Commodity price shocks, trade policy shocks, and internal migration: Evidence from Indonesia*

Rizki Nauli Siregar†

University of California, Davis

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Abstract

I study how regions respond to price shocks when there is internal migration. I examine Indonesia in the 2000s as it faced both a commodity boom and initiated its import restrictions on rice, a staple food for its large population. I measure exposure to shocks using the variation in the importance of palm-oil and rice across district economies. I find that districts exposed to palm-oil price shocks have significantly higher expenditure per capita and hence receive more migration. However, exposure to rice price shocks did not materialize as higher purchasing power to exposed districts. I estimate that the overall welfare increased by 0.39% in Indonesia over the period of 2005 to 2010, with one third of the increase is accounted for internal migration.

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

1 Introduction

How do macro shocks such as commodity price shocks and trade policy shocks affect different regions in an economy? How do labor market respond to such shocks and what is the role of such labor response? Various studies in macroeconomic literature show that commodity price shocks matter and their influence to macro performance matter even more in the first decade of the second millenia.[1] Facing such challenges, some countries revert to trade policies with the idea that being less open could prevent them from such volatility or use the challenges as political pressure to pursue certain protection.[2] Indeed, Atkin and Khandelwal (2020) show that developing economies put more concerns or are using more of traditional trade policies such as tariff and duties in their policy set.[3] Despite the fact that developing economies face both commodity price shocks and pressure from protectionism simultaneously all the time, there is a lack of studies in understanding the impact of these shocks locally, especially when exposure of the shocks are not uniform across regions and when factors of production such as labor diffuse the impacts of the shocks.

The goal of this paper is to study how a multi-region economy responds to price shocks stemmed from commodity price shocks and trade policy shocks when there is internal migration. I take the context of Indonesia in the 2000s as it faced both the commodity boom and started to ban the import of rice, a staple food for its 260 million population. This paper contributes to the literature with a case when trade shocks provide sufficient incentive for labor to move. In addition, the shocks in this context are export shocks and positive income shocks. [4] With about three fourth of one billion internal migrants in the world and intensity of internal migration range from as low as 6% in India and as high as almost 50% in Chile (Lucas, 2015), understanding how labor respond through mobility in the face of trade shocks is a relevant question to many developing countries.[5] Indeed, I find that districts exposed by palm-oil price shocks stemmed from the commodity boom enjoyed higher expenditure per capita. They also attract more net-inward migration. This finding emphasizes that shocks were no longer localized and that internal migration was one of the means to diffuse such shocks.

Indonesia is an excellent context in studying the impact of price shocks in developing economies

[1] For example, Fernández et al. (2017) show that 30% of domestic output fluctuations are driven by world shocks that stem from commodity prices.

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

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

[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.

[5] Lucas (2015) also mentions that despite many studies on internal migration focuses on urbanization, the actual dominant flows varies accross 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 studies on the role of internal migration in closing rural-urban gap.

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. Even 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 with most developing economies. Second, there is a wide heterogeneity in terms of comparative advantage across regions in Indonesia. Hence, Indonesia provide the perfect lab to understand the impact of price changes across countries. The context of Indonesia can answer one of the warnings that Goldberg and Pavcnik (2007) mention in running cross-country analysis in studying the impact of international trade and globalization. Indeed, Indonesia also has data that is regionally representative to allow one to study 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 choice to be market-driven choices as well.[6]

In order to answer the research question, I perform a set of empirical and quantitative analysis guided by a simple model of specific-trade model and spatial framework as in Redding (2016). To motivate the environment of the model, I collect three facts from the context of Indonesia in 2000-2015. First, I choose agriculture sector as the sector of interest as farmers can adjust crop choices as they face changes in crop prices. In contrast, mining decisions are driven by very exogeneous endowment. Thus, I revert from studying impact of the increase in mining prices during the commodity boom. Second, I choose palm oil and rice as the they share around half of agriculture land. The two crops are also contrast in terms of their source of shocks. Palm-oil price increase was driven by the commodity boom, while rice price increase was driven by import restrictions. Third, gravity equation on migration flows reveals that regions face upward-sloping labor supply. This result implies that labor do move to regions with higher earnings.

Guided by these three facts, I construct a measure of exposure to shocks for palm-oil price shocks and rice price shocks based on the prediction of the simple model. In the econometrics analysis, I use the computed exposure to shocks to run difference-in-difference specification. In particular, I study the difference across districts in three margins: between exposed and non-exposed, heterogeneity in exposure and spillover to non-exposed districts. I analyze the impact of price shocks on several outcome variables, such as real expenditure per capita as the main proxy for welfare and net-inward migration rate for labor-mobility outcome. I support the findings in the empirical results with some mechanisms that drive the results. Specifically, I analyze the responses of factors of production 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.

[6] According to Artuc et al. (2015), migration costs in Indonesia is approximately at the mean of the sample of 56 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.

I present three main findings. First, districts exposed to palm-oil shocks have significantly higher real expenditure per capita compared to the non-exposed ones but there is not much significant difference between districts exposed by rice price shocks and those not exposed. I find that labor respond to the incetive from higher real expenditure per capita in districts exposed to palm-oil price shocks. Accordingly, these districts attract more net-inward migration. Since I follow districts performance overtime, I find evidence that the impact of the shocks are quite temporary. As the boom slows down, the difference between exposed and non-exposed districts also dissipates. This fact shows that the subnational level also follows the cyclicality of the world market. In analysis of the mechanisms that drive the result, I also find that the growth in palm-oil sector has been spurred by land expansion and not by increase in actual yield. This result further justifies the cyclicality of the impact of palm-oil price shocks.

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 no not fully localized. It has indirect impact on non-exposed districts especially 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 this period. Gains from migration accounts for one third of these gains or 36% of the gains. Meanwhile, gains from trade explains the other two-third or 64% of the gains.

This paper is related to three strands of the literature. First, it relates to a broad literature on the impact of changes in and engagement with the world market to the labor markets in the domestic economy. 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) for the case of India or Kovak (2013) for the case of Brazil, world price changes as in Adão (2015) for the case of Brazil during the commodity boom in the 2000s, and trade cost changes such as Donaldson (2018) for the case of railroad introduction in the colonial India, or their combination such as Sotelo (2015) for the case of reduction in transportation cost and impact of Doha round to Peruvian economy. Meanwhile, the quantity channel can stem from implied technological changes such 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. 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 very relevant to developing economies but are rarely studied together despite countries face them simultaneously all the time.

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.[7] Recent papers show evidence of the importance of taking into account internal migration. For example, Tombe and Zhu (2019) quantifies 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 stem from reduction in internal migration cost instead of the more commonly believed to be the reduction in international trade cost as China joined the WTO. Meanwhile, Pellegrina and Sotelo (2020) shows that internal migration can shape regions' and ultimately country's comparative advantage using the case of Brazil. I contribute to this literature by showing some evidence in how local labor markets adjust and diffuse trade shocks through internal migration.

Third, I complement the literature on trade, internal migration and regional dynamics. Using trade liberalization in Brazil, Dix-Carneiro and Kovak (2017) shows that regions facing larger liberalization experienced increasingly lower growth in wages and employment. It shows that the lack of internal migration and slow capital adjustment amplify the effects of trade liberalization. On the other hand, using the accession of China to the WTO, Fan (2019) shows the importance to take into account internal migration to better estimate the impact of trade liberalization on interregional inequality and wage inequality. Meanwhile, Méndez-Chacón and Van Patten (2019) study the regional dynamics in Costa Rica due to foreign direct investment flows. They show that the easiness of internal migration dampens a monopsonist's market power to push down wages. 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 translate as positive income shocks can be no longer localized. In contrast to what Dix-Carneiro and Kovak (2017) find in the context of Brazil, I find that 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 intenal migration. Indeed, I find that regions experiencing positive income shocks diffuse the benefit of the shocks by attracting labor from other regions. In particular, districts exposed by palm-oil price shocks expand the sector by land expansion. Such extensification method may have increased labor demand in these districts. This increase in labor demand materialized as higher real expenditure per capita and net-inward migration.

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 protectionist measures regarding rice imports in Section 2. In the same section, I draw three facts that motivates 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 shocks in Section 5. In Section 6, I describe the quantitative results

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

of welfare changes estimation. Lastly, in Section 7, I conclude.

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[8], 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 biggest population in the world with more than 260 million population in 2018.

Indonesia is rich in natural resources. Such natural comparative advantages make Indonesia as an important producer of primary commodities, including agriculture and mining commodities. The contribution of agriculture sector and mining sector are consecutively 9-11% and 7% of GDP in 2000-2010.[9] Despite the relatively small contribution to the size of the economy, agriculture sector has the biggest contribution to employment in the economy. It accounts for 45% and 38% of employment in 2000 and 2010 respectively.[10]

In the end of 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 reform but also political reform. The economy took sometime to 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. Moreoever, given the significant differences in economic and political institutions before and after the AFC, I take the start of most of the period of interest in year 2000 or 2001.

Meanwhile in the second half of the 2000s, Indonesian economy is 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.[11] Consecutively, nominal and real expenditure per capita grew 15.8% and 7.4% per year between 2005-2010. In general, various economic indicators indicate higher growth in the second half of the 2000s compared to its prior and subsequent period.

Table 1 also shows some statistic on recent migration in Indonesia. Recent migration is defined as changes of residence between survey year and five years prior to the survey year.[12] In addition,

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

[9] Ibid.

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

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

[12] 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

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.[13]

Table 1: Selected economic indicators

Indicator	**2000-2005**	**2005-2010**	**2010-2015**
GDP growth (% pa)	4.7	5.7	5.5
Export growth (% pa)	4.5	12.9	-0.1
Growth of expenditure per capita (% pa)	13.0	15.8	11.1
Growth of real expenditure per capita (% pa)	3.3	7.4	5.0
	2000	**2010**	**2011-2014 or 2014**
National recent migration rate (% of population)	5.2	4.0	3.2
Net-migration rate of the top 10% district	7.4%	4.5%	3.1%
Net-migration rate of the bottom 10% district	-6.6%	-3.1%	-2.3%
	2001m1 - 2005m12	**2006m1- 2010m12**	**2011m1 - 2015m12**
Price of palm oil, world market (USD/ton)	361.6	700.6	817.0
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.

variables.

