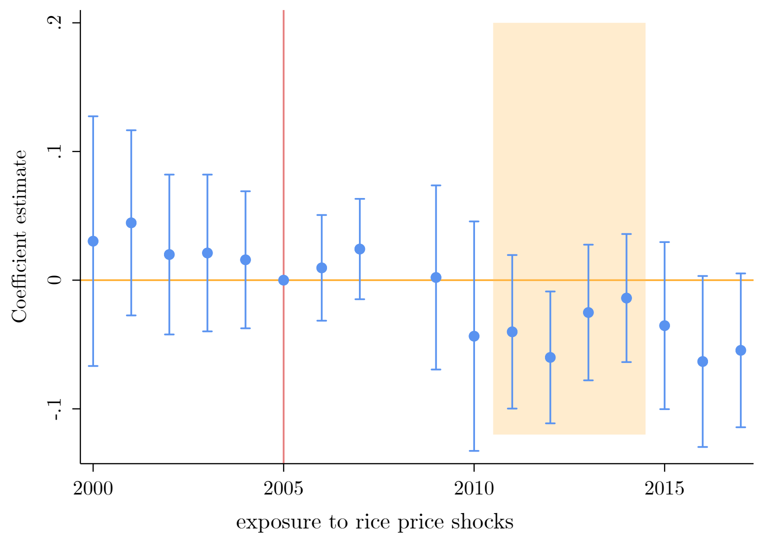
[38] Figure A.14 in Appendix compares the distribution of net-inward migration rates by districts in these different data sources while Table A.4 tabulates their main statistics.

migration rate.[39]

5.3 Impact of the rice price shocks

Districts exposed to rice price shocks, in contrast, did not enjoy higher real expenditure per capita compared to the non-exposed districts relative to the base year . Figure 14 plots the estimated β_{ir}s and their respective 95% confidence intervals for the rice price shocks from running Equation 30. Throughout most of the post-treatment period, the impact of rice price shocks on real expenditure per capita is not significantly different than zero, i.e. the trade protection on rice has not materialized as an increase in purchasing power to rice-producing districts. The coefficient is negative and statistically significant for one year, i.e. in 2012.

Figure 14: Impact of rice price shocks on real expenditure per capita



Notes: The dependent variable is the log of (district average) real expenditure per capita. The model includes control variables, districts and year fixed-effects. Regression is run on panel of districts over year with population in 2011 as weights. Standard errors are clustered in district-level. Point estimates are relative to year 2005, the omitted category. The 95% confidence intervals for coefficients are shown by the range plots. Shaded area shows post-treatment period.

Since rice is a staple food for the population in Indonesia, one may suspect that real benefit of the trade protection would be captured by main rice producers. In order to investigate this, I run equation 31 to study any heterogeneity in the impact of rice price shocks. Figure A.16 plots the coeffiecients of impact of rice price shocks across terciles. It shows that districts with the the most exposure to rice price shocks did not experience higher real expenditure per capita due to the trade protection.

[39]See Figure A.15 for net-inward migration rate as the outcome variable.

In order to see whether the rice price shocks affect agriculture and non-agriculture households differently, I run the main specification on the real expenditure per capita of agriculture households and non-agriculture households. Figure A.17 plots the coefficients on rice price shocks and their 95% confidence interval. Confirming the previous results, districts exposed by rice price shocks, on average, do not have a significant difference from the non-exposed ones in both agriculture households and non-agriculture households. This is an interesting result as agriculture households, who can represent rice producers, also did not gain from the higher rice prices.

Comparing agriculture households in districts exposed to rice price shocks across terciles in Figure A.18, I also find that in all terciles agriculture households were not impacted by the rice price shocks. In contrast, non-agriculture households in districts with some exposure to rice price shocks have equal or even less real expenditure per capita compared to the non-exposed districts as shown in Figure A.19. This result implies that if the import restriction was intended to provide stimulus to rice producers, the policy seems to be ineffective. Instead, it may actually hurt some part of consumers. Since most of rice farmers are small in terms of scale, they may not be able to easily expand despite having the binding trade protection. Meanwhile, as they are also part of the consumers of rice, so the increase in rice prices may not increase their purchasing power by much.

5.4 Spillover to non-exposed districts

Booming districts may also demand more goods and services from nearby districts since it is cheaper to purchase from nearer ones due to lower transportation and transaction costs. I focus on the exposure to palm oil shocks, which have so far shown a significant impact on the exposed districts. In order to see whether there is any spillover of impacts of exposure to palm oil price shocks to non-exposed districts, I run the following specification.

$$y_{dt} = \alpha + \sum_{g \in 1,2,3,4} \sum_{r \neq 2005} \beta_{gr} \left(I^{g}_{dt} \cdot \mathbb{1} \left(year_r = t \right) \right) + \delta^{rice}_{d} + \boldsymbol{\gamma} \boldsymbol{X_d} + \delta_d + \delta_t + \nu_{dt} \tag{32}$$

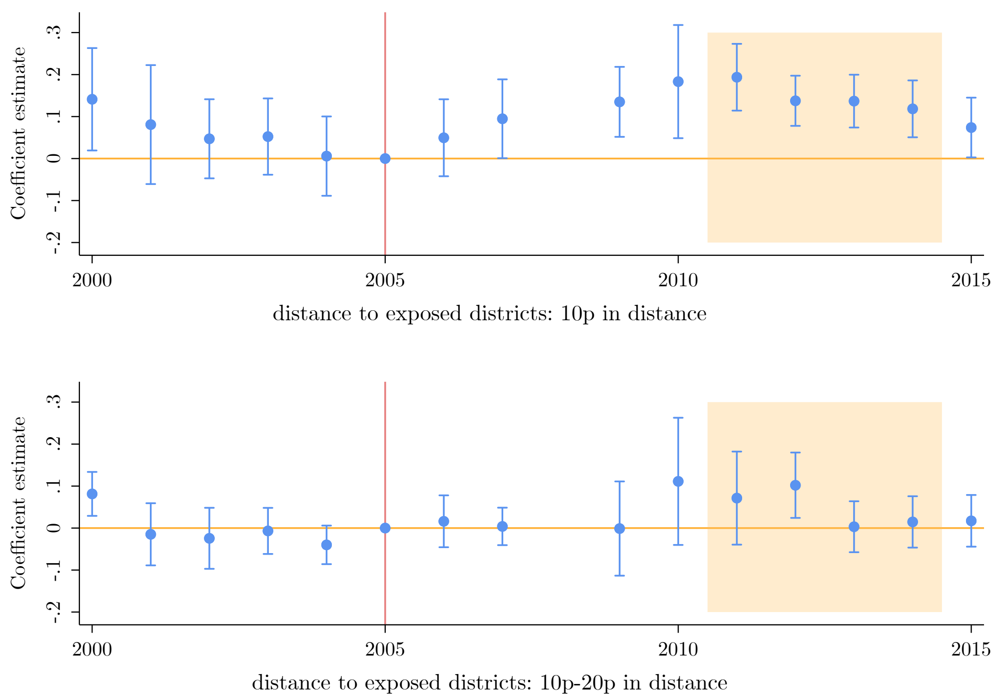
In Equation 32, the outcome variables are real expenditures per capita and migration flows. As the previous specifications, I include a set of control variables, district fixed effects and year fixed effects. I also add status of exposure to rice price shocks. I run the specification on a panel of districts that are not exposed to the palm oil price shocks. In order to capture heterogeneity due to proximity to exposed districts, I created four dummy variables. Each dummy variable indicates each four of the lowest percentiles of minimum distance to exposed districts.[40] Hence, the coefficients of interest are β_{gr}s. These coefficients capture the difference of district of percentile g in year r compared to districts in the 5th to 10th percentiles (the control group) relative to the base year 2005.

First, I find that the nearest non-exposed districts to districts exposed to palm oil price shocks

[40] Distance between two districts is computed as the distance between their centroids.

also had higher real expenditure per capita. Figure 15 below plots the coefficients of interest with (ln) real expenditure per capita as the outcome variable. These coefficients are positive and statistically significant from zero for the nearest non-exposed districts. Compared to the non-exposed districts in the control group, the districts with the lowest percentile of minimum distance have almost 20 log points higher in 2011 compared to the base year. Following the trend in the impact to the exposed districts, these coefficients also shrink over the outcome period. The second lowest percentile in distance to exposed districts also have a positive difference compared to the control group. Although it is only statistically significant in 2012 with 10 log points difference to the control group.

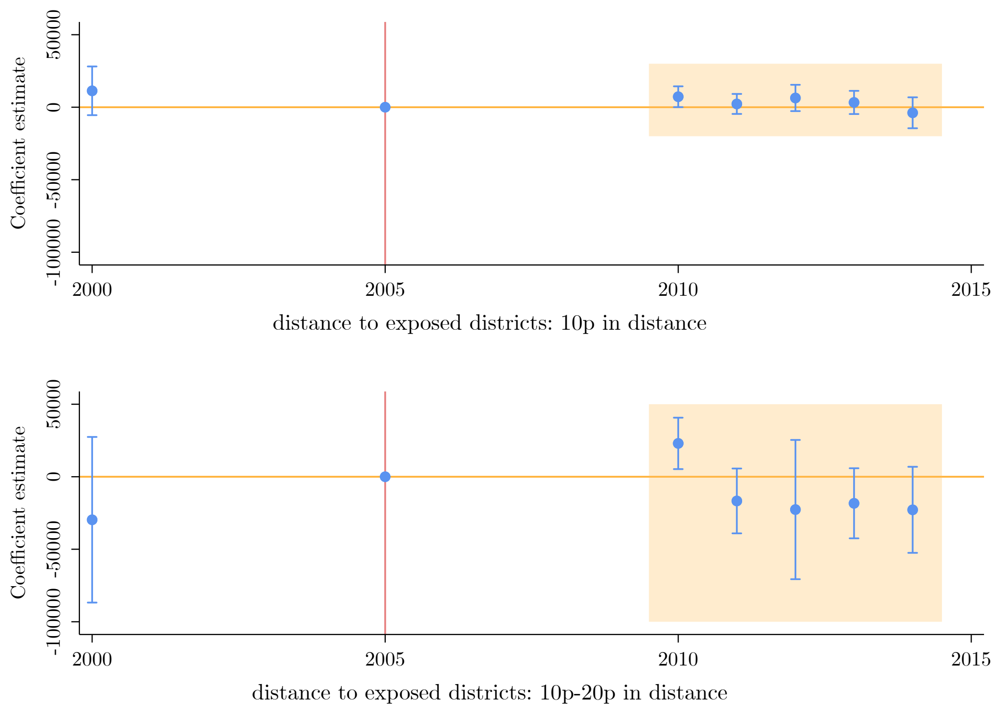
Figure 15: Spillover to districts non-exposed by palm oil price shocks: Real expenditure per capita



Notes: The dependent variable is (ln) real expenditure per capita. The model includes control variables, status of exposure of rice price shocks, districts and year fixed-effects. Regression is run on panel of districts that are non-exposed to palm oil price shocks over year with population in 2011 as weights. Standard errors are clustered in district-level. Point estimates are relative to year 2005, the omitted category. The 95% confidence intervals for coefficients are shown by the range plots. Shaded area shows post-treatment period.

In response to the spillover indicated by higher expenditure per capita in the neighboring districts of booming regions, I find also that the nearest non-exposed districts to districts exposed to palm oil price shocks also receive more net-inward migration. Figure 16 below plots the estimated β_{gr}s for net-inward migration as the outcome variable. Supporting the result above, labor seems to respond to higher purchasing power provided by these nearest districts. These districts receive more net-inward migration compared to the control grou; although, the coefficient is statistically significant only in 2010.[41]

Figure 16: Spillover to districts non-exposed by palm oil price shocks: Net-inward migration



Notes: The dependent variable is number of net-inward migration. The model includes control variables, status of exposure of rice price shocks, districts and year fixed-effects. Regression is run on panel of districts over year with population in 2011 as weights. Standard errors are clustered in district-level. Point estimates are relative to year 2005, the omitted category. The 95% confidence intervals for coefficients are shown by the range plots. Shaded area shows post-treatment period.

5.5 Mechanisms

The empirical evidence above show that exposure, especially to palm oil price shocks, benefit exposed districts for some years. I also show that as these districts become relatively richer, they also attract more inward migration. In addition, non-palm oil producing districts nearest to producing districts also benefit from the boom as they also have a higher expenditure per capita in the post-treatment period. In contrast, rice price shocks that stemmed from trade protection did not provide significant stimulus to producing districts. All of these results show evidence that the impacts of exogenous trade shocks are not trivial to assess.

In this subsection, I provide several mechanisms focusing on the response of factors of production. The idea is that the shocks may have lasted long enough as well as were big enough in

[41]Due to the combination of various sources of data for migration, I also loosely take 2010 as part of outcome period here.

terms of the magnitude that factors of production also responded to the shocks. First, I provide justification that labor do respond through internal migration by analyzing the impact of the price shocks on district premia. Second, since I focus on agricultural commodities, I analyze two possible methods through which the agriculture sector expands: extensification by land expansion and intensification by increasing yield.