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

2.2 A tale of two crops

During the decade of the 2000s, Indonesia's agriculture sector experienced a 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 the decade. Meanwhile, as the country grew to be more a democratic nation and as it recovered from the Asian Financial Crisis in 1997-1998, the pressure from political groups that claim to represent farmers also grew. So in contrast to the windfall from immersing in the world market, 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.

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.[14] During the Global Financial Crisis in 2008-2009, the commodity prices also plummeted but quickly rose back 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.[15] 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.

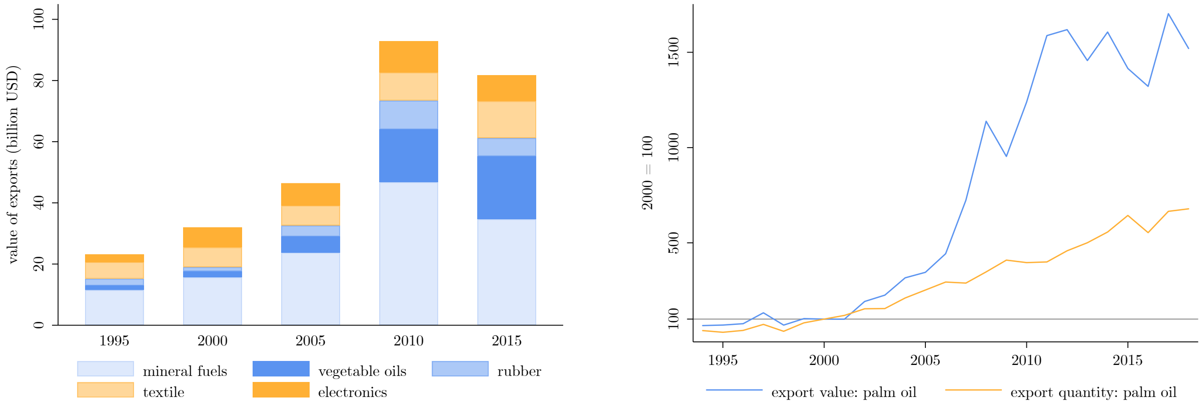
Such extraordinary magnitude and length of the commodity boom provoked two key changes to Indonesia's export profile in that period. First, as shown in Table 1, exports grew faster than GDP. Second, Indonesia's exports composition transformed during this period. As commodity exports became more valuable,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

[14] 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.

[15] 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.

Figure 1: Indonesia's exports



(a) Indonesia's exports transformation (b) Indonesia's palm oil exports

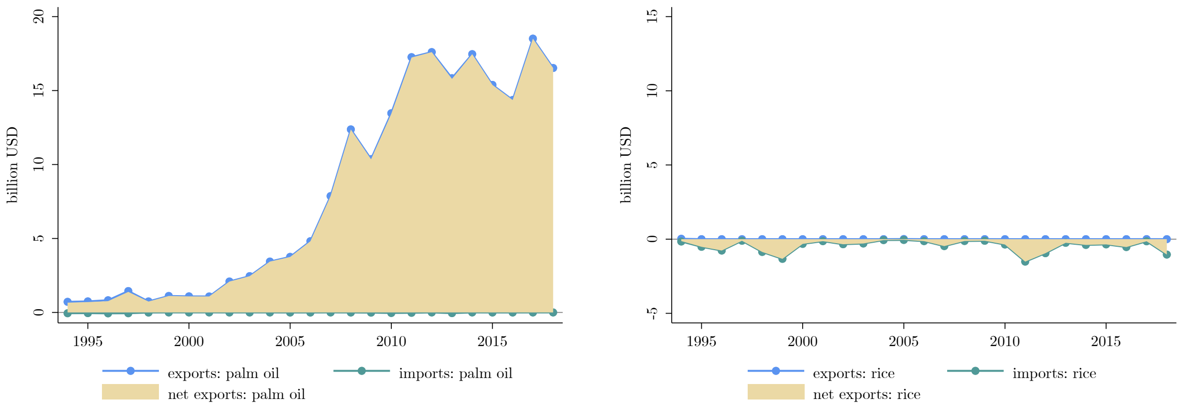
Source: UNCOMTRADE, author's calculation.
Notes: Mineral fuels refer to HS 27. Vegetable oils refer to HS 15, rubber refers to HS 40, textile refers to HS 61 to HS 64. Electronics refers to HS 85. Panel (a) shows selected exports goods. Palm-oil in panel (b) refers to HS 1511.

One may argue that as one of the biggest exporter of palm oil, Indonesia is not a price taker in the world market of palm oil.[16] 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 strong link between energy commodity prices and non-energy commodity prices. Palm oil itself is used widely in both category: biofuel as energy commodity as well as cooking oil and numerous consumer goods as non-energy commodity. Hence, it is plausible to treat Indonesia as a small-open economy in the world market for palm oil.

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

[16]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 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 agriculture commodity in Indonesia. It is the main staple food for most of 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 are rice farmers. However, only 6% of those have control over more than 0.5 ha of rice field (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 political situation as well.[17] Since the early 1970s to late 1990s, rice price stabilization was achieved through imports. Particularly, the national logistic agency (Bulog) was given a mandate to do rice price stabilization. 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 1990s, Indonesia became the world's largest rice importer (Warr, 2011).[18]

[17] 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.

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

Meanwhile in 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 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.[19] 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 prices have surged. In addition, discrepancy between domestic prices and price of imported rice increased eversince, 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 an export ban on rice to shield the country from the exorbitant level of world price fueled by export restrictions from main rice exporters and other trade distortion measures.[20] Despite the import ban has continued to be binding afterwards and hence there was lack of incentive to export, the export bans remain in place.[21]

Another observation that we can see on Figure 3 is that price variation across provinces increased after the enactment of the ban. Before the ban, variaton of rice prices across provinces are relatively negligible. This fact may indicate lax arbitrage across provinces after the ban started. Sim (2020) proposed several plausible reasons. First, Bulog may have a weaker role and or resources to stabilize domestic price. Second, there was a disruption of trade relationship between private importers and international source markets that were built during the more liberal period in late 1990s to 2004. Third, Warr (2005) estimates that the elasticity of supply is 0.2 - 0.4. Despite there is 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 rice price stabilization policy during the period of import ban may instituonally make it less obvious for the government to tackle price hike in terms of regional variation. In 2005, the government started to regulate the rice price stabilization mechanism by allowing local governments to propose provision

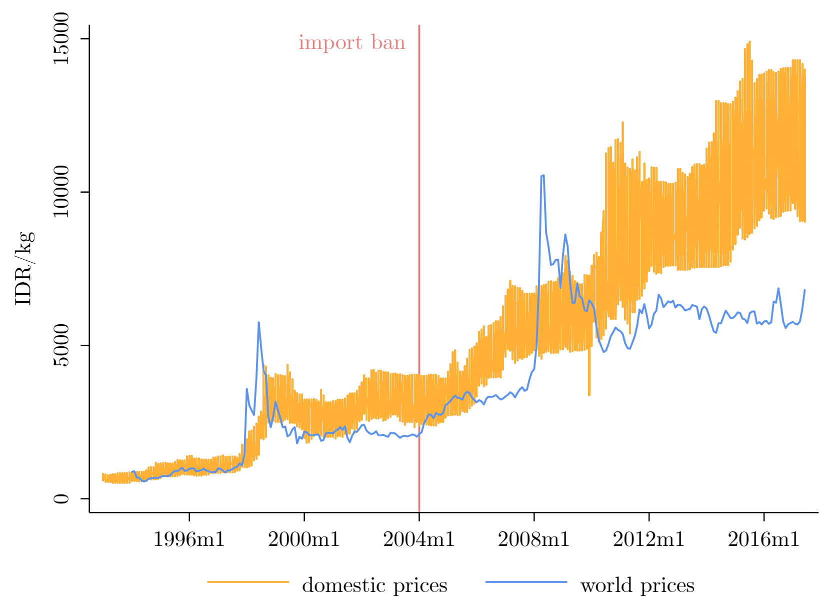
[19] These trade policies on rice are stipulated by Minister of Industry and Trade Regulation No. 9/2004, Minister of Trade Regulation No. 12/2008, and Minister of Trade Regulation No. 19/2014.

[20] 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).

[21] 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.

of stabilization measures in the face of regional price hikes. Once such proposal is approved by the central government, Bulog performs the stabilization program of open market operation in the concerned region. The general procedure remain until 2018.[22] Since price hikes are reported from local government to central government, there may be silos in observing provincial rice prices and thus less attention to the price variation across regions.