5.5.1 District premia and the role of internal migration

One may argue that, structurally, districts exposed to palm oil price shocks have different labor and sectoral composition that may drive their higher expenditure per capita at the peak of the boom. Another argument that prevents welfare to equalize across districts is that there may exist frictions in labor mobility which prevents this equalization force. I follow the two-step method used by Dix-Carneiro and Kovak (2017) in analysing evolution of district premia over the period of study. First, in order to control for labor and sectoral characteristics, I run a Mincerian-type regression on household-level expenditure per capita by controlling with household head's economic and demographic variables. In order to avoid selection bias due to any labor market biases, I follow Bryan and Morten (2019) by imposing some selection criteria. That is, I include households with male head of households between the ages of 15 to 61. I also take only those who report to have income in the past three months prior to the survey. Equation 33 below shows the Mincerian equation.

$$y_{\omega dt} = \alpha + \boldsymbol{\beta X_{\omega dt}} + \delta_{dt} + \delta_{it} + \delta_{st} + \epsilon_{\omega dt} \tag{33}$$

The outcome variable is individual ω's real expenditure per capita in year t, living in district d. I include the vector of the household head's controls such as years of education, years of experience and years of experience squared. I run this regression separately for each year $t \in [2002, 2005, 2011, 2012, 2013, 2014]$[42] and take the estimated district fixed effects, δ_d, as the district premia. Note that I also add fixed effects for sector of employment, δ_i, and status of employment (self employed, employee, etc.), δ_s. Fixed-effects on sector of employment is particularly important to take any premium from working in a particular sector, including the agriculture sector that faced the price shocks. Thus, the district premia explain the premium on real expenditure per capita by just living in a particular district.

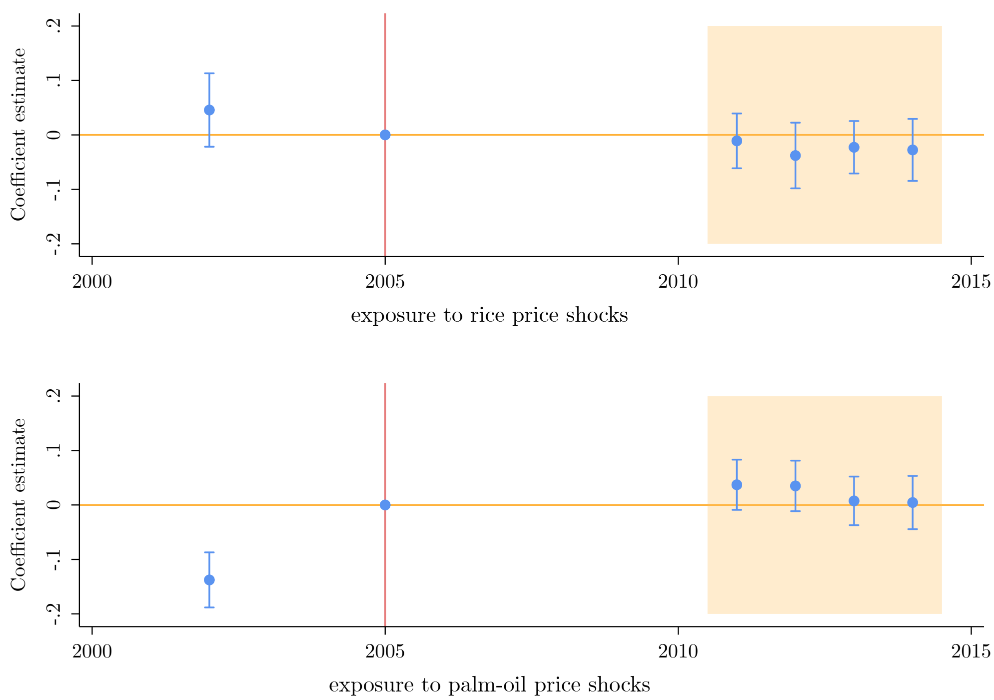
Second, I run Equation 30 with the estimated district premia as the outcome variable. Figure 17 shows the estimated coefficients of interest that show the difference on district premia between exposed and nonexposed districts. Both sets of coefficents on exposure to palm oil and rice price shocks are not statistically different from zero. This result implies that after controlling labor composition as well as sectoral premium, there is no significant difference between the exposed

[42] Due to insufficient representativeness of the selected sample in *Susenas* 2008, I exclude 2008 from the estimation of district premia. Appendix A provides more details on the data and estimation construction.

and non-exposed districts. It also implies that the positive impact of palm oil price shocks on exposed districts are not driven by labor market friction.

This result stands in contrast to what Dix-Carneiro and Kovak (2017) find in the case of the impact of trade liberalization in Brazil where frictions to labor mobility amplified impact of trade shocks locally. In the Brazilian case, the district premia grew more negative over time as the labor cannot move out of the regions where trade liberalization hit industries relatively worse. Meanwhile, in this study, the fact there is no significant impact on district premia due to exposure to rice price shocks and palm oil price shocks also implies that there are no frictions that are significant enough to prevent people from moving in order for the district premia to equalize across districts. In regards to the positive impact of the palm oil price shocks to real expenditure in palm oil districts, the finding on district premia shows that labor is mobile enough to diffuse the income-enhancing shocks from the exposure to palm oil price shocks.

Figure 17: Impact of palm oil and rice price shocks to district premia



Notes: The dependent variable is the estimated district premia obtained from running Mincerian regressions on real expenditure per capita at the household level. The model includes control variables, districts and year fixed-effects. Regression is run on panel of districts over year with population in 2011 as weights. Standard errors are clustered in district-level. Point estimates are relative to year 2005, the omitted category. The 95% confidence intervals for coefficients are shown by the range plots. Shaded area shows the post-treatment period.

5.5.2 Extensification versus intensification

In order to find the drivers of the growth of crop, I use changes in harvested area as the outcome variable for crop extensification and changes in actual yield for crop intensification. Using difference-in-difference specification, I use a two-period panel of districts to see the difference before and after the price shocks. In particular, I use the year 2001 as pre-treatment period and 2011 as post-treatment period.

The palm oil crop expanded through extensification. Table A.5 shows that especially for the bottom tercile of exposed districts, the coefficients for the post-treatment period on the harvested area are positive and significant. Given that there was more land to work on, demand for labor may have increased. This increase in demand is consistent with the increase in real expenditure per capita and net-inward migration in exposed districts as discussed above.

Meanwhile, there is no indication that the palm oil crop expanded through intensification. Table A.7 shows that the coefficients for the post-treatment period on actual yield are not significantly different from zero. Furthermore, it is worth noting that as the commodity boom did not last forever, the impact of the price shocks due to the boom also lowered as commodity prices started to decline. It may also provide some cautions to policy-makers that palm oil sector may not provide a sustainable source of growth if the sector keeps relying on growth from land expansion.

On the other hand, rice crops did not show any sign of extensification nor intensification. Table A.6 and A.8 show the coefficients on consecutively harvested area and actual yield for rice. The empirical evidence discussed in detail above show that the rice price shocks did not materialize as stimulus for rice producers. Hence, we also see that there is no indication for investment on land expansion nor increase in yield for rice.

Rice farmers are mostly small-scale. Only 6% of rice farmers have land of at least 0.5 ha. Hence, the increase in rice price may not have benefited rice farmers because it did not necessarily increase their real income and they may not have had enough collateral to get financing for expansion. This result provides some evidence on ineffectiveness of the trade protection on rice in either providing increase in earnings to rice farmers or stimulating the production of rice. In addition, if there is incomplete market problems faced by rice farmers, e.g. financial markets and insurance market, trade protection may not be the appropriate second-best policy to provide assistance to rice farmers.

Furthermore, so far I assume that trade costs and mark-up margins between retail rice price and farm-gate rice price do not change over the period of study. However, if the wedges between retail provincial rice prices and farm-gate prices vary over time for example due to increasing market power of intermediaries, then the trade protection may exacerbate the problem as farm-gate price may be reduced even lower. This question can be of the interest of further investigation but is beyond the scope of this paper.

5.5.3 Discussion on deforestation

Globally, commodity-driven deforestation is rampant.[43] In a meta-analysis on drivers of deforestation, Busch and Ferretti-Gallon (2017) mention that agricultural price as one of the drivers associated with higher deforestation. Indonesia also is also special in this issue as it experienced the largest increase in forest loss.[44] In the case of Indonesia, various studies show that palm oil expansion was the main driver of deforestation, at least until 2014. Figure A.20 shows the trend of annual forest loss driven by palm oil plantation in Indonesia and real palm oil prices. We can see that there is quite strong positive correlation.

The main finding I find on the impact of palm oil price shocks is that palm oil producing districts benefited some windfall for several years. However, I also find that this gain does not last permanently. As world prices started to decline in 2013-2014 and that there is no increase in actual productivity, the return to palm oil for these districts dissipates. This evidence may better inform policymakers and the public in understanding the impact of the commodity boom in palm oil while taking into account the potential social cost that deforestation causes for longer period of time. In this regard, I echo the concern emphasized by Wheeler et al. (2013) that the success of fores conservation efforst need to acknowleged the fluctuation in world markets and decisions made by financial authority on the exchange rate and the interest rate. This finding can be of the interest of monetary authority in taking the reliance on primary commodity as the backbone of exports and hence source of foreign reserve, as a caution. As shown in Section 2, Indonesia's export profile has become more commodity-intensive since the commodity boom in the mid 2000s. Meanwhile, as local leaders may have more power in land concession as shown by Burgess et al. (2012), this evidence offer more realistic assessment on the opportunity cost of forest. Recent study on the spillover impact of cash transfer on deforestation by Ferraro and Simorangkir (2020) shed lights on the importance of creating outside option as source of income regions that are prone to deforestation. Lastly, the fact that there is no lingering benefit enjoyed by palm oil producing districts highlights that new palm oil concessions may not provide more benefit than costs to the people there.

6 Quantitative estimation

In this section, I quantify the welfare changes that occurred in the period between 2005 and 2010. I use the decomposition of welfare changes that I derived in the section on the theoretical framework. Specifically, I decompose the source of the welfare changes into gains from trade and gains from migration. I use (internal) migration flows data and the Inter-Provincial Input Output Table to estimate these gains. I estimate that there was a 0.39% increase in welfare between 2005 and 2010.

[43] See Curtis et al. (2018) and Seymour and Harris (2019)

[44] See Hansen et al. (2013) and Seymour and Harris (2019).

Gains from migrations account for one-third of these gains. This result provides the importance of taking into account internal migration in welfare analysis.

6.1 Data and parameters

I present below the equation of welfare changes as stated in Proposition 2 for reference. In estimating the gains from migration and terms-of-trade gains, I use several dataset sources. First, I compute the regional expenditure shares, φ_n , as total households expenditures by district by multiplying the average expenditure per capita with population of each district. I use data from *Susenas* 2011. I also obtain net-inward migration rate from the same dataset. Extracting from its recent migration questions, I obtain data on changes in district's labor, $\hat{L}_n$, as well as the population shares, λ_n.

$$\hat{U} = \underbrace{\left(\frac{1}{\epsilon} + (1-\alpha)\right) \sum_n \hat{L}_n \left(\varphi_n - \lambda_n\right)}_{\text{gains from migration}} - \underbrace{\frac{\alpha}{\theta} \sum_n \hat{\pi}_{nn} \varphi_n}_{\text{gains from trade}} \tag{34}$$

Meanwhile, in order to be able to estimate the gains from trade, I need to have data on domestic (regional) trade shares, π_{nn}. Since there is no data on inter-district trade, I use a more aggregate version of inter-regional trade measures extracted from the Inter-Provincial Input-Output Table 2005 constructed by Resosudarmo and Nurdianto (2008) and the Inter-Provincial Input-Output Table 2010 by Resosudarmo and Hartono (2020).

Next, I assume the value of parameters as shown in Table 6. I use conservative values as assumptions for parameters, as employed also by Redding (2016) and Bryan and Morten (2017).

Table 6: Assumption for parameters

parameter	description	value
α	share of tradable goods in consumption basket	0.75
θ	Fréchet parameter for productivity	4
ϵ	Fréchet parameter for amenity	3

Armed with data on expenditure shares, population shares, domestic trade shares as well as the parameters, I compute gains from migration for each district and gains from trade for each province.