Figure 3: Rice prices (IDR/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

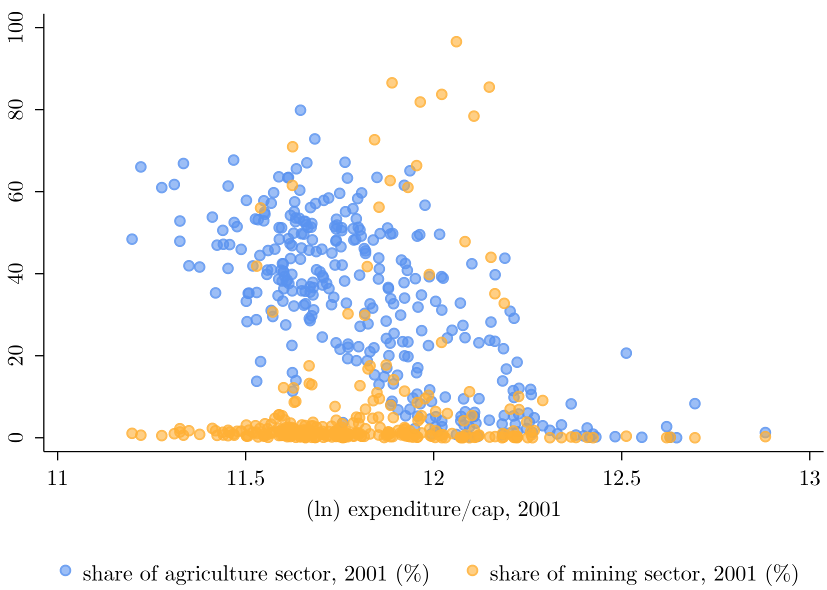
I document three motivating facts that guide me in building the theoretical framework and running empirical exercises to answer what the impacts of the price shocks from the commodity boom and import restrictions to Indonesian economy are. The first fact guides me to understand the variation of the importance 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.

[22] 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.

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

Figure 4 compares the shares of agriculture sector and mining sector in districts' gross domestic products againts 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 bigger share of agriculture sector. This fact is not surprising given the relatively small share of 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 higher mining sector to be in poorer or richer districts. In addition, mining sector also depends on natural endowments that are not easily substituted as in agriculture sector. Given the importance of agriculture sector to the labor force in the economy, I focus on the exposure of price shocks in the agriculture 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 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. It added 1 million hectare 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 hectare of palm-oil plantation. Over a decade later, its area has increased threefold to 6 million hectare. 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 crop land and hence decreased in terms of shares.

Table 2: Land shares of main crops

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

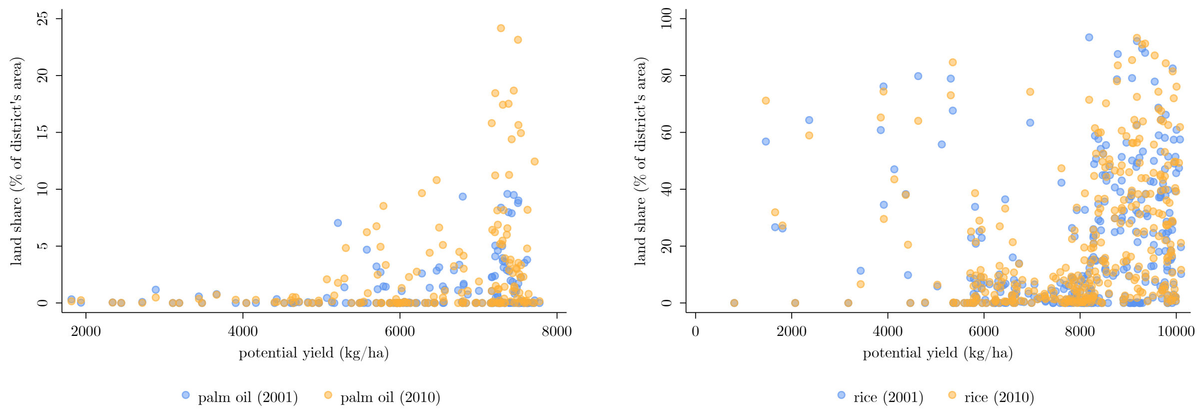
Sources: FAO, author's calculation.

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 occured mostly in districts with high potential yield in producing palm oil. Comparing the ratio of palm oil plantation relative to district's total area in 2001 and 2011 in Figure 6a, the increase in these shares tend to be larger, the higher the potential yield in the district is. 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 field nationally as shown in Table 2 above.[23]

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

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 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.

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. Especially for palm oil, 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.[24] 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 as an income crop while rice as a necessity crop.

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 lasted for relatively substantial period of time. Such circumstances allow people to adjust and maximize their welfare by cahnging their residency. Starting in 2011, the Indonesia's Social and Economic Household surveys (*Susenas*) allows us to observe these movements as the surveys record recent migration, i.e. residence in 5-year prior to survey year. Table 3 shows the results of running gravity equation on these recent migration flows across districts in 2011-2014. This period captures precisely internal migration during the high commodity prices period.

The results of running gravity equation on recent migration flows provides an evidence that people move to districts that offer higher expenditure per capita, 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

[24]Another crop that is potential to be taken into account is rubber. However, FAO does not estimate potential yield for rubber.

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 2011-2014. Estimated amenities are predicted first components from running principal component analysis (PCA) on selected variables from the Village Census (PODES) 2005 and 2008.

In order to see the variation of net-inward migration rate across regions, Table 4 below 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.[25]

Table 4: Net-inward migration rates by crop suitability

Year	**palm oil**			**rice**		
	p20	**p50**	**p80**	**p20**	**p50**	**p80**
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.

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

3 Theoretical framework

The commodities or the industries of interest in this study are crops. Unlike manufacture sector, data on employment by crop 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 local labor market to face an upward-sloping labor supply. The main difference with 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 assymetric preference on amenities in these regions.[26] 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 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 in 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.

[26]This setup implicitly assumes that migration frictions are more pronouced 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 amenitiesprovided by the region n, b_n, where she 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 take an independent and idiosyncratic draw on amenities for each region n from 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 worker for each region. In this set up, 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 supply inelastically. Each worker receives wages for the labor services she 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 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 as the following:

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

Residential Choice Each worker maximizes her utility in (1) by taking into account her idiosyncratic preferences on amenities for each region. Using the properties of 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 upward-sloping labor supply, in which we can expect higher share of population will choose to live in regions with relatively higher income and amenity levels. Since each worker supplies one unit of labor in her 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 $n \in N$ that solves the following system of equation:

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

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

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

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

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

3.1.2 Exogenous Price Shock

We would like to analyze the impact of an exogeneous price shock to wages in different regions. If labor had full labor mobility and homogenous 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, provide a framework between the two extreme cases explained above. From the labor-supply side, each worker will consider all regions and maximize her 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 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 $\gamma_{n2} \equiv \frac{\alpha p_2 Y_{n2}}{\alpha(Y_{n1}+p_2 Y_{n2})}$, 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 shocks, the impacts on wages across regions differ. The changes in wages at each region depends on the region's share of 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 expose regions differently. Meanwhile, the increase in demand for labor in sector 2 in each region pushes up the wage in region there, which simultaneously attracts workers to move to region with the booming sector. The movement of workers now 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 relatively higher amenity level attracts more workers or likewise retain more workers. Thus, for a given price shocks and sectoral composition, the higher the amenity level of a region is, the less the impact of price shocks on changes in the region's wage.

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 Frechet distibution with shape parameter ϵ. Meanwhile, production for tradable goods are performed in monopolistic competiotion with many firms. Each region has productivity drawn from Frechet distribution with shape parameter θ.

The welfare gains from trade in this set up 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 tradable goods and services, θ as the shape parameter of the distribution of productivity and ϵas 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,[27] 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:

[27] 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 no population growth, i.e. $\frac{d\bar{L}}{\bar{L}} = 0$, and substract equation 25 with the right-hand side of equation 26:

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

Proposition 2. *Assumming there is no population growth in each district, 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.*

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

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 prediction of the theoretical model, I apply it to the case of exogenous price shocks stemmed from the global commodity boom faced by Indonesia and the imposed import restriction policy on rice. 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.[28] The heads of districts as well as parliamentary memberships at the district level are elected directly by residents of the districts. 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.[29] Over the course of the period studied here, there has been numerous district and province proliferation. I use the administrative district definition in 2000 to maintain the same set of districts over time of 321 districts.[30]

In this section, I proceed with explanation on data sets used in this study. Then, I lay out the timeline as a reference for defining pre-treatment period, treatment period and post-treatment period. Applying this timeline, I describe the measure of exposure to price shocks that I use in empirical analysis.

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 as guided by the theoretical framework. I describe the main variables and datasets I use in this subsection. I lay out more details in Appendix A.

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.[31] 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.[32]

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

[29]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.

[30]The complete set has 342 districts. In most empirical exercises I use a panel of 321 districts. There is no other reason of not getting the full set than data availability.

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

[32]IFLS is nationally representative. The first wave was conducted in 1993-1994. 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`.

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 in this study. First, I use the total district average, which include the whole sample for each district. Second, I computed district-average expenditure per capita by sector of employment of the head of households. I categorize sectors of employment into 2 groups: agriculture and non-agriculture.[33] 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 year 2011 to 2016, I extract data on migration flows across districts from *Susenas*. Meanwhile, for earlier years, I obtain migration flow data from 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 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 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 1960-1990. I argue that the use of such a single-measure yield is a plausible stance as farmers care more on long-run cycles, instead of high-frequency variable such as daily rainfall, in non-horticulture crop mix decision 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 area by districts and crop from the Ministry of Agriculture's statistics website.[34] The data of harvested area include all types of plantation, i.e both large and smallholders plantation. For national aggregate crop area, I use the FAO database. 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

[33] 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.

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

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.[35] 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.

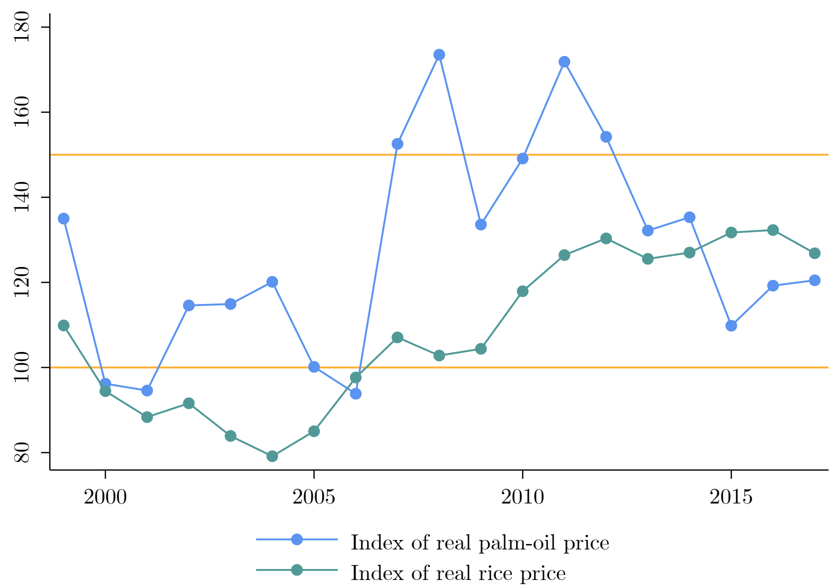
4.2 Exposure to price shocks

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

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 7 below. Figure 6 shows the trend of real rice prices and real oil-palm prices. I define treatment period as the onset of the commodity boom for oil palm 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 despite 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 subsequent 3-5 years after the treatment period.

[35] Ideally, one would use farm-gate price of oil palm instead. However, since Indonesia is a price-taker in the world market and if we assume trade costs do not vary over the onset of the commodity boom, the changes in world price and price level suffice to represent the changes in prices received by oil-palm farmers as these trade costs cancel out.

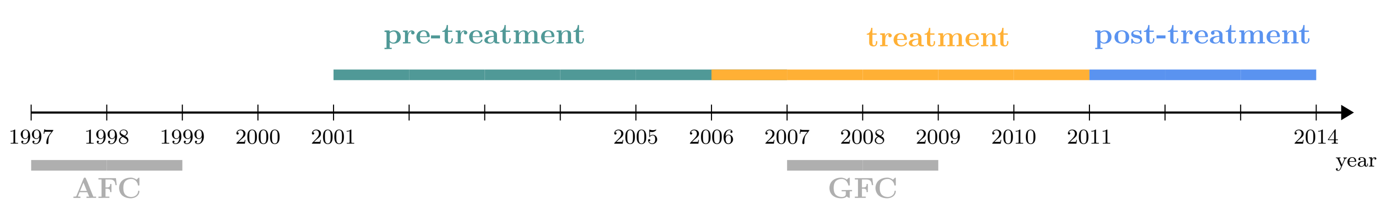
Figure 6: Real prices: rice and palm oil (Jan 2000 = 100)



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.

Specifically, 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-boom period. The outcome period is a period spanning 2011 to 2014.

Figure 7: Timeline



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

Inspired by the results in the theoretical framework that impact of exogeneous price changes to income depends on the importance 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 towards uniform price shocks. 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 provincial level. I assume that farmers in each districts are price taker to these provincial rice prices. Such assumption is plausible given the relative size of each farmer to the province aggregate.

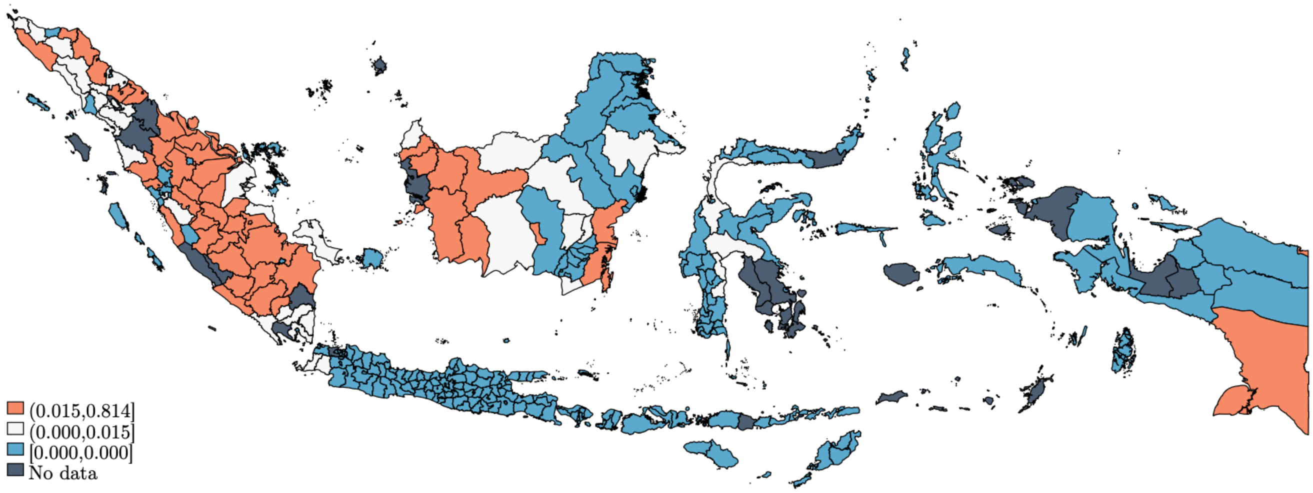
$$S_{id} = \hat{p}_i \frac{Y_{id0}}{GDP_{d0}} = \hat{p}_i \frac{p_{i0} \cdot T_{id0} \cdot \psi_{id}}{GDP_{d0}} \tag{29}$$

Crop i refers to palm oil and rice. Meanwhile, the subindex 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, Y_{di0}, is computed using the pre-treatment average price of crop i, p_{i0}; pre-treatment harvested area crop of 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 oil and gas sector in pre-treatment period.

Meanwhile, variation across districts on estimated production of palm oil and rice are determined by variation in harvested area in pre-boom 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 for rice, the import ban on rice was enacted in 2004. I assume that rice farmers could not have predict 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 oil and gas sector as I assume that this measure better represents the pie of the economy that are distributed locally in the district.

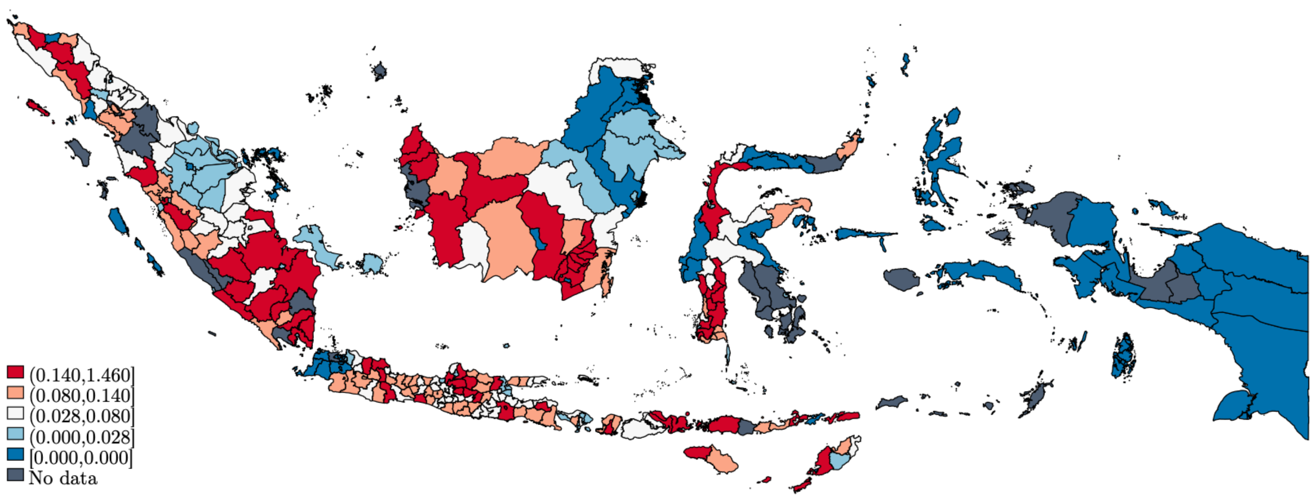
Figure 8 and 9 display the computed exposures of price shocks of palm oil and rice across districts. The exposure to shocks of palm-oil price is higher in districts in Sumatra and Borneo. Meanwhile, the exposure to shocks of rice price is higher in districts in Java. Table A.3 exhibits the summary statistic of the computed exposure to price shocks.

Figure 8: Exposure to price shocks: palm oil



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

Figure 9: Exposure to price shocks: rice



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

5 Empirical evidence

I use the constructed exposure to 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 first run analysis on the average difference between exposed districts and non-exposed districts. Accordingly, exposure is differentiated by palm oil and rice. I show that districts exposed to palm oil price shocks have higher expenditure per capita. Hence, these districts also receive more net-inward migration. However, this impact is temporary as these booming districts materialize the windfall from the commodity boom in land expansion and not on intensification through for instance investment to increase yield. In contrast, districts exposed with rice price shocks did not enjoy higher expenditure per capita and hence did not particularly attract on more net-inward migration. Interestingly, I found also that the rice price shocks may have actually hurt more the non-agriculture households in exposed districts. This evidence implies that the rice price shocks also increase cost of living as rice is a staple commodity for most households. Thus, rice price shocks did not cause increase in real purchasing power to those exposed. Second, I study spillovers of the shocks to non-exposed districts. I found that nearest non-exposed districts to districts exposed by palm-oil price shocks also have higher expenditure per capita from the shocks. These empirical results provide evidence when shocks can no longer localized. I further show some mechanism through analysis on district premium and land share for crops. In addition, I confirm that the shocks stemmed from the commodity boom remain temporary and exogenous as it did not induce growth in actual productivity. Hence, as the commodity boom ends, exposed districts do no longer enjoy particularly higher expenditure per capita compared to non-exposed districts. Meanwhile, the trade protection on rice also did not induce any significant increase in either land expansion nor intensification through yield.

5.1 Specification

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 shock to rice price. The latter fact is not surprising because rice is the staple food for most population. Many districts produce some amount on their own despite 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 exposure value of higher than 40 percentile. Meanwhile, I define districts with value of exposure to rice price shocks in the bottom 40% as non-exposed districts for rice. The final set of these exposed and non-exposed districts are summarized in the table below and ilustrated on 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

I use event study for econometrics specification to study the impact of palm oil price shocks and rice price shocks to districts economies. Specifically, I use equation 30 to show the average differences between exposed and non-exposed districts overtime. Meanwhile, I use equation 31 to show any heterogeneity in the impact of the shocks.