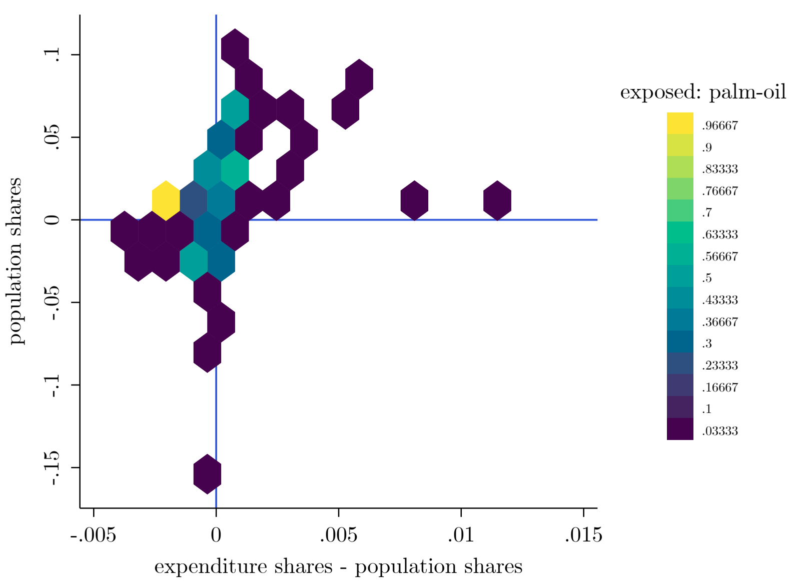
6.2 Results

The total welfare gains over the period of 2005 to 2010 is 0.39% (proportional change to the initial state in 2005) welfare increase. Decomposing the welfare gains, gains from migrations account for one third of the gains while gains from trade account for two-thirds of the gains. This overall size of the welfare gains seem to in line with welfare estimation in the literature. For example, **?** estimate that US consumers experienced 2.6% of GDP welfare gains from expanded import varieties between 1972 and 2001.

Gains from migration Gains from migration in this paper are quantified from two variables: districts' population shares and the difference between district's expenditure shares and population shares. Figure 18 and 19 compare these two variables according to exposure to palm oil price shocks and rice price shocks. The color of each hexagon on the graphs represent the share of exposed districts in that particular bin of population shares and difference between expenditure shares and population shares.[45]

We can see that the distribution of districts exposed to palm oil price shocks and the distribution of districts exposed to rice price shocks are quite distinct. Many districts exposed to palm oil price shocks gain through migration as they have positive value for the difference in expenditure shares and population shares, i.e., the districts are relatively richer. These districts received positive net-inward migration. Some portion do have around zero or negative net-inward migration, but their values for the difference of expenditure shares and population shares are also negative. For such districts, they gain from experiencing outmigration.

Figure 18: Distribution of drivers of gains from migration by exposure to palm oil price shocks



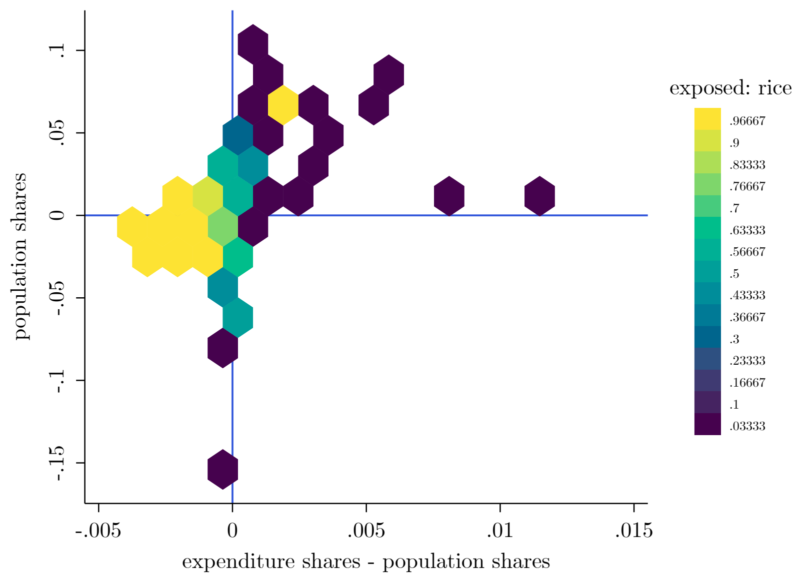
Notes: Each bin represents a group of districts. The colors of the bins represent the share of districts exposed to palm oil price shocks at each particular bins.

In contrast, many districts exposed to rice price shocks experienced negative net-inward migra-

[45] Figure A.21 and A.22 in Appendix show the same comparisons but with districts as unit of observations.

tion. They also have negative values for the difference between expenditure shares and population shares, indicating that they are relatively poorer districts. Indeed, these districts gain from migration by more people moving out of these districts. Some smaller portion of districts exposed to rice price shocks are relatively richer. These districts gain from receiving positive net-inward migration.

Figure 19: Distribution of drivers of gains from migration by exposure to rice price shocks



Notes: Each bin represents a group of districts. The colors of the bins represent the share of districts exposed to rice price shocks at each particular bins.

Gains from trade Meanwhile, given that there is no data for district-level domestic trade shares, I use provincial level (a more aggregated level than district level) domestic trade shares in order to compute gains from trade. The result for each province is presented on Table A.9 in Appendix A. Several palm oil producers are the main contributors for the gains, such as Kalimantan Selatan, Kalimantan Timur, Kalimantan Barat and Sumatera Utara. However, some others experienced losses such as Jambi and Riau. Meanwhile, main rice producers experienced losses such as Jawa Barat, Jawa Tengah, and Jawa Timur.

These results are driven by changes in (provincial) domestic trade shares. palm oil producing provinces tend to have lower domestic trade shares in 2010 compared to 2005 as their export shares in their economy roared due to the commodity boom. Meanwhile, rice producing provinces may have increased their domestic trade shares in 2010 compared to 2005. These results show that despite the trade protection on rice that aim to stimulate production, these provinces were not able to increase their net trade to other provinces as well.

7 Conclusion

Developing economies are prone to changes in the world commodity markets as well as their own trade policies. This paper studies the impact of price shocks, rooting each factor using the context of Indonesia in the mid-2000s. In this period, the economy experienced two massive price shocks. First, as a primary commodity producer, it received windfall from the commodity boom in the 2000s. Second, its government initiated a large and on-going import restriction on rice, a staple food for its population. Given the magnitude and the length of these shocks, factors of production, including labor may respond to these shocks by moving to districts exposed by the shocks. In particular, I study the impact of price shocks to different districts in the presence of internal migration.

I present three main findings. First, palm oil price shocks benefitted producing districts with higher real expenditure per capita, while rice price shocks did not. However, the impact of palm oil price shocks was temporary. I find that the palm oil sector grew through land expansion without any significant growth in actual yield. The increase in land that needed to be cultivated is responded by more inward migration and higher real expenditure per capita. Meanwhile, I find no indication of growth in the rice sector.

The second main result is that there is evidence of spillover of the shocks to non-exposed districts. In particular, the non-exposed districts nearest to districts exposed to palm oil price shocks also experienced higher real expenditure per capita and net-inward migration. The intuition behind this is straightforward. Booming districts may demand more goods and services due to the income shocks they enjoy. Hence, they demand more from their surrounding districts as trade and migration costs are lower if they buy from nearby sources.

Third, I estimate that there is a 0.39% welfare increase between 2005 and 2010 in the economy. One-third of the welfare gains during the period of interest is associated with gains from migration. Meanwhile, gains from trade account for the remaining two-thirds of the welfare increase. These results shed light on the importance of taking into account internal migration in welfare analysis.

With these results, I propose to draw two policy-relevant lessons. First, the results on the impact of palm oil price shocks provide evidence that we can see the cyclicality of global prices at the sub-national level. The result then questions the sustainability of relying on cash crops through land expansion. The concern on sustainability is even more critical if we take into account the social costs from land expansion that causes deforestation. This evidence can inform not only local governments who have the interest in creating development strategy and the authority of land concessions but also to national-level fiscal and monetary authority. In addition, the concern on commodity-driven deforestation is not exclusive to Indonesia as we can also see the same pattern in other crop-exporting regions. For the case of Indonesia, Edwards (2018) shows the trade-off between poverty reduction and deforestation in districts producing palm oil.

The second lesson relates to the effectiveness of trade protection. I find that districts exposed to rice price shocks do not particularly enjoy higher real expenditure per capita. If the trade protection aims to give higher earnings to rice farmers, the results here provide the evidence that the that aim has not been achieved. Meanwhile, if the trade protection's objective is to stimulate the production of rice, I also provide the proof that such a goal has not been accomplished. In conclusion, I provide evidence that trade protection is not a sufficient tool for both types of objectives. In addition, future study on the drivers of the wedges between retail rice price and farm-gate rice price may provide a more complete picture on the distributrional impacts of the trade protection beyond its inter-regional impact as I present here.

References

Adão, R. (2015): "Worker heterogeneity, wage inequality, and international trade: Theory and evidence from brazil," *Unpublished paper, MIT.*

Aldaz-Carroll, E. (2010): "A trade development report: boom, bust and up again," *Evolution, Drivers and Impact of Commodity Prices: Implications for Indonesia: Executive Summary. World Bank, Washington DC*, 1.

Aldaz-Carroll, E., T. Slayton, and P. Timmer (2010): "Pricking the Price Bubble to Avert a World Rice Crisis," *Background paper, World Bank, Washington, DC.*

Allen, T. and C. Arkolakis (2014): "Trade and the Topography of the Spatial Economy," *The Quarterly Journal of Economics*, 129, 1085–1140.

Anderson, K. and W. Martin (2011): "DP8494 Export Restrictions and Price Insulation During Commodity Price Booms," .

Artuc, E., D. Lederman, and G. Porto (2015): "A mapping of labor mobility costs in the developing world," *Journal of International Economics*, 95, 28–41.

Atkin, D. and A. K. Khandelwal (2020): "How Distortions Alter the Impacts of International Trade in Developing Countries," *Annual Review of Economics.*

Austin, K. G., A. Schwantes, Y. Gu, and P. S. Kasibhatla (2019): "What causes deforestation in Indonesia?" *Environmental Research Letters*, 14, 024007.

Autor, D., D. Dorn, and G. H. Hanson (2013): "The China syndrome: Local labor market effects of import competition in the United States," *American Economic Review*, 103, 2121–68.

Baffes, J. and T. Haniotis (2010): "Placing the 2006/08 commodity price boom into perspective," *World Bank Policy Research Working Paper.*

Bazzi, S. (2017): "Wealth heterogeneity and the income elasticity of migration," *American Economic Journal: Applied Economics*, 9, 219–55.

Bouët, A. and D. L. Debucquet (2012): "Food crisis and export taxation: the cost of non-cooperative trade policies," *Review of World Economics*, 148, 209–233.

BPS (2019): *Statistical Yearbook of Indonesia 2019*, BPS-Statistics Indonesia.

Bryan, G. and M. Morten (2017): "The Aggregate Productivity Effects of Internal Migration: Evidence from Indonesia," Working Paper 23540, National Bureau of Economic Research.

——— (2019): "The aggregate productivity effects of internal migration: Evidence from indonesia," *Journal of Political Economy*, 127, 2229–2268.

Burgess, R., M. Hansen, B. A. Olken, P. Potapov, and S. Sieber (2012): "The political economy of deforestation in the tropics," *The Quarterly Journal of Economics*, 127, 1707–1754.

Busch, J. and K. Ferretti-Gallon (2017): "What drives deforestation and what stops it? A meta-analysis," *Review of Environmental Economics and Policy*, 11, 3–23.

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.

Curtis, P. G., C. M. Slay, N. L. Harris, A. Tyukavina, and M. C. Hansen (2018): "Classifying drivers of global forest loss," *Science*, 361, 1108–1111.

Dawe, D. (2008): "Can Indonesia trust the world rice market?" *Bulletin of Indonesian Economic Studies*, 44, 115–132.

Deaton, A. (1997): *The analysis of household surveys: a microeconometric approach to development policy*, The World Bank.

Diamond, R. (2016): "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000," *American Economic Review*, 106, 479–524.

Dix-Carneiro, R. and B. K. Kovak (2017): "Trade liberalization and regional dynamics," *American Economic Review*, 107, 2908–46.

Donaldson, D. (2018): "Railroads of the Raj: Estimating the impact of transportation infrastructure," *American Economic Review*, 108, 899–934.

Edwards, R. B. (2018): "Export agriculture and regional development: evidence from Indonesia," Tech. rep., mimeo.

Fan, J. (2019): "Internal geography, labor mobility, and the distributional impacts of trade," *American Economic Journal: Macroeconomics*, 11, 252–88.

Fane, G. and P. Warr (2008): "Agricultural protection in Indonesia," *Bulletin of Indonesian Economic Studies*, 44, 133–150.

Fernández, A., A. González, and D. Rodriguez (2018): "Sharing a ride on the commodities roller coaster: Common factors in business cycles of emerging economies," *Journal of International Economics*, 111, 99–121.

Fernández, A., S. Schmitt-Grohé, and M. Uribe (2017): "World shocks, world prices, and business cycles: An empirical investigation," *Journal of International Economics*, 108, S2–S14.

——— (2020): "Does the Commodity Super Cycle Matter?" Tech. rep., National Bureau of Economic Research.

Ferraro, P. J. and R. Simorangkir (2020): "Conditional cash transfers to alleviate poverty also reduced deforestation in Indonesia," *Science Advances*, 6, eaaz1298.

Giordani, P. E., N. Rocha, and M. Ruta (2016): "Food prices and the multiplier effect of trade policy," *Journal of International economics*, 101, 102–122.