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

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

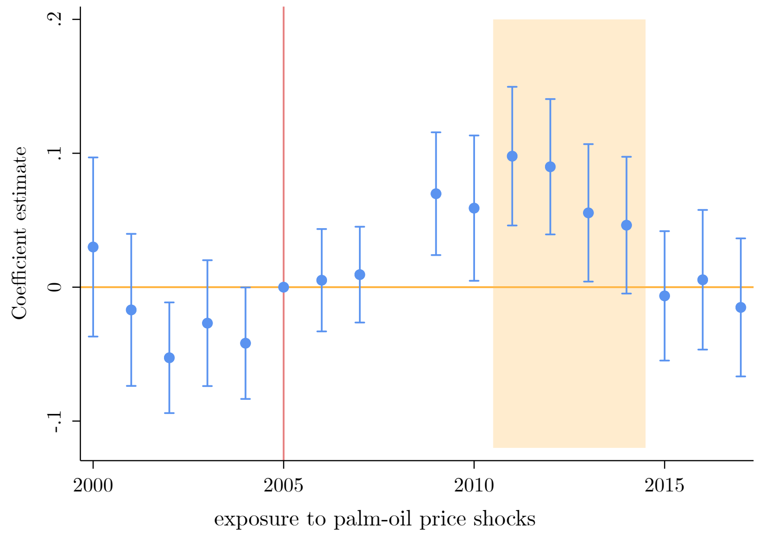
The outcome variables, y_{dt}, are average real expenditure per capita and net-inward migration. Our coefficient of interest is β_{jr}s, i.e. the coefficient for indicator variable for exposure status for crop $j \in \{palm, rice\}$ in year r, or coefficient β_{jgr}s, i.e. the coefficient for tercile g in exposure to shocks of crop j in year r. These coefficients show the difference of districts exposed by price shocks in crop j 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 high agriculture share in their economies may be structurally different with those that rely less on agriculture sector. Hence, I include a matrix of control variables. These controls include the percentage of rural population in 2000, the share of villages with asphalt road in 2000 and the length of district road in bad condition. I also include the size of district GDP in mining sector in 2000 to take into account any diferrences across districts due to the exposure of the commodity boom on mining commodities. In addition, I control for year and district fixed-effects. Thus the coefficients of interest capture the within-district changes in the outcome variables.

5.2 Exposure to palm-oil price shocks

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

Figure 10: Event study on average impact of expsoure to palm-oil price shocks



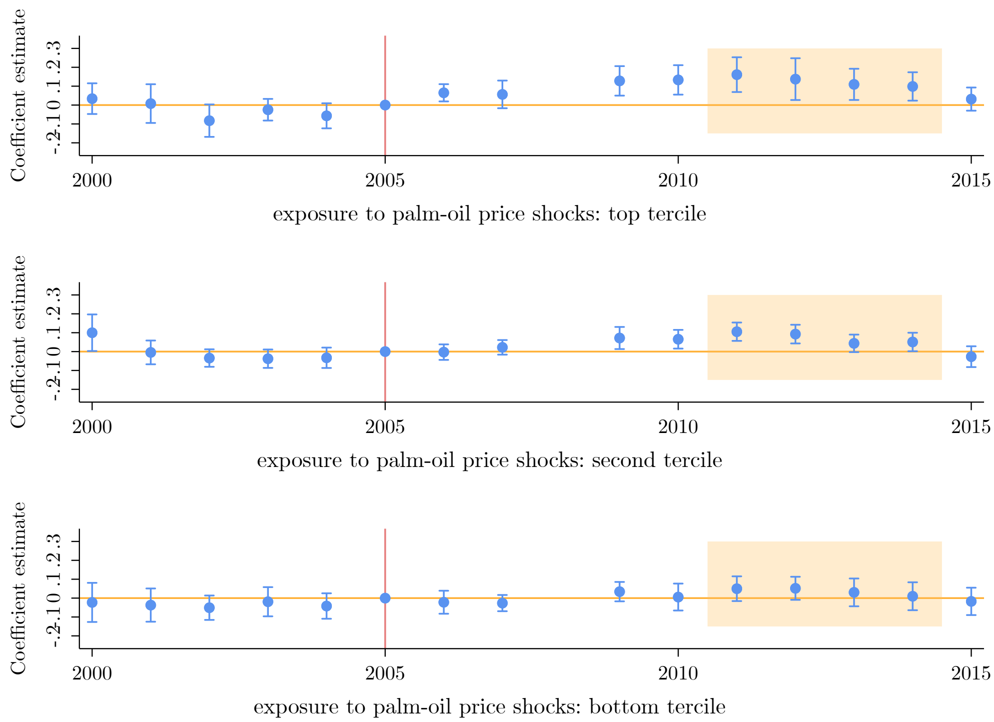
Notes: Dependent variable is the log of (district average) real expenditure per capita. Model includes control variables, districts and year fixed-effects. Regression is run on panel of districts over year with population in 2011 as weights. Standard errors are clustered in district-level. Point estimates 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 10 also shows that the exposed and non-exposed districts were not significantly different in the pre-treatment period of 2000-2004 relative to the base year 2005. One exception is that districts exposed by palm-oil price had significantly lower (ln) real expenditure per capita in 2002. However, the difference is neglible in other years.

Meanwhile, during the post-treatment period, the difference between districts exposed by palm-oil price shocks and those that were not reached 10 log points or approximately 10 percent relative to the base year in the peak of the boom in 2011. Such difference 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 boom decays afterwards with lower coefficient overtime until 2013. The cycle seems to follow directly the commodity boom cycle as it slows down in 2013-2014 as well. This is the first evidence that the commodity boom affects subnational regions differently and that these regions did not gain permanently from the boom.

I study further whether there is heterogeneity in the positive impact from exposure to palm oil price shocks by running equation 31 on (ln) real expenditure pe capita. Figure 11 below plot the estimated coefficient for three terciles of palm-oil price shocks over time. Districts in the top two terciles of palm-oil price shocks significantly had higher (ln) expenditure per capita during the outcome period compared to the non-exposed districts. For the top tercile, the difference reached 16 log points or around 17 percent 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 percent higher in 2011 relative to 2005. Following the trend in the overall difference of exposed and non-exposed districts, the impacts shrink over the outcome period and become significantly not different from zero by 2014 or 2015.

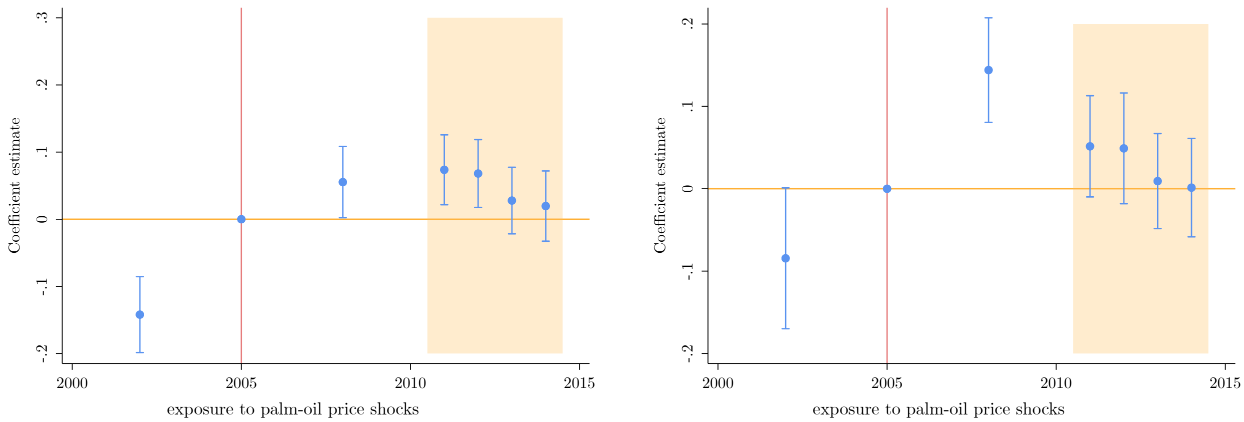
Figure 11: Impact of palm-oil price shocks to real expenditure per capita across groups



Notes: Dependent variable is (ln) real expenditure per capita. 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.

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

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



(a) agriculture households

(b) non-agriculture households

Notes: Dependent variable is the log of (district average) expenditure per capita of agriculture households and non-agriculture households. 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.

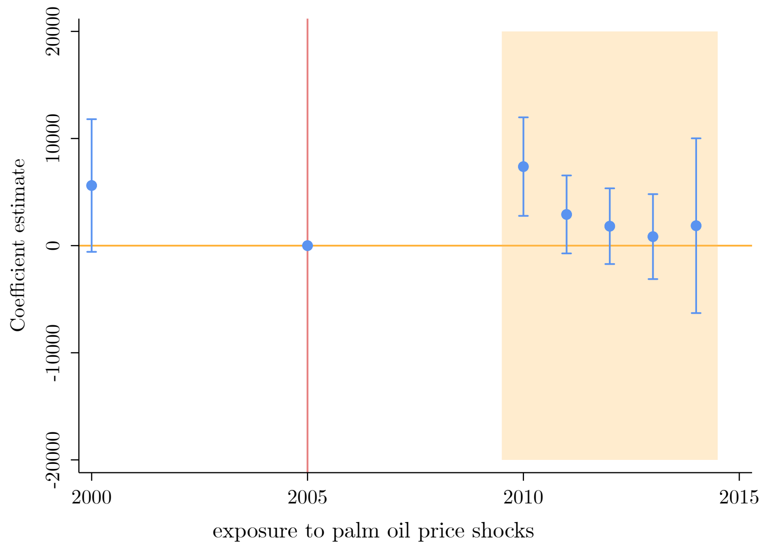
I find that agriculture households in districts exposed by palm-oil shocks have on average higher real expenditure per capita in the first two years of the peak of the boom. Specifically, agriculture households in districts exposed to palm-oil shocks have 7 log points higher real expenditure per capita 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 2011-2014, despite showing significance during the treatment period of 2008.

As districts exposed with palm-oil price shocks had higher expenditure per capita, they may attract labor to move to these exposed districts. To test whether districts exposed with the shocks receive more migration, I run equation 30 on net-inward migration.

Figure 13 below plots the estimated β_{jr}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 limitation. Since recent migration data was not collected annually before 2011, I combine several dataset to construct recent migration flows data over time. For year 2000 and 2010, I use Census Population that is provided by IPUMS. While for year 2005, I extract recent migration flows from Inter-census Population Survey, provided by IPUMS. For the year 2011 to 2014, I use the Socio-economic Household Survey(*Susenas*) datasets. Hence, there maybe some structural differences in the sampling of these datasets.[36] In this regard, in analysis on migration as the outcome variable, I loosely also include the year 2010 as part of post-treatment period.

[36]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.

Figure 13: Event study comparing net-inward migration between exposed and non-exposed ditricts: palm-oil price shocks



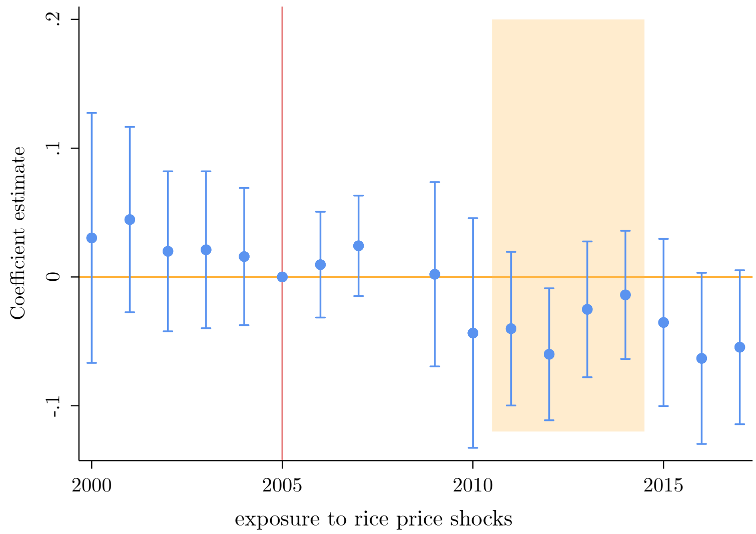
Notes: Dependent variable is the net-inward migration. Model includes control variables, districts and year fixed-effects. Regression is run on panel of districts over year. Standard errors are clustered in district-level. Point estimates are relative to year 2005, the omitted category. The 95% confidence 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 by palm-oil price shocks become more attractive for labor to move to these regions. Since we find that labor respond to incentive to move to booming regions, the price shocks were also no longer fully localized.

5.3 Exposure to rice price shocks

Districts exposed with rice price shocks, in contrast, did not enjoy higher real expenditure per capita relative to the base year compared to the non-exposed districts. Figure 14 plots the estimated β_{jr}s and their respective 95% confidence intervals for the rice price shocks from running 30. These coefficients represent the average difference between exposed and non-exposed districts. This is the first indication that price shocks from rice price seem to be also absorbed as an increase in the cost of basket of consumption. Thus, despite the price shocks may benefit producers of rice, there is no real increase in purchasing power.

Figure 14: Event study on average impact of expsoure to rice price shocks



Notes: Dependent variable is the log of (district average) real expenditure per capita. 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.

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.15 plots the coefficients on rice price shocks and their 95% confidence interval. Confirming the previous result, districts exposed by rice-price shocks on average do not have significant difference with the non-exposed ones in both agriculture households and non-agriculture households.

In order to capture any heterogeneity, I also run 31 on agriculture and non-agriculture households. Figure A.16 and Figure A.18 in Appendix depicts the coefficients for consecutively agriculture and non-agriculture households. In these figure, each coefficient shows the difference for a particular tercile g of shocks j in year $r$compared to the non-exposed districts relative to year 2005.

The impact of rice price shocks are more pronounced in non-agriculture households. In particular, 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. However, there is no significant difference between districts exposed to rice price shocks in any of its tercile compared to the non-exposed ones for agriculture households. This result on rice price shocks imply that if the import restriction is intended to provide stimulus to rice producers, the policy seems to be ineffective in achieving such objective. 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 also part of consumers of rice, the increase in rice price may not increase their purchasing power unless they are big enough farmers.

5.4 Spillovers to non-exposed districts

Booming districts may also demand more goods and services from nearby districts since its cheaper to purchase from nearest ones due to lower transportation costs and transaction costs. For this last set of econometrics exercise, I focus on the exposure to palm-oil shocks which so far show significant impacts 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.

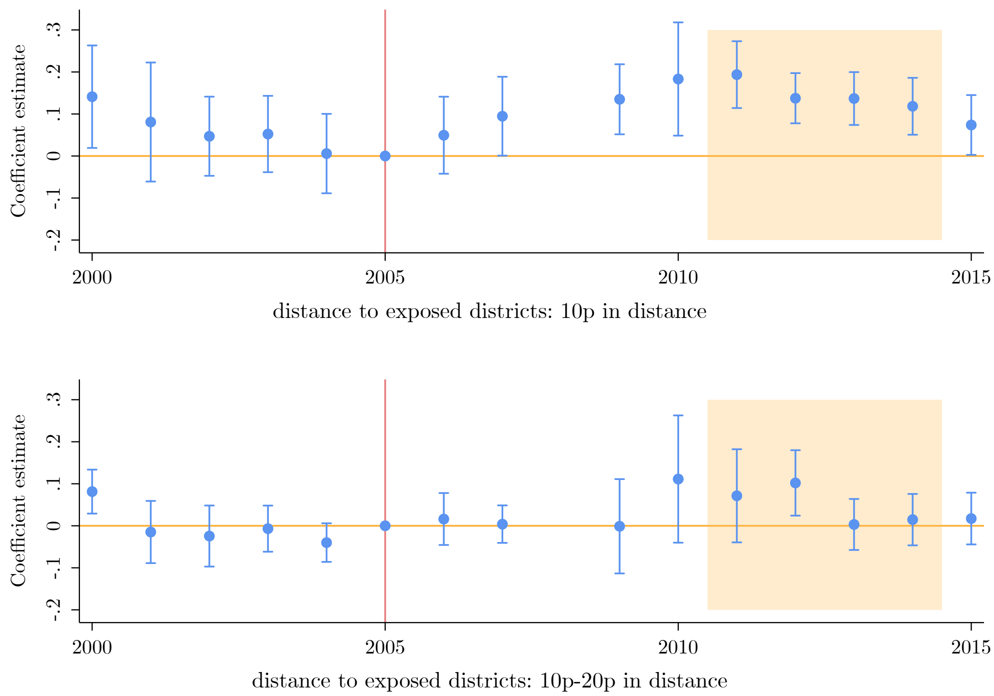
$$y_{dt} = \alpha + \sum_{g \in 1,2,3,4} \sum_{r \neq 2005} \beta_{gr} \left(I^{g}_{dt} \cdot \mathbb{1} \left(year_r = t \right) \right) + \delta^{rice}_{d} + \boldsymbol{\gamma X_d} + \delta_d + \delta_t + \nu_{dt} \tag{32}$$

In equation 32, the outcome variables are real expenditure 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 by the palm-oil price shocks. In order to capture heterogeneity due to proximity to exposed districts, I created four dummy variables. Each dummy variable indicate each four lowest percentiles of minimum distance to exposed districts.[37] 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 by palm-oil price shocks also have 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 positive difference compared to the control group. Although it is only statistically significant in 2012 with 10 log points difference to the control group.

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

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

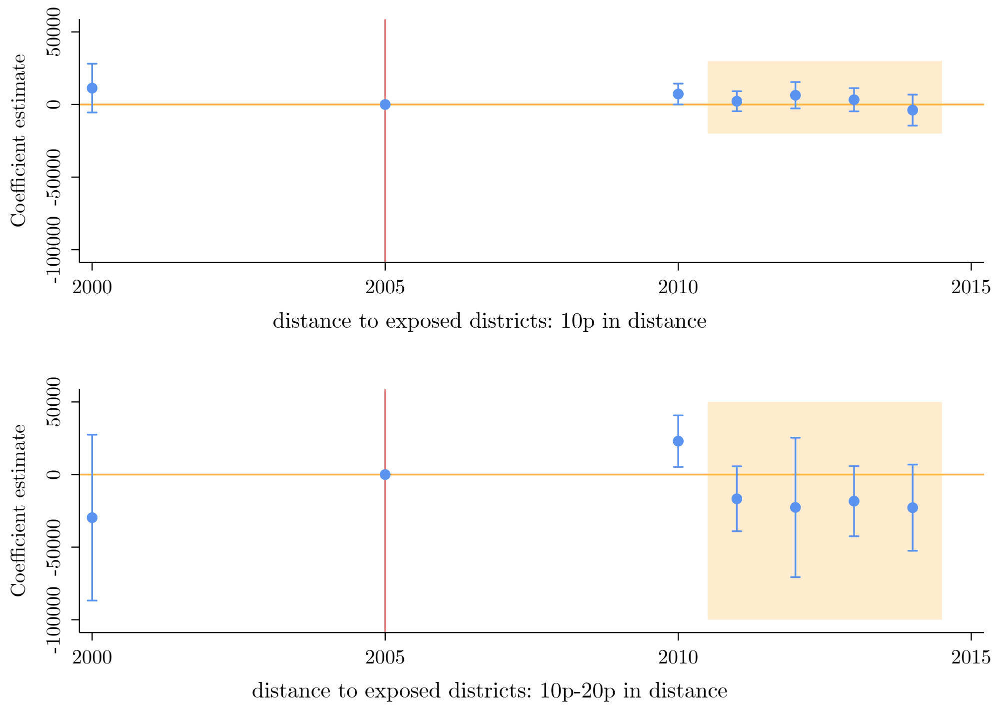


Notes: Dependent variable is (ln) real expenditure per capita. Model includes control variables, status of exposure of rice price shocks, districts and year fixed-effects. Regression is run on panel of districts that are non-exposed to palm-oil price shocks over year with population in 2011 as weights. 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 spillovers indicated by higher expenditure per capita in the neighboring districts of booming regions, I find also that the nearest non-exposed districst to districts exposed by 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 Result 7 above, labor seem to respond to better outcomes in these nearest districts. These districts receive more net-inward migration compared to the control group, although the coefficient is statistically significant only in 2010.[38]