Goldberg, P. K. and N. Pavcnik (2007): "Distributional effects of globalization in developing countries," *Journal of economic Literature*, 45, 39–82.

Hansen, M. C., P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, S. Stehman, S. J. Goetz, T. R. Loveland, et al. (2013): "High-resolution global maps of 21st-century forest cover change," *science*, 342, 850–853.

Headey, D. (2011): "Rethinking the global food crisis: The role of trade shocks," *Food Policy*, 36, 136–146.

Kovak, B. K. (2013): "Regional effects of trade reform: What is the correct measure of liberalization?" *American Economic Review*, 103, 1960–76.

Lagakos, D. (2020): "Urban-rural gaps in the developing world: Does internal migration offer opportunities?" *Journal of Economic perspectives*, 34, 174–92.

Lucas, R. E. (2015): "Internal migration in developing economies: An overview," *KNOMAD Working Paper*, 6.

Marks, S. V. (2017): "Non-tariff trade regulations in Indonesia: Nominal and effective rates of protection," *Bulletin of Indonesian Economic Studies*, 53, 333–357.

McCulloch and Timmer (2008): "Rice policy in Indonesia: a special issue," *Bulletin of Indonesian Economic Studies.*

McCulloch, N. (2008): "Rice prices and poverty in Indonesia," *Bulletin of Indonesian Economic Studies*, 44, 45–64.

Méndez-Chacón, E. and D. Van Patten (2019): "Multinationals, Monopsony and Local Development: Evidence from the United Fruit Company," Tech. rep., Working Paper. 5.

Pavcnik, N. (2017): "The impact of trade on inequality in developing countries," Tech. rep., National Bureau of Economic Research.

Pellegrina, H. S. and S. Sotelo (2020): "Migration, Specialization, and Trade: Evidence from the Brazilian March to the West," .

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

Resosudarmo, B. and D. Hartono (2020): "Inter-Province Input Output Table," Tech. rep., ANU.

Resosudarmo, BP, D. and D. Nurdianto (2008): "Inter-Island Economic Linkages and Connections in Indonesia," *Economics and Finance Indonesia*.

Seymour, F. and N. L. Harris (2019): "Reducing tropical deforestation," *Science*, 365, 756–757.

Sienaert, A., A. Lnu, M. Adriani, M. Crystallin, F. Fitrani, A. Ihsan, E. A. Mileva, V. Vulovic, E. T. Vashakmadze, M. M. Wihardja, et al. (2015): "Indonesia economic quarterly: High expectations," Tech. rep., The World Bank.

Sim, A. (2020): "Import Restriction, Price Shock, and Local Policy Responses: Evidence from Indonesia," Ph.D. thesis, Cornell University.

Sotelo, S. (2015): "Domestic trade frictions and agriculture," in *University of Michigan Research Seminar in International Economics Discussion Paper*, vol. 641.

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

Topalova, P. (2010): "Factor immobility and regional impacts of trade liberalization: Evidence on poverty from India," *American Economic Journal: Applied Economics*, 2, 1–41.

Vibrianti, D. (2014): "The Effect of Socio-Demographic Variables on Household Saving in Indonesia (The Analysis of the 2007 IFLs Data)," *Developing Country Studies. Vol*, 4, 2225–0565.

Warr, P. (2005): "Food policy and poverty in Indonesia: a general equilibrium analysis," *Australian Journal of Agricultural and Resource Economics*, 49, 429–451.

Warr, P. G. (2011): "Food security vs. Food self-sufficiency: the Indonesian case," *Crawford School Research Paper*.

Wheeler, D., D. Hammer, R. Kraft, S. Dasgupta, and B. Blankespoor (2013): "Economic dynamics and forest clearing: A spatial econometric analysis for Indonesia," *Ecological Economics*, 85, 85–96.

Appendix

A Data

A.1 INDO-DAPOER

This dataset presents various economic indicators disaggregated to the province and district level. The dataset is summarized from different official datasets and compiled by the World Bank. I obtain district-average expenditure per capita as proxy for regional welfare and local earnings from this dataset. In addition, I also get sectoral GDP, area, and population for each district from this dataset. For each year, I crosswalk districts to the districts defined in 2000.

Control variables in reduced-form exercises are obtained from INDO DAPOER dataset as well. These variables are:

- Percentage of rural population in 2000
- (ln) Regional GDP in mining and quarrying sector in 2000
- (ln) Length of district road in bad condition in 2000
- Percentage of villages with asphalt road in 2000.

A.2 National Socio-Economic Survey (*Susenas*)

This household survey provides the most comprehensive household's expenditure pattern and other social and economic indicators annually for the Indonesian economy. The database is sampled from around 300,000 households and is representative up to the district level. *Susenas* is also the source for INDO DAPOER's data on expenditure per capita. In general, the survey has two sets of questionnaires: the core and the modul. The core questionnaire asks basic economic and social indicators to members of households and households. Before 2011, the consumption modul questionaire was included every three years. In this regard, the matching between the core and modul questionnaire before 2011 can be done for survey year 2002, 2005, and 2008. Given this construction, I compute the district average expenditure per capita by non-agriculture and agriculture households only in these years for the pre-2011 period. The estimation of district premia in the pre-2011 period is also possible every three years. Nevertheless, due to insufficient representativeness in the inviduale matched sample in 2008, I do not include 2008 for the district premia estimation.

A.2.1 Non-agriculture and agriculture households

I define whether a household as non-agriculture or agriculture by the sector of employment of household heads. Agriculture households include households with households heads working in food crops, horticulture, plantations, and forestry and other agriculture services. Meanwhile, non-agriculture includes all other sectors. There are some changes in sector classification in the *Susenas* over the period of the study. Table A.1 below presents the exact sectors that I use in each of the survey year.

Table A.1: Sector classification in *Susenas*

Survey year	sector code included as agriculture
2002	1, 11, 13, 14, 2, 20
2005	1, 2
2008	1
2011-2014	1, 2, 3, 6

A.2.2 Recent migration

Since 2011, *Susenas* includes questions on migration behaviour that were previously can only be captured every five years using census and between-census population survey. I constructed migration flow matrix across districts from these migration questions. Then I compute recent migration rate per district destination from this dataset. Recent migration is defined as a change of residential location between survey years and five years prior to the survey years.

A.3 Population Census and Inter-Census Population Survey from IPUMS

I obtain past recent migration patterns from the Population Census in 2000. Inter-Census Population Survey 2005 and Population Census 2010 provided by IPUMS. This dataset is a 10% sample of the complete census and is representative up to the district-level.

A.4 Prices data

A.4.1 IMF Commodity Price Series

I use commodity prices in IMF Commodity price series as benchmark for world prices. In this regard, benchmark world price for palm oil is the palm oil prices of the Malaysia Palm Oil Futures (first contract forward) 4% to 5% FFA in USD per metric ton. Meanwhile, the benchmark world price for rice is the 5 percent broken milled white rice of the Thailand nominal price quote in USD per metric ton. Since I am using domestic retail prices for rice, I follow Dawe (2008) by adding 20 USD per ton for rice shipping and 10% mark-up in order to translate world rice price to retail price for imported rice in Indonesia.

A.4.2 Retail prices data for rice from BPS

Domestic retail prices for rice is available for the main city of each province.

A.4.3 Exchange Rates from FRED

I retrieve monthly USD to IDR exchange rate and Indonesian CPI from the FRED database. I use the exchange rates to convert USD prices into IDR prices. Then, I deflate nominal prices with Indonesian CPI to get real prices.

A.4.4 CPI from BPS

National CPI data is obtained from BPS.

A.5 Tree Crops and Food Crop Statistics from Ministry of Agriculture

I obtain data of harvested area for palm oil and rice by districts as provided by the tree crops and food crop statistics published by the Ministry of Agriculture. Moreover, I compute actual yield by district using harvested area and production data by districts published by these datasets as well. I do not take the yield data directly from this dataset because I would like to use the same districts definition over time.

A.6 FAO Global Agro-Ecological Zones (FAO - GAEZ)

Data on estimated potential yield for palm oil and rice is retrieved from the Global Agro-Ecological Zones by the FAO.[46] For each crop I take the some assumptions on water supply and input level as shown on the Table A.2 below. I also take the estimated potential yield for the period of 1961-1990.

Table A.2: Assumptions on water supply and input level

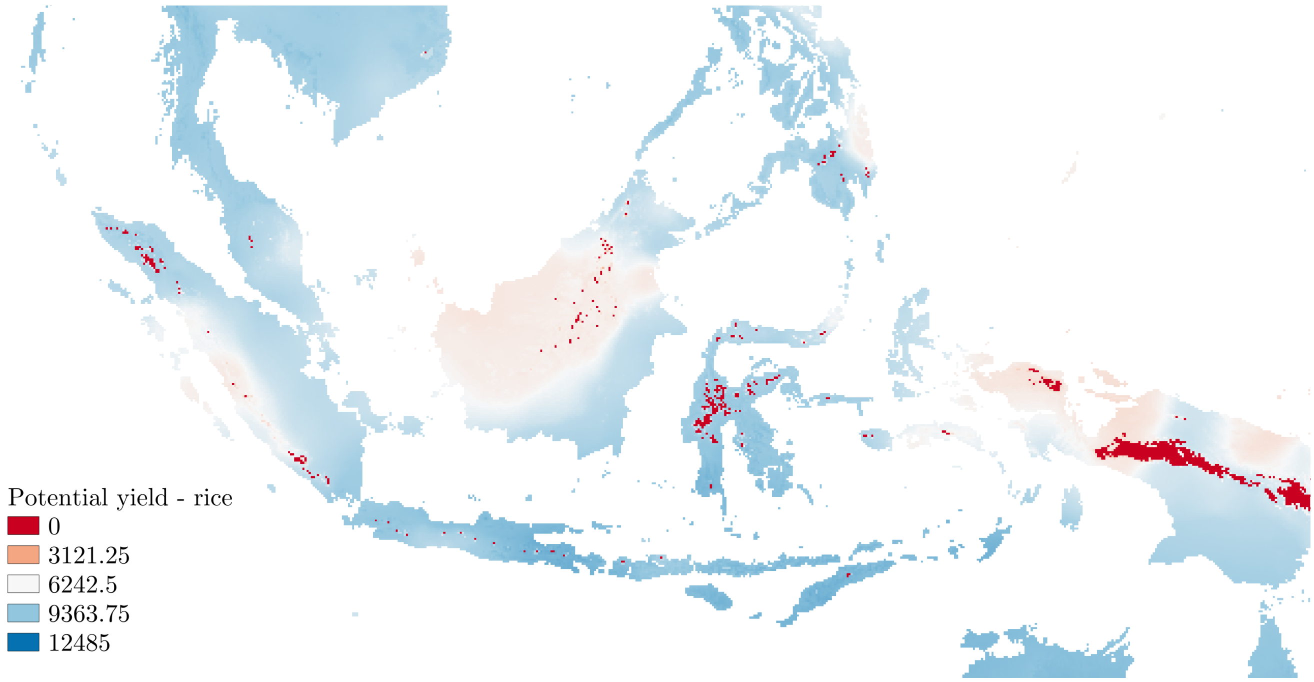
Crop	water supply	input level
Palm oil	rain-fed	high input
Rice	irrigated	high input

Raw data from FAO GAEZ is presented in a five-grid level raster data. Figure A.3 and Figure A.1 show the raw potential yield data for, respectively, palm oil and rice in Indonesia and the surrounding area. For district-level analysis in this paper, I take the district averages for each crop. District average is computed by dividing the sum of potential yield over pixels in each district with the count of pixels overlaid on each district. For districts with less than 1 pixel, I divide the sum of potential yield with 1 pixel. Figure A.2 shows the distribution of the district-average potential

[46] Data can be dowloaded here : http://www.fao.org/nr/gaez/en/.

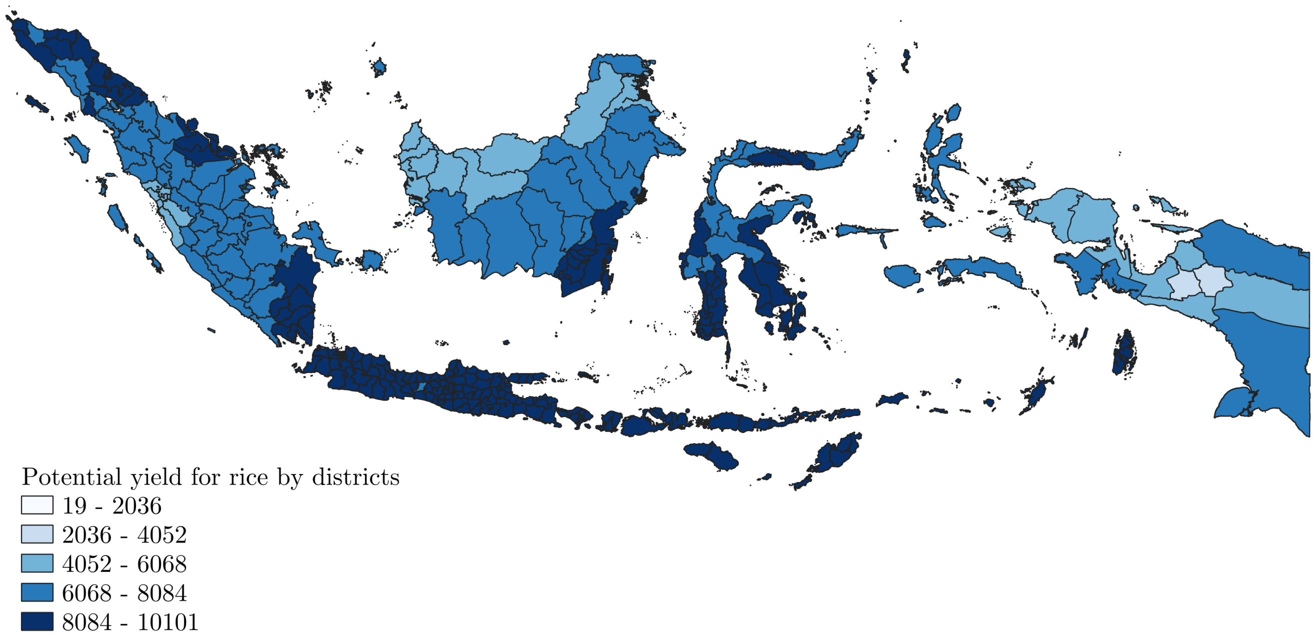
yield for rice. Meanwhile, Figure A.4 shows the distribution of the district-average potential yield for palm oil.

Figure A.1: Potential yield for rice in 5-grid level



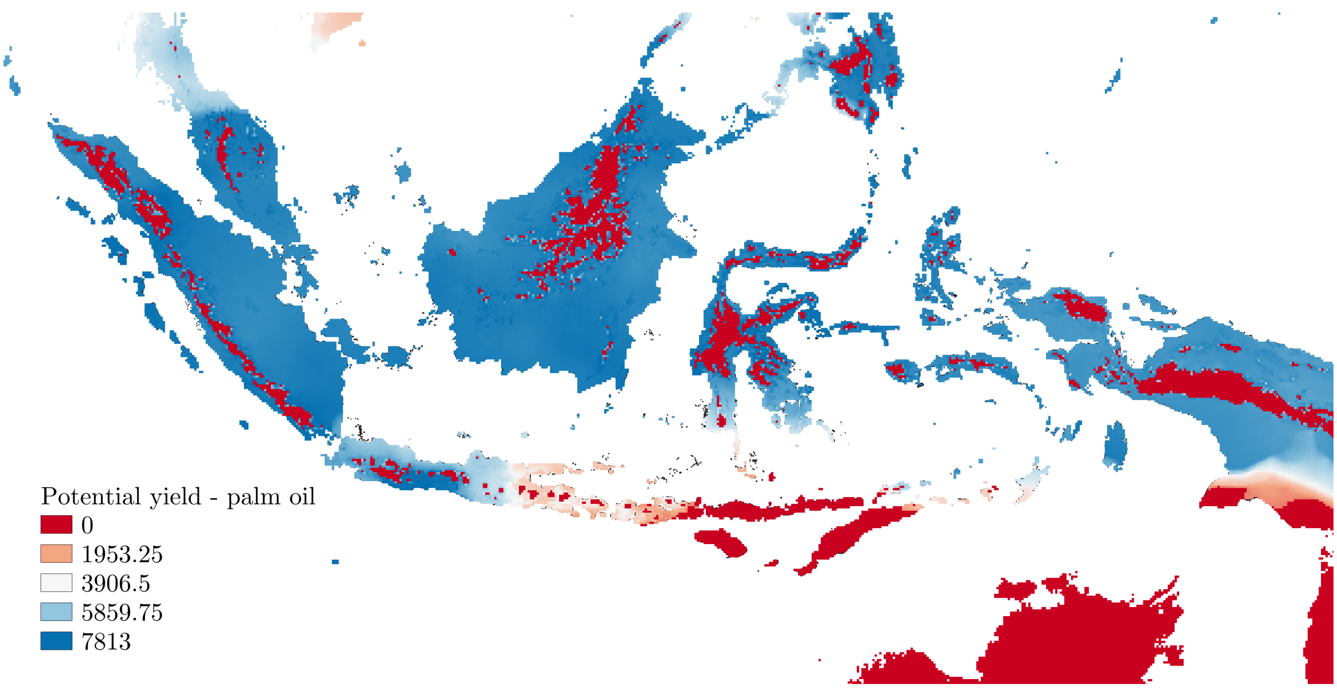
Source: FAO GAEZ.
Notes: Potential yield is in kg DW/ha.

Figure A.2: District-average potential yield for rice (kg DW/ha)



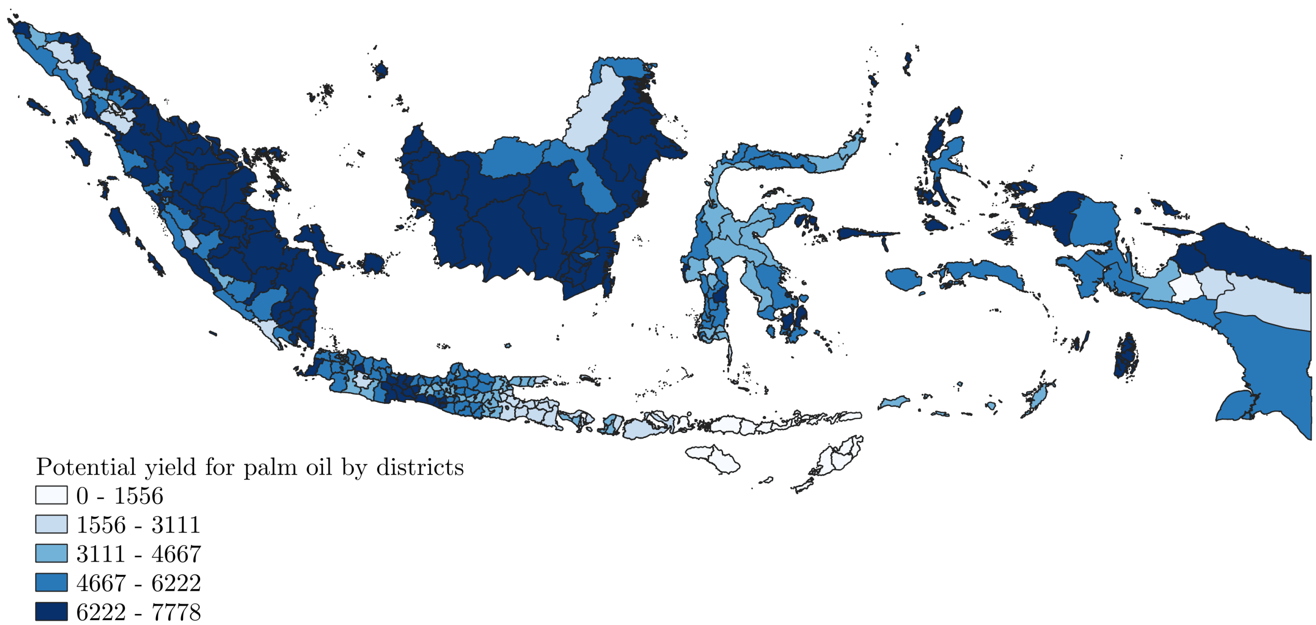
Source: FAO GAEZ, author's calculation.
Notes: Potential yield is in kg DW/ha. Districts use the district definition from 2000.

Figure A.3: Potential yield for palm oil in 5-grid level



Source: FAO GAEZ
Notes: Potential yield is in kg DW/ha.

Figure A.4: District-average potential yield for palm oil (kg DW/ha)



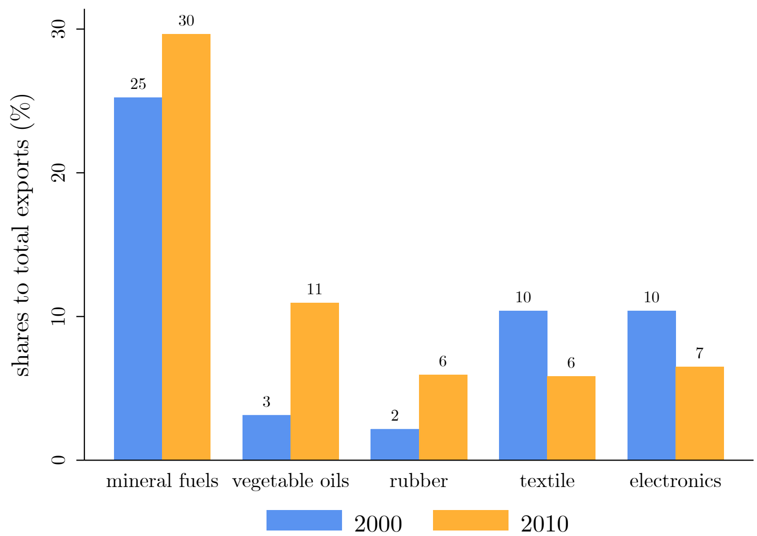
Source: FAO GAEZ, author's calculation.
Notes: Potential yield is in kg DW/ha. Districts use the district definition from 2000.

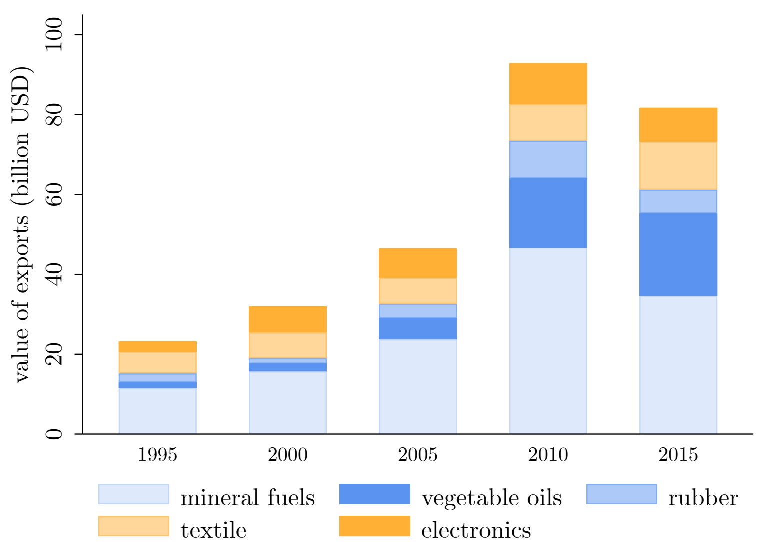
A.7 Village Census (*Podes*)

Podes is a triannual census covering information of social, economic and geographic condition of all villages in Indonesia. It includes questions on demographics, natural resources, quality and quantity of infrastructure, and other various economic variables. I use the 2005 and 2008 census to get measures on observed amenities during the period of five years prior to *Susenas* 2011-2014. For each variable of observed amenities, I take the district average using population as weights. Then as in the literature such as Diamond (2016) and Bryan and Morten (2019), I employ Principal Component Analysis (PCA) to get measures of observed amenities. I group various amenities indicators from *Podes* into two types of observed amenities: favorable amenities and less favorable amenities.

B Indonesia's exports pattern

Figure A.5: Transformation of Indonesia's exports

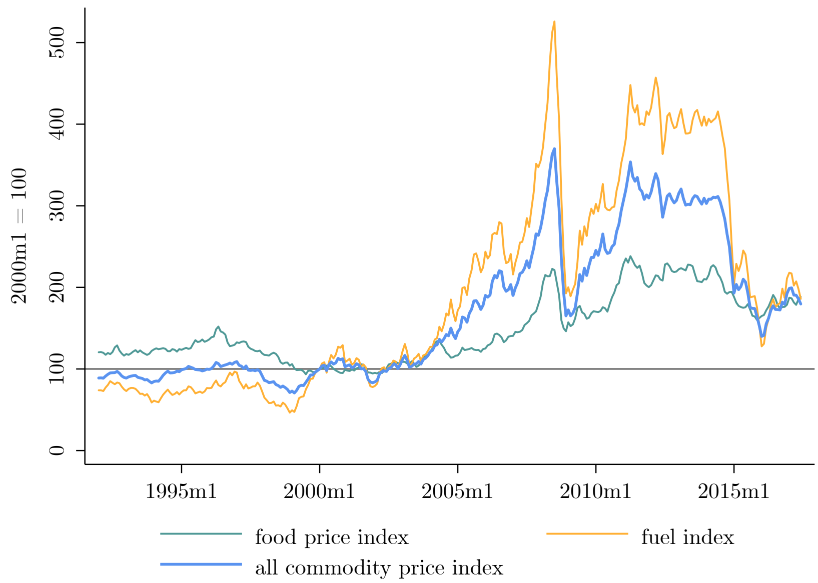




Source: UNCOMTRADE, authors calculation.
Notes: Mineral fuels refer to HS 27, vegetable oils refer to HS 15, rubber refers to HS 40, textile etc. refer to HS 61 to HS 64, electronics refer to HS 85. These figures show selected export goods. Hence their shares do not add up to 100%.