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

Figure 16: Spillovers to districts non-exposed by palm-oil price shocks: net-inward migration



Notes: Dependent variable is number of net-inward migration. 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 to especially palm-oil price shocks benefit exposed districts for some years in post-treatment period. I show also that as these districts become relatively richer, they also attracted more inward migration. In addition, non-palm oil producing districts that are nearest neighbors to producing districts also benefit from the boom as it also had higher expenditure per capita in post-treatment period. In contrast, rice price shocks stemmed from trade protection did not provide significant stimulus to producing districts.

All of these results show evidence that the impact of exogenous trade shocks can no longer be localized. In particular, the shocks may last long enough and were big enough in terms of the magnitude that factors of production also respond to the shocks. In this subsection, I provide several mechanism focusing on the response of factors of production. First, I provide justification that labor do respond through internal migration by analyzing district premia. Second, since I focus on agricultural commodities, I analyze two possible ways in which agriculture sector expands: extensification by land expansion and intensification by increasing yield. I find that palm-oil as the booming crop grew by land expansion with no evidence of significant intensification. Meanwhile, I also find no evidence of land expansion nor increase in yield for rice. This result particularly provides some light on the ineffectiveness of trade protection in stimulating production for rice.

5.5.1 District premia

One may argue that perhaps, structurally, districts exposed by palm-oil price shocks have different labor 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 there maybe frictions in labor mobility that prevents this equalization force. In order to control for labor characteristics and to see whether there is any inherent frictions, I run a Mincerian-type regression on household-level expenditure per capita by controlling with the 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 and with age between 15-61. 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.

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

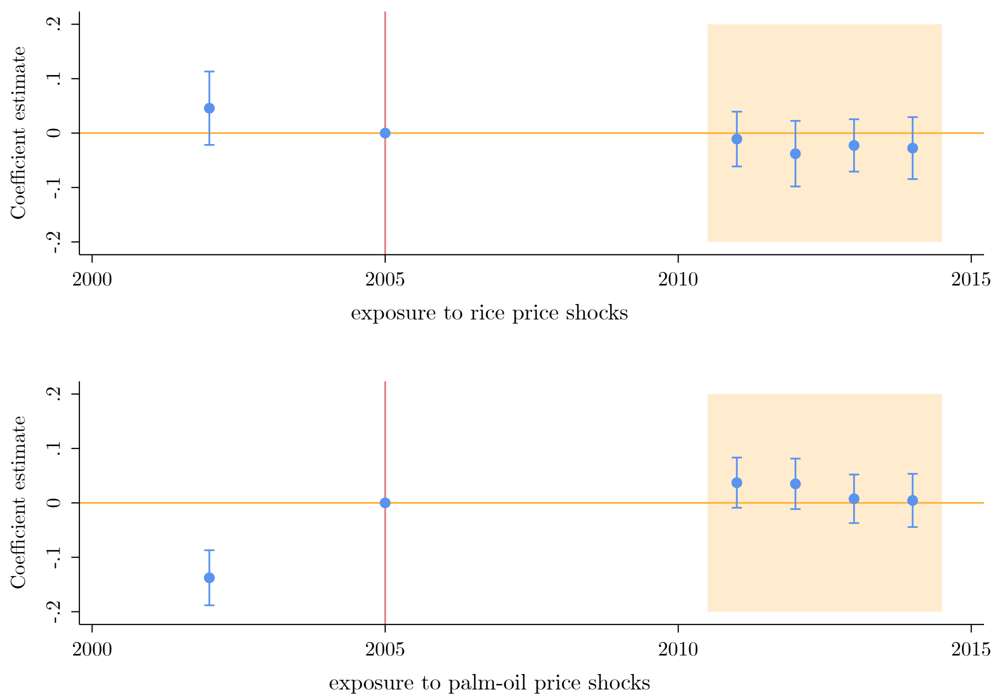
The outcome variable is individu ω's real expenditure per capita, living in district d. I include the vector of the household head's controls such as years of education, years of experience and years of experience squared. I follow the method used by Dix-Carneiro and Kovak (2017) by running this regression separately for each year $t \in [2002, 2005, 2011, 2012, 2013, 2014]$[39] and take the estimated district fixed effects as the district premia. Note that I also add fixed effects for sector of employment, status of employment (self employed, employee, etc.). 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. I collect district premia from the estimated distict fixed effects by running the mincerian regressions. Thus, the district premia explain the premium of just being in a particular district.

Using the estimated district premia as the outcome variable, I run equation 30. Figure 17 shows the estimated coefficients of interest that shows the difference on district premia between exposed and nonexposed district. Both sets of coefficents on exposure to shocks by rice price and palm-oil price are not statistically different from zero. This result implies that after controlling labor composition as well as sector premium, there is no significant difference between the exposed and non-exposed district. This result on district premia basically says that the positive impact of palm-oil price shocks on exposed districts are not driven by labor market friction that may amplify local shocks (for example as in Dix-Carneiro and Kovak (2017) for the case of the impact of trade

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

liberalization in Brazil). This result also implies that there may not be frictions that are significant enough to prevent people from moving in order for the district premia to equalize across districts. Hence, conditioning on the labor and sectoral composition, there is no significant difference in purchasing power provided by living in a particular district.

Figure 17: Event study comparing district premium between exposed and non-exposed ditricts



Notes: Dependent variable is the estimated district premia obtained from running mincerian regression on real expenditure per capita at the household level. 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.

5.5.2 Extensification versus intensification

In order to see 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 two-period panel of districts to see the difference before and after the price shocks. In particular, I use the year 2001 as pre-shocks period and 2011 as post.

Palm-oil crop expanded through extensification. Table A.5 shows that especially for the bottom tercile of exposed districts, the coefficients for post-period on harvested area are positive and significant. Given that there are 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 that we learn above.

Meanwhile, there is no indication that palm-oil crop expanded through intensification. Table A.7 shows that the coefficients for post-period on actual yield are not significantly different from zero. This result also justifies the robustness of the palm-oil price shocks as exogenous shocks. In this regard, as the commodity boom did not last forever, the impact of the price shocks due to the boom also resigned as the boom resumed. It may also provide some cautions to policy makers that palm-oil sector may not provide sustainable source of growth if the sector keep relying growth from land expansion.

On the other hand, rice crop 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 that we cover 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. This result provides some evidence on ineffectiveness of the trade protection on rice in stimulating production of rice.

6 Quantitative simulation

In this section, I quantify the welfare changes occured in the period between 2005 and 2010. I use the decomposition of welfare changes that I derived in the section on 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 Inter-province Input Output Table to estimate these gains. I estimate that there was a 0.39% increase in welfare between 2005 and 2010. 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 Estimation

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 sources of datasets. 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.

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

Next, I assume the value of parameters as shown in Table 6 below. I use conservative values for 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	Frechet parameter for productivity	4
ϵ	Frechet parameter for amenity	3

Lastly, in order to be able to estimate the gains from trade, I need to have data on domestic (regional) trade shares, π_{nn}, in order to get the aggregate domestic trade shares, π. Since there is no data on inter-district trade, I use a more aggregate version of inter-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).

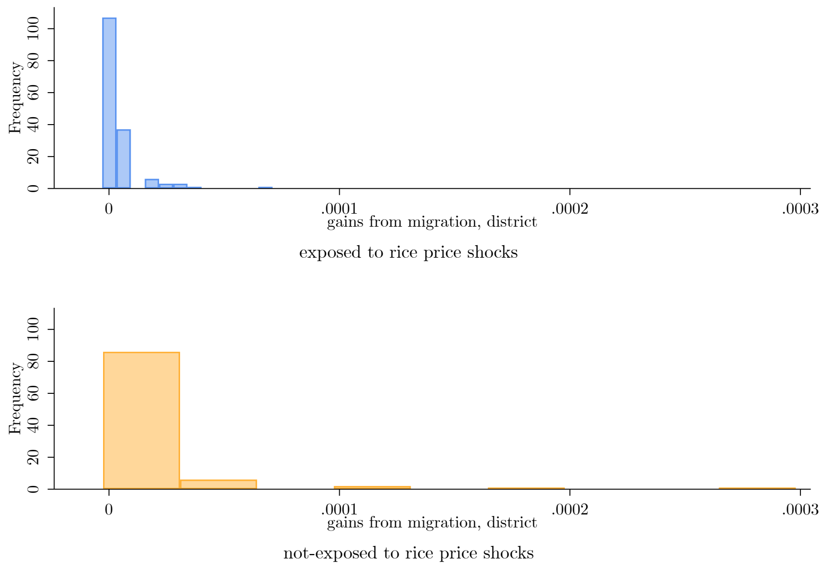
Armed with data on expenditure shares, population shares, domestic trade shares as well as the parameters, I compute gains from migration for each district and terms-of-trade gains for each province.

6.2 Results

The total welfare gains over the period of 2005-2010 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.