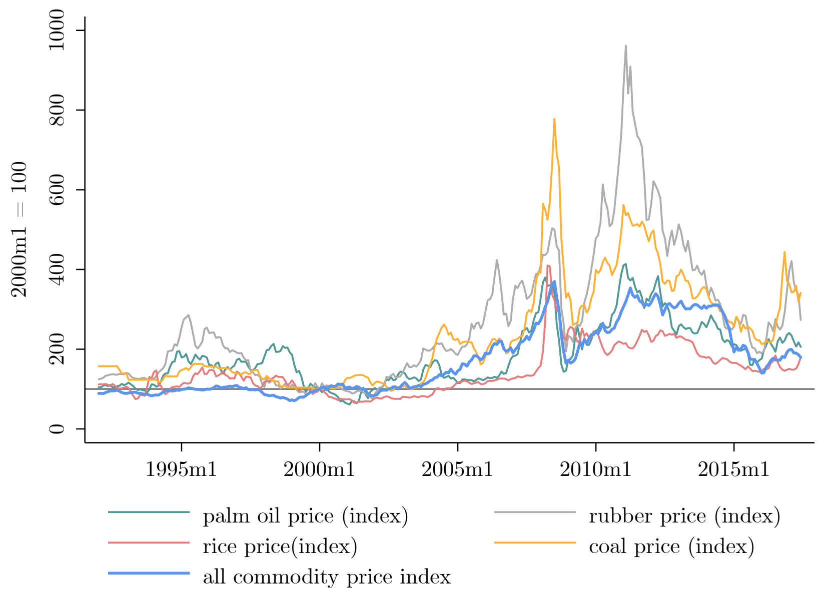
C The commodity boom in the 2000s and rice import-restriction era in Indonesia

Figure A.6: Trend of main world price indices



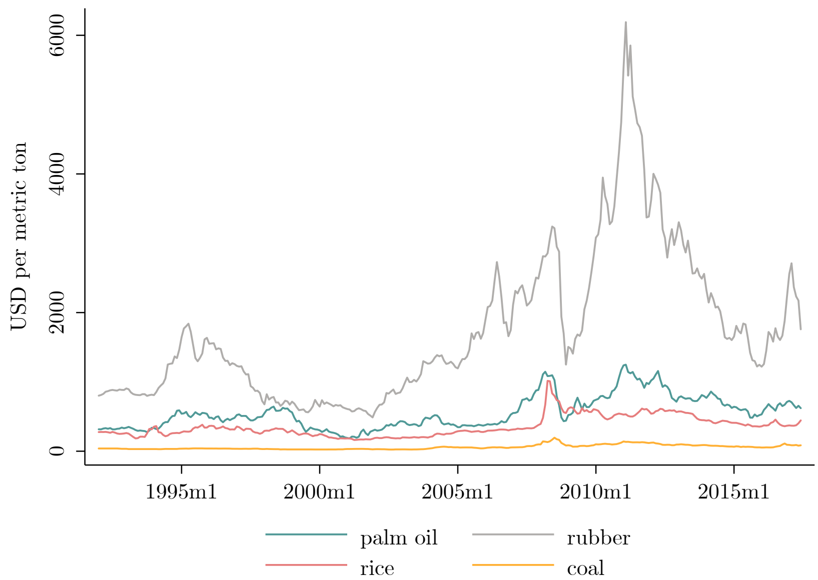
Source: IMF Commodity Price Series.

Figure A.7: Trend of world price indices of Indonesia's main commodities



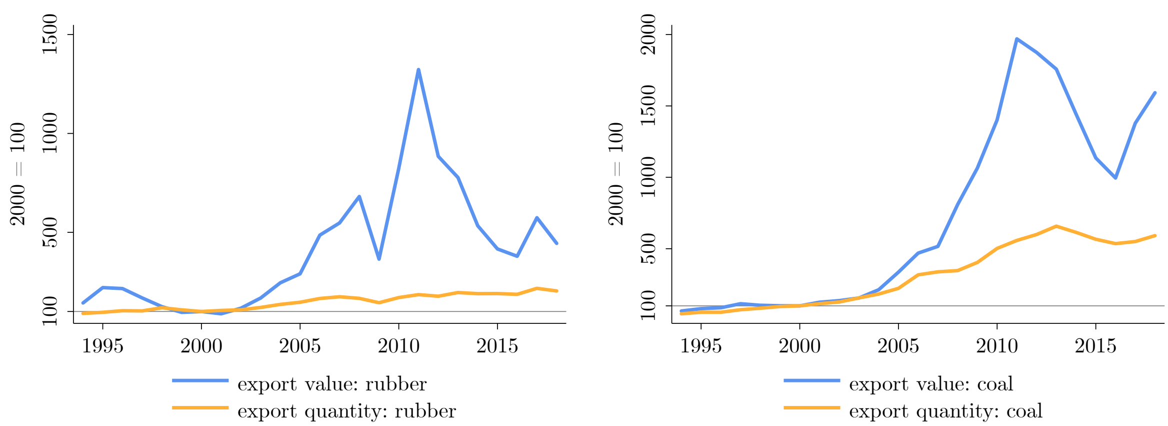
Source: IMF Commodity Price Series, author's calculation.

Figure A.8: Trend of world prices of Indonesia's main commodities



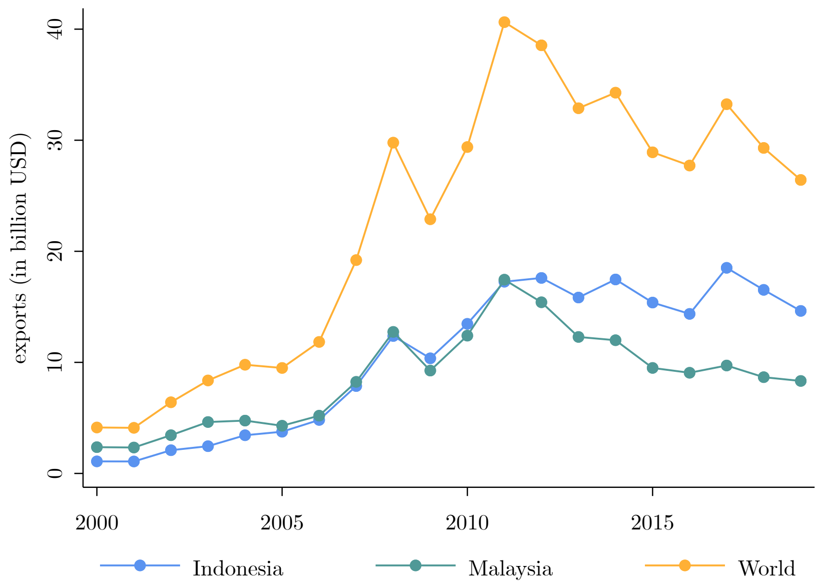
Source: IMF Commodity Price Series.

Figure A.9: Indonesia's exports: Rubber and coal



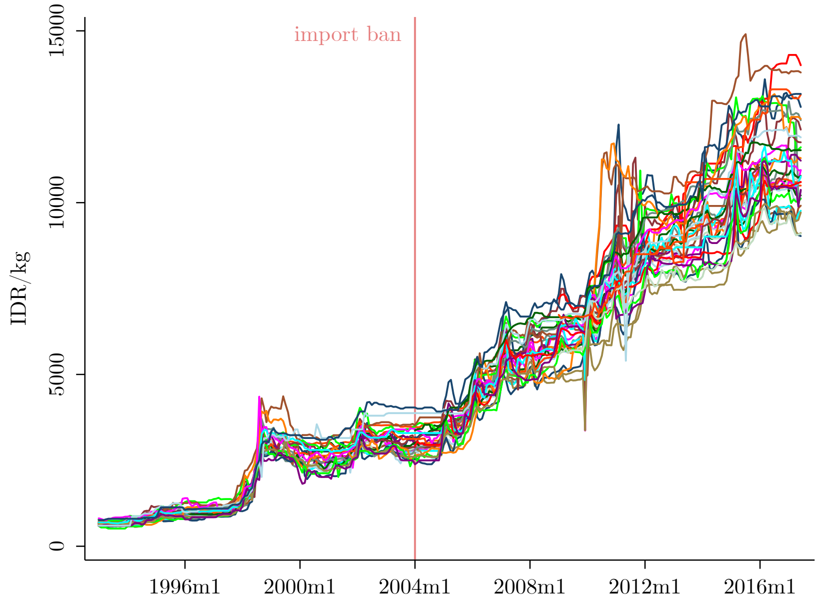
Source: UNCOMTRADE, author's calculation.
Notes: Rubber refers to HS 4001. Coal refers to HS 2701.

Figure A.10: Trend of palm oil exports



Source: UNCOMTRADE.

Figure A.11: Domestic rice prices (Indonesian Rupiah/kg)



Source: BPS

Notes: Each line refers to the retail prices in the main city for each province.

D Exposure to price shocks

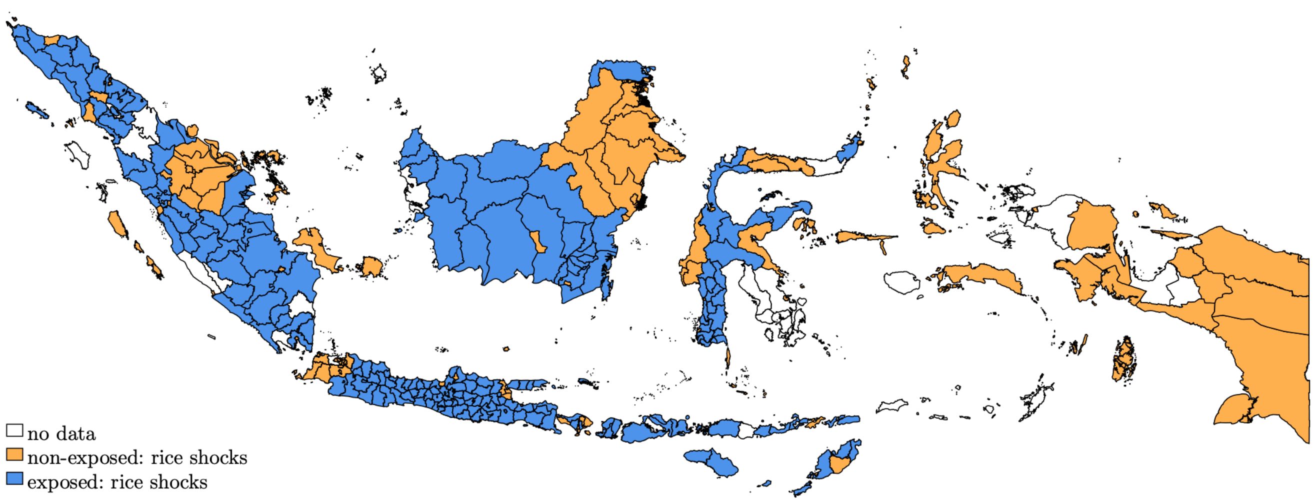
D.1 Summary statistics

Table A.3: Summary statistic of exposure to price shocks

Statistic	rice	palm oil
p10	0	0
p20	0.0001	0
p30	0.002	0
p40	0.016	0
p50	0.044	0
p60	0.068	0
p70	0.089	0
p80	0.117	0.0005
p90	0.170	0.015
p100	0.431	0.143
mean	0.094	0.016

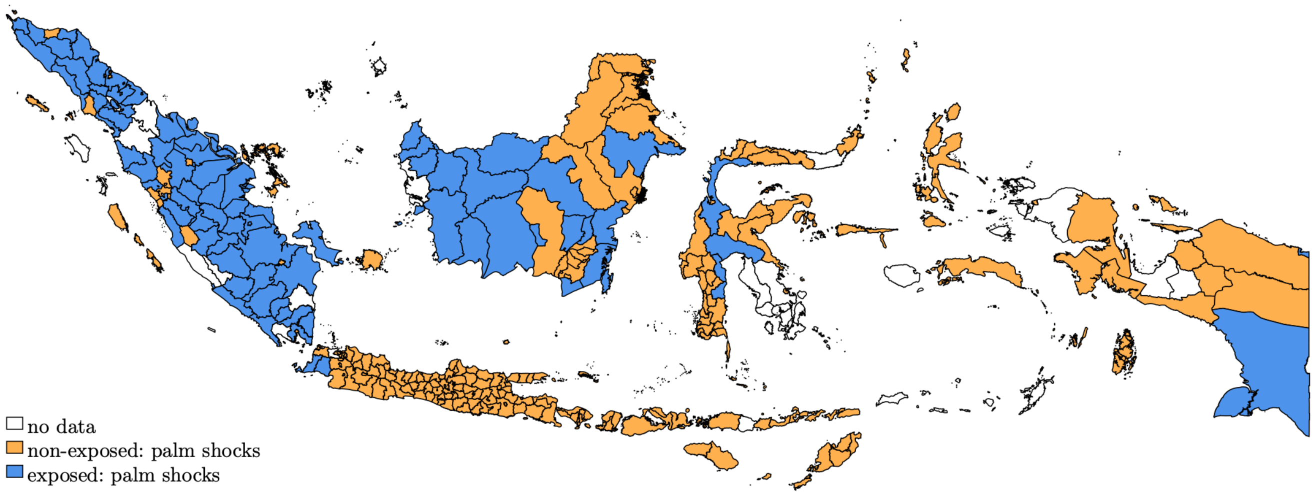
D.2 Exposed and non-exposed districts

Figure A.12: Exposed and non-exposed districts: Rice price shocks



Notes: District definition and border are district definition in 2000. Exposed districts are defined as districts with exposure of rice price shocks of above the 40 percentile.

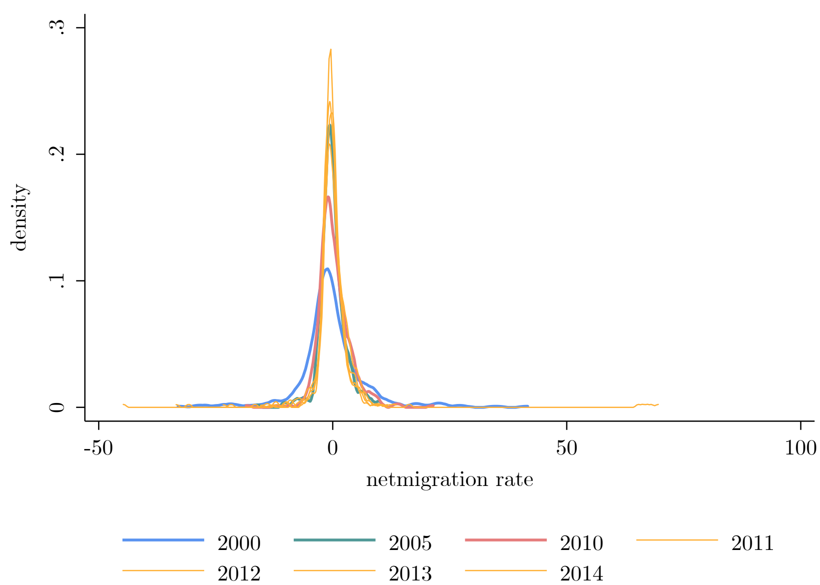
Figure A.13: Exposed and non-exposed districts: Palm oil price shocks



Notes: District definition and border are district definition in 2000. Exposed districts are defined as districts with positive value of exposure of palm oil price shocks.

E Recent Migration Data

Figure A.14: Distribution of net-inward migration rates by districts



Sources: Population Census 2000 and 2010 from IPUMS, Inter-Census Population Survey 2005 from IPUMS, *Susenas* 2011-2014. Author's calculation.

Table A.4: Summary statistics of net-inward migration rate by year (in percent)

Year	N	mean	p50	p10	p90	sd
2000	339	-0.29	-0.94	-6.6	7.44	7.73
2005	317	-0.14	-0.38	-2.8	3.26	2.89
2010	342	0.26	-0.30	-3.09	4.50	3.57
2011	342	0.10	-0.25	-2.37	3.46	2.82
2012	342	-0.06	-0.14	-2.4	2.99	3.2
2013	342	-0.16	-0.27	-2.18	2.51	2.97
2014	342	0.37	-0.3	-2.32	2.73	8.4

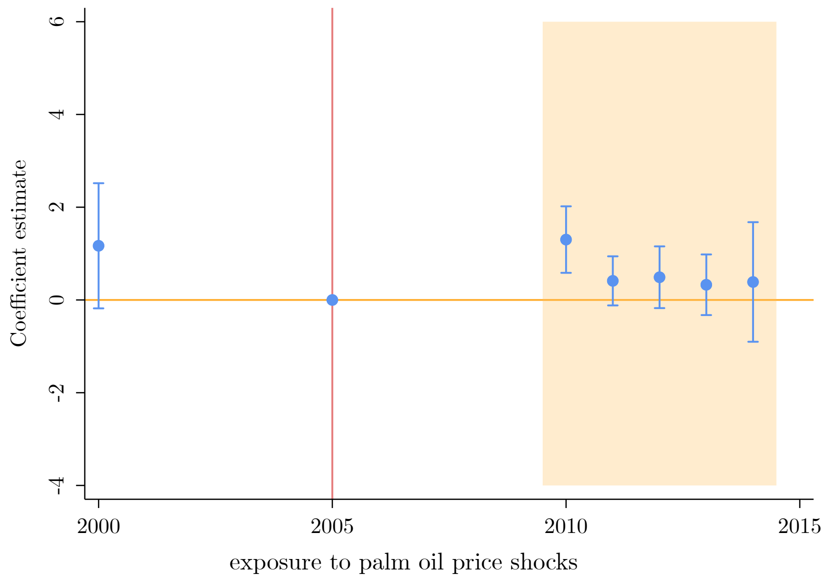
Sources: Population Census 2000 and 2010 from IPUMS for year 2000 and 2010, Inter-Census Population Survey 2005 for 2005 from IPUMS, *Susenas* for 2011-2014. Author's calculation.

Notes: Net-inward migration rates are calculated in district level. as defined in 2000. Inter-Census Population Survey 2005 does not include districts in the Nanggroe Aceh Darussalam Province.

F Econometrics results

F.1 Impact of palm oil price shocks

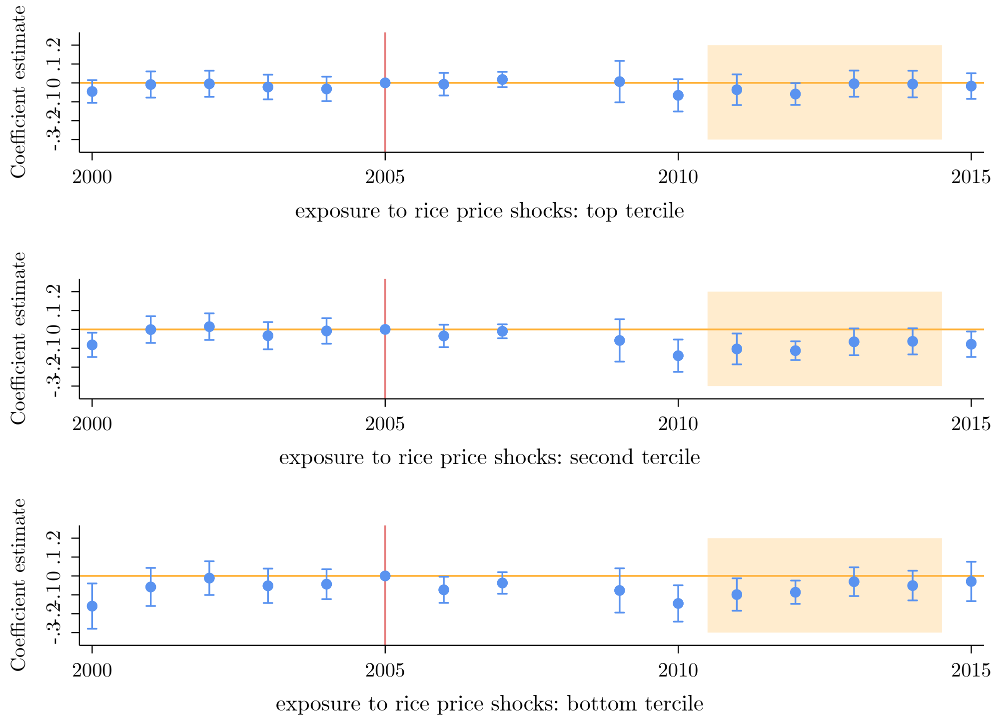
Figure A.15: Impact of palm oil price shocks on net-inward migration rate



Notes: The dependent variable is the net-inward migration rate. The model includes control variables, districts and year fixed-effects. Regression is run on panel of districts over year. Standard errors are clustered in district-level. Point estimates are relative to year 2005, the omitted category. The 95% confidence intervals for coefficients are shown by the range plots. Shaded area shows post-treatment period.

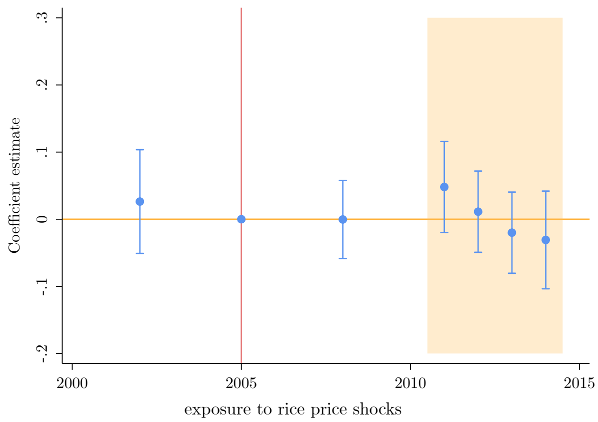
F.2 Impact of rice price shocks

Figure A.16: Impact of rice price shocks to real expenditure per capita across terciles

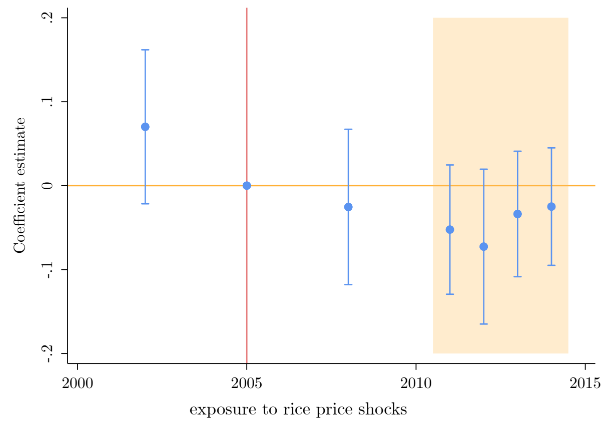


Notes: The dependent variable is (ln) real expenditure per capita. The model includes control variables, districts and year fixed-effects. Regression is run on panel of districts over year with population in 2011 as weights. Standard errors are clustered in district-level. Point estimates are relative to year 2005, the omitted category. The 95% confidence intervals for coefficients are shown by the range plots. Shaded area shows post-treatment period.

Figure A.17: Impact of rice price shocks: Agriculture households and nonagriculture household



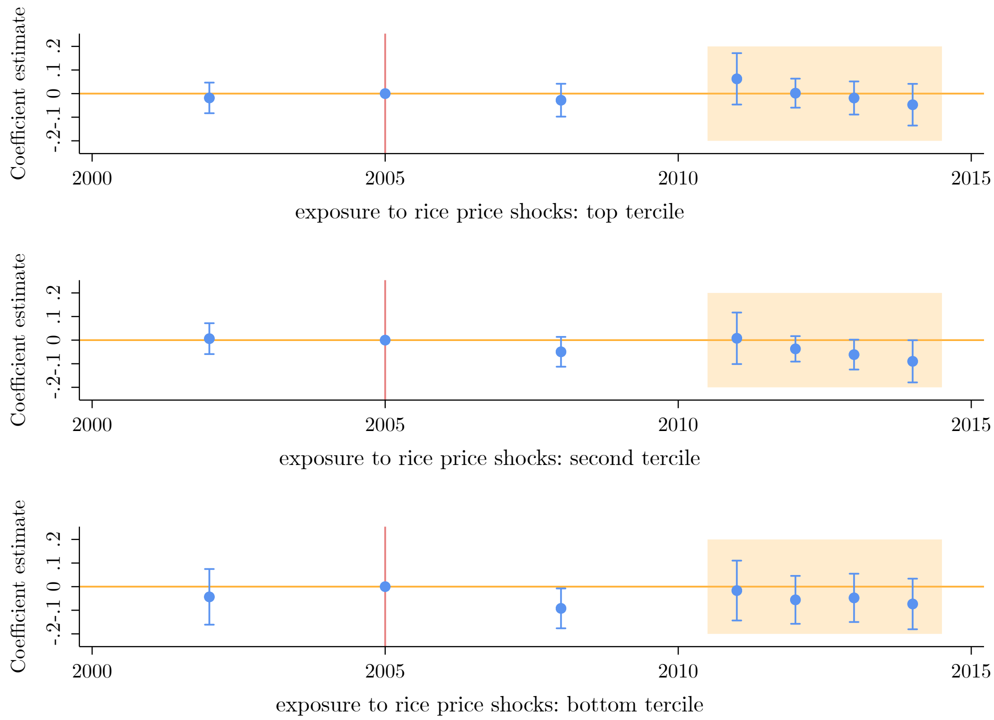
(a) agriculture households



(b) nonagriculture households

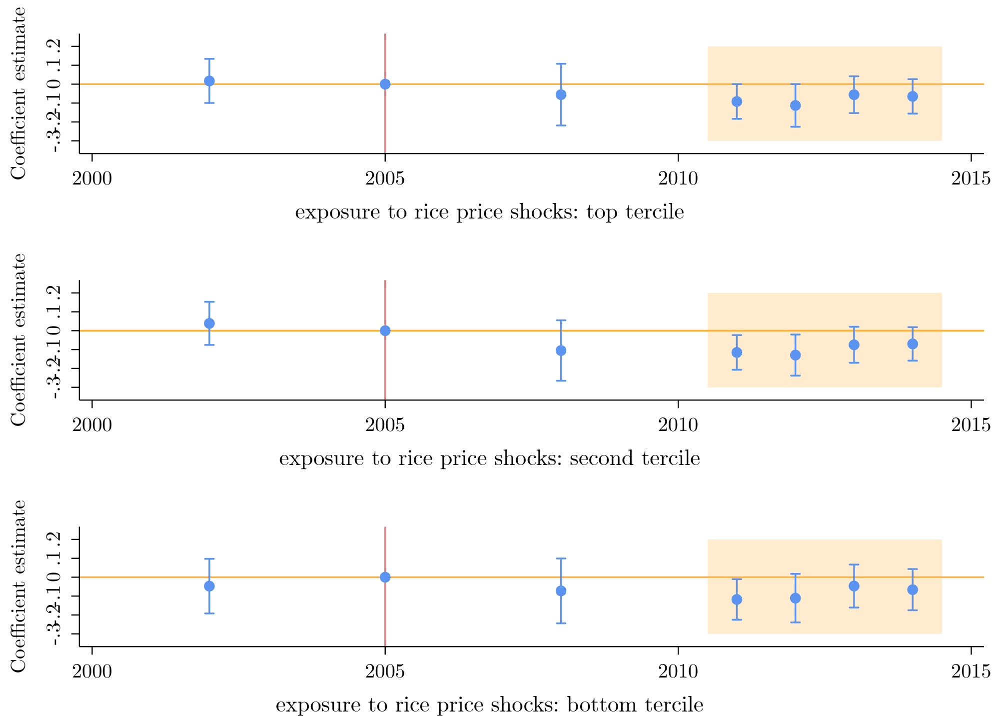
Notes: The dependent variable is the log of (district average) expenditure per capita of agriculture households and non-agriculture households. The model includes control variables, districts and year fixed-effects. Regression is run on panel of districts over year with population in 2011 as weights. Standard errors are clustered in district-level. Point estimates are relative to year 2005, the omitted category. The 95% confidence intervals for coefficients are shown by the range plots. Shaded area shows post-treatment period.

Figure A.18: Impact of exposure to rice price shocks to real expenditure per capita of agriculture households across terciles



Notes: The dependent variable is (ln) real expenditure per capita of agriculture households. The model includes control variables, districts and year fixed-effects. Regression is run on panel of districts over year with population in 2011 as weights. Standard errors are clustered in district-level. Point estimates are relative to year 2005, the omitted category. The 95% confidence intervals for coefficients are shown by the range plots. Shaded area shows outcome period.

Figure A.19: Impact of exposure to rice price shocks to real expenditure per capita of non-agriculture households across terciles



Notes: The dependent variable is (ln) real expenditure per capita of non-agriculture households. The model includes control variables, districts and year fixed-effects. Regression is run on panel of districts over year with population in 2011 as weights. Standard errors are clustered in district-level. Point estimates are relative to year 2005, the omitted category. The 95% confidence intervals for coefficients are shown by the range plots. Shaded area shows outcome period.

F.3 Crop extensification: Expansion on land for crops

Table A.5: Crop extensification: Palm oil

	Dep. var: harvested area		
	(1)	(2)	(3)
Bottom tercile, 2011	2.195***	2.195***	2.195***
	(0.546)	(0.547)	(0.549)
Second tercile, 2011	0.248	0.251	0.251
	(0.273)	(0.274)	(0.275)
(ln) Potential yield: palm-oil		1.310**	1.310**
		(0.543)	(0.545)
Price shocks: rice			-0.0729
			(0.523)
N	197	197	197
R2	0.507	0.526	0.527

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is (ln) harvested area for palm oil. The regressions are run on panel of districts with two periods. The two periods are year 2001 and 2011. The coefficients for each tercile are relative to the top tercile in exposure to palm oil price shocks. Year FEs are included in all specifications. I use robust standard error.

Table A.6: Crop extensification: Rice

	Dep. var: harvested area		
	(1)	(2)	(3)
Bottom tercile, 2011	0.00268	0.00381	0.00380
	(0.087)	(0.087)	(0.087)
Second tercile, 2011	0.0511	0.0511	0.0511
	(0.053)	(0.053)	(0.053)
(ln) Potential yield: rice		1.422^{***}	1.447^{***}
		(0.242)	(0.248)
Price shocks: palm			0.730
			(0.764)
N	565	565	565
R2	0.487	0.528	0.529

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is (ln) harvested area for rice. The regressions are run on panel of districts with two periods. The two periods are year 2001 and 2011. The coefficients for each tercile are relative to the top tercile in exposure to rice price shocks. Year FEs are included in all specifications. I use robust standard error.

F.4 Crop intensification: Actual yield of crops

Table A.7: Crop intensification: Actual yield for palm oil

	Dep. var: actual yield		
	(1)	(2)	(3)
Bottom tercile, 2011	0.513	0.512	0.556
	(0.546)	(0.561)	(0.562)
Second tercile, 2011	0.316	0.317	0.317
	(0.410)	(0.411)	(0.413)
(ln) Potential yield: palm-oil		0.00332	-0.00512
		(0.493)	(0.467)
Price shocks: rice			-1.755***
			(0.605)
N	180	180	180
R2	0.100	0.100	0.133

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is (ln) actual yield for palm oil. The regressions are run on panel of districts with two periods. The two periods are year 2001 and 2011. The coefficients for each tercile are relative to the top tercile in exposure to palm oil price shocks. Year FEs are included in all specifications. I use robust standard error.

Table A.8: Crop intensification: Actual yield for rice

	Dep. var: actual yield		
	(1)	(2)	(3)
Bottom tercile, 2011	0.100	0.101	0.101
	(0.083)	(0.083)	(0.083)
Second tercile, 2011	0.226	0.226	0.226
	(0.180)	(0.180)	(0.180)
(ln) Potential yield: rice		0.0574	0.0250
		(0.104)	(0.098)
Price shocks: palm			-0.921**
			(0.455)
N	557	557	557
R2	0.0159	0.0161	0.0216

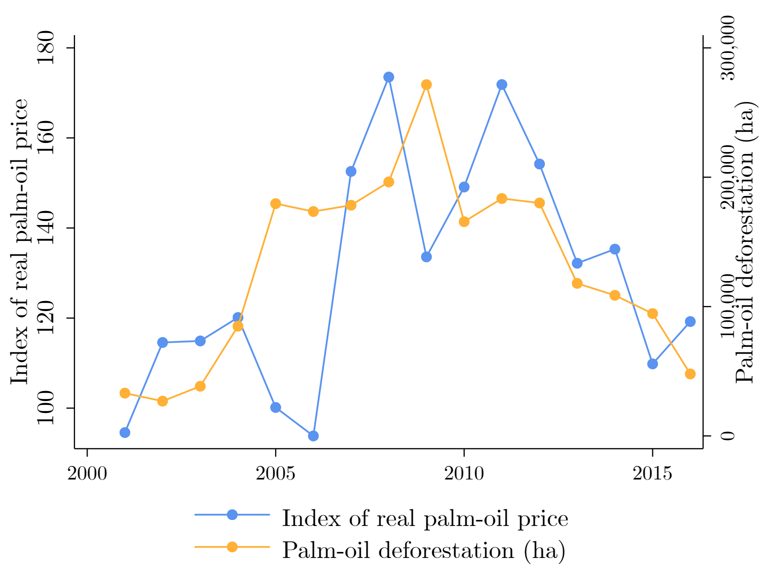
Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is (ln) actual yield for rice. The regressions are run on panel of districts with two periods. The two periods are year 2001 and 2011. The coefficients for each tercile are relative to the top tercile in exposure to rice price shocks. Year FEs are included in all specifications. I use robust standard error.

F.5 Deforestation

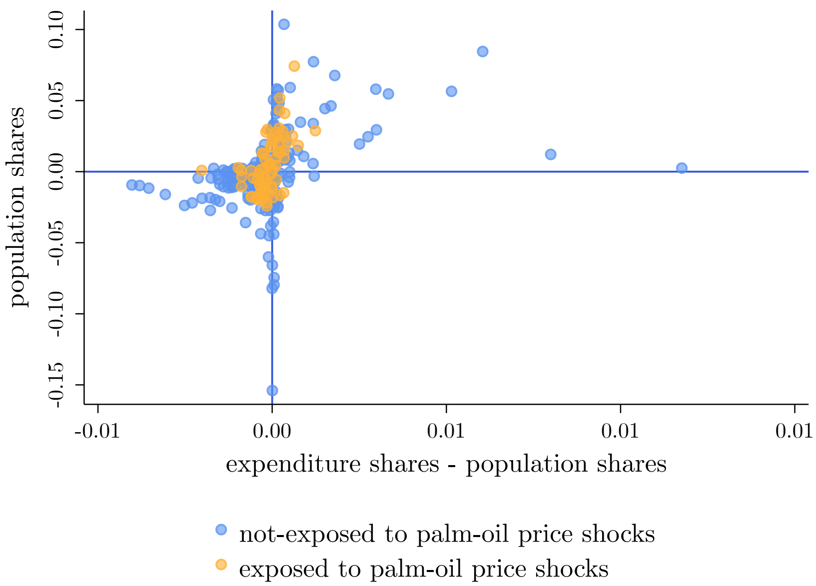
Figure A.20: Deforestation driven by palm oil plantation and palm oil price



Source: Table 3 of the Supplementary Materials of Austin et al. (2019) for deforestation data. IMF Commodity price series for world palm oil prices, index calculated by author.

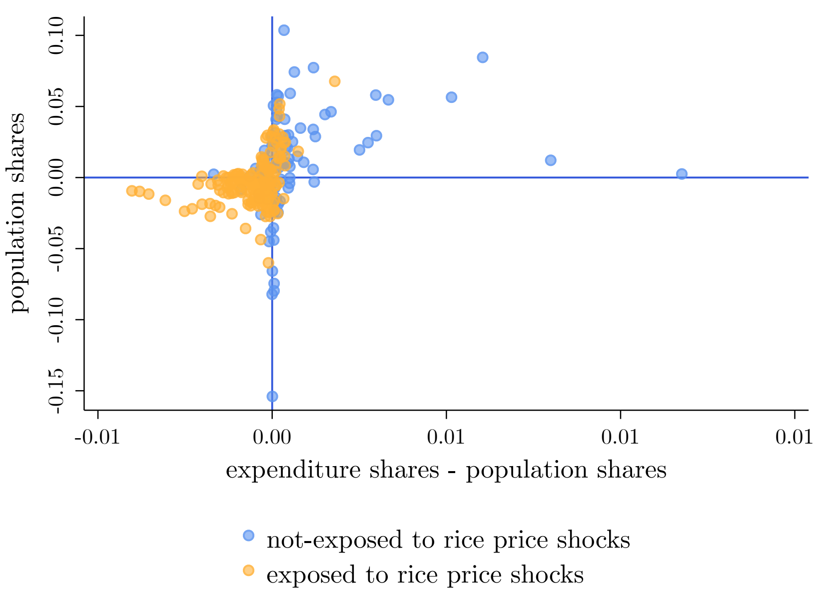
G Gains from migration

Figure A.21: Drivers of gains from migration by exposure to palm oil price shocks



Notes: Each dot represents a district. Calculated using Susenas 2011.

Figure A.22: Drivers of gains from migration by exposure to rice price shocks



Notes: Each dot represents a district. Calculated using Susenas 2011.

H Gains from trade

Table A.9: Gains from trade

Province	gains from trade gains (% from initial welfare)	output share, φ_n (% of national)
NAD	-2.66	1
Sumatera Utara	0.98	5
Sumatera Barat	1.32	1
Riau	-0.43	7
Jambi	-0.42	1
Sumatera Selatan	0.41	3
Bangka Belitung	0.78	1
Bengkulu	-0.15	0.3
Lampung	-0.10	2
DKI Jakarta	2.45	16
Jawa Barat	-0.07	16
Banten	-2.16	4
Jawa Tengah	-3.39	9
DI Yogyakarta	1.10	1
Jawa Timur	-0.27	14
Kalimantan Barat	1.28	1
Kalimantan Tengah	-0.24	1
Kalimantan Selatan	16.71	1
Kalimantan Timur	0.79	6
Sulawesi Utara	0.43	1
Gorontalo	-0.04	0.1
Sulawesi Tengah	0.48	1
Sulawesi Selatan	-1.38	2
Sulawesi Tenggara	0.91	0.5
Bali	1.02	2
Nusa Tenggara Barat	2.81	1
Nusa Tenggara Timur	1.18	0.4
Maluku	7.49	0.1
Maluku Utara	11.73	0.1
Papua	-1.71	2