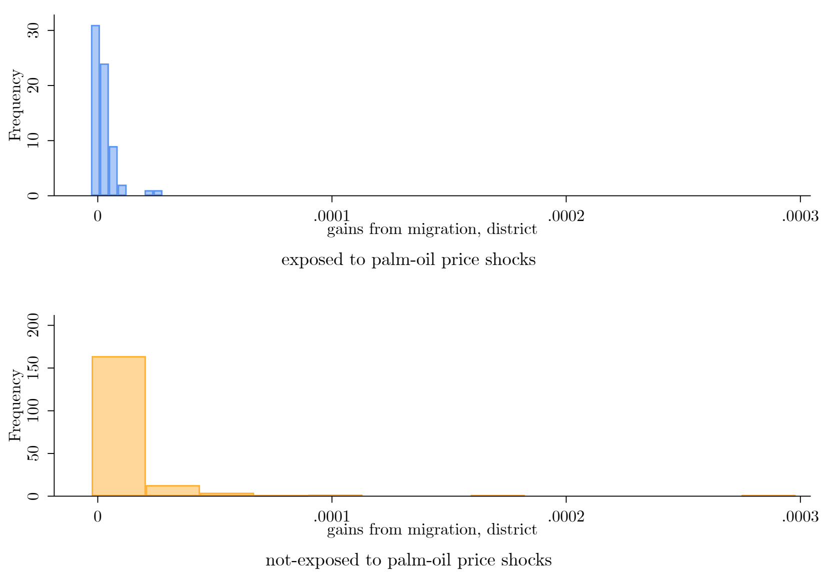
Gains from migration Figure 18 and Figure 19 below show the distribution of gains from migration across districts classified by consecutively exposure to rice price shocks and exposure to palm-oil price shocks. There is no significant difference between the distribution of gains from migration according to status of exposure to shocks. Districts with higher expenditure shares attract more people, while districts which let go labors also gain if their expenditure shares is lower from the population shares. This result in regard to the distribution is not surprising as exactly due to labor mobility, welfare equalizes across districts. In equilibrium state, the expected utility from living in any district should be the same everywhere.

Figure 18: Distribution of gains from migration by exposure to price shocks: rice price shocks



Notes: The graphs show the distribution of gains from migration at the district level. I exclude districts in the bottom and top percentiles to better compare the distribution in visuals. The gains from migration is estimated using equation 34. The value of gains from migration refer to the proportional changes to initial level in 2005-2006.

Figure 19: Distribution of gains from migration by exposure to price shocks: palm-oil price shocks



Notes: The graphs show the distribution of gains from migration at the district level. I exclude districts in the bottom and top percentiles to better compare the distribution in visuals. The gains from migration is estimated using equation 34. The value of gains from migration refer to the proportional changes to initial level in 2005-2006.

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. Several palm-oil producers are main contributors for the gains, such as Kalimantan Selatan, Kalimantan Timur, Kalimantan Barat and Sumatera Utara. However, some others experienced loss such as Jambi and Riau. Meanwhile, main rice producers experienced loss such as Jawa Barat, Jawa Tengah, and Jawa Timur.

This result is 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 increase their domestric trade shares in 2010 compared to 2005 as they may have not been able to enjoy some terms-of-trade gains (also compared to other provinces) as the real price of their product, i.e. rice, did not increase much compared to goods and services that they import from other provinces.

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 from both factors using the context of Indonesia in the 2000s. In this period, the economy experienced two massive price shocks. First, as primary commodity producers, it received windfall from the commodity boom in the 2000s. Second, it 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 booming regions. In particular, I study the impact of price shocks to different districts when there is labor mobility across districts.

I present three main findings. First, price shocks on palm oil benefit producing districts with higher real expenditure per capita, while price shocks on rice not. As an income crop, price shocks on palm oil may increase purchasing power more than price shocks to rice. An increase in price of rice may not increase purchasing power by much as it also increases the price of the consumption basket. Meanwhile, exposure to palm-oil price shocks appears as income shocks. Responding to higher real expenditure per capita in districts exposed with palm-oil price shocks, I find also that these districts attract more net-inward migration.

The second main result is that there is evidence of spillovers of the shocks to non-exposed districts. In particular, non-exposedd district nearest to districts exposed by palm-oil price shocks also experienced higher real expenditure per capita and net-inward migration. The intuition 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 near sources.

Third, I estimate that there is 0.39% welfare increase between 2005 and 2010. One-third of the welfare gains during the period of interest is associated to gains from migration. Meanwhile, gains from trade accounts for the rest two-third of the welfare increase. This results sheds light on the importance of taking into account internal migration in welfare analysis.

With these results, this paper provides micro-evidence of the impact of macro shocks and how these shocks diffuse. I show that one important channel of this diffusion is internal migration. I would like to draw also two other lessons from the study. First, it matters greatly how macro shocks pass through domestic price of consumption basket. The case of palm-oil and rice contrasts two cases when price shocks are pass through less to the cost of living in palm-oil and more in rice. Given the high pass-through of rice price shocks as well, import restriction that aims to stimulate production may not be effective. Second, as we can follow the performance of district economy over time, we also observe the cyclicality of world shocks and how the cyclicality is also observed in micro-level, e.g. average household in districts. This may provide avenue for social planner to conduct aggregate savings in times of boom and desavings in times of bust. But such study is beyond the scope of this paper. This cyclicality also raises the question how countries or even particularly districts can transform the windfall as investment to increase productivity to sustain growth after the boom is over. For the case of Indonesia, the increase in price of palm oil incentivizes the sector's growth. In particular, the growth was spurred by land expansion and no significant increase in yield. Hence, as the boom resumes, we see evidence that districts exposed by palm-oil shocks do not necessarily enjoy higher growth as during the boom.

This paper is so far agnostic on the environmental impact of the price shocks. One of the crops of interest, palm oil, has grown to be a controversial crop. Edwards (2018) for example show the trade-off between poverty reduction and deforestation in districts producing palm oil in Indonesia. I find so far that the gain has been relatively short compared to the length of the boom and has not been expanded to the period when the commodity boom started to slow down in 2014. In addition, it is questionable whether the palm-oil sector can grow sustainably by relying on the business-as-usual extensification strategy.

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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 disctricts definition 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 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 is 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 pre-2011 period. The estimation of district premia in pre-2011 period is also possible every three years. Nevertheless, due to insufficient representativeness in the invidual matched sample in 2008, I do not include 2008 for district premia estimation.

A.2.1 Non-agriculture and agriculture households

I define wheher 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 5 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 10% sample of the complete census and is representative up to 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) 4-5 percent 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 rie 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.[40] 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.

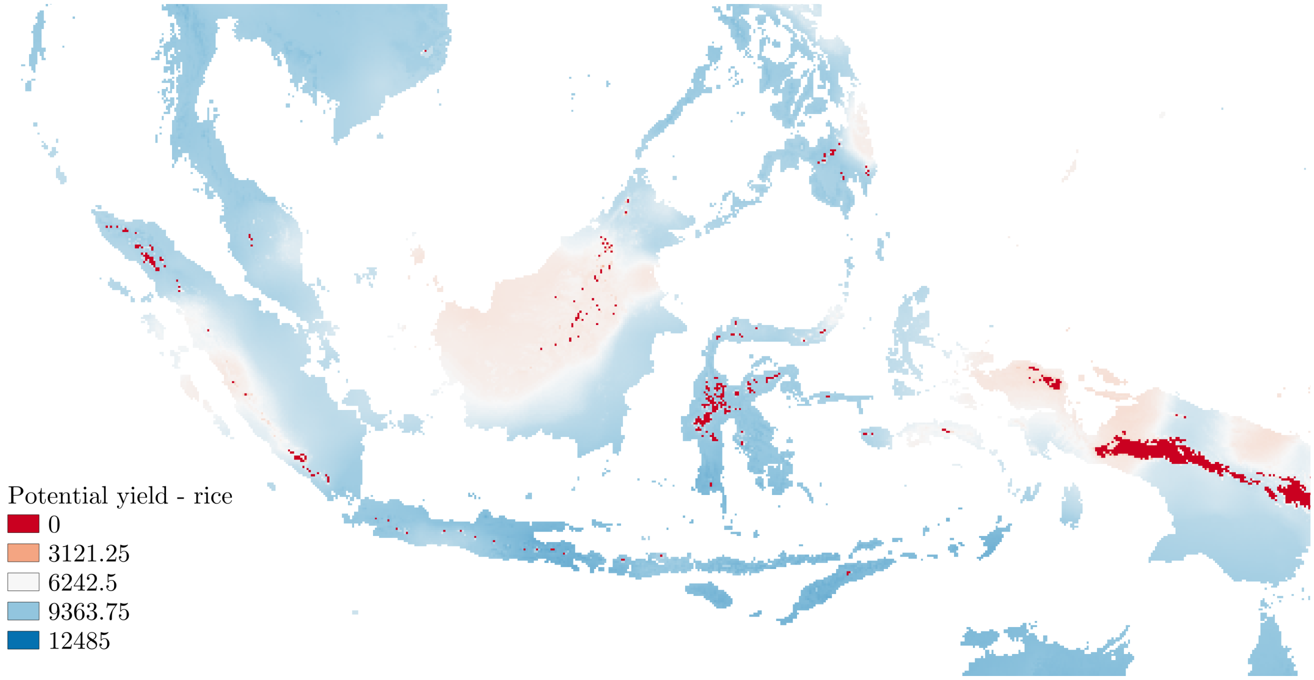
Table A.2: Assumptions on water supply and input level

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

Raw data from FAO GAEZ is presented in 5-grid level raster data. Figure A.3 and Figure A.1 show the raw potetial yield data for respectively palm oil and rice in Indonesia and its surrounding. 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 one pixel. Figure A.2 shows the distribution of the district-average potential yield for rice. Meanwhile, Figure A.4 shows the distribution of the district-average potential yield for palm oil.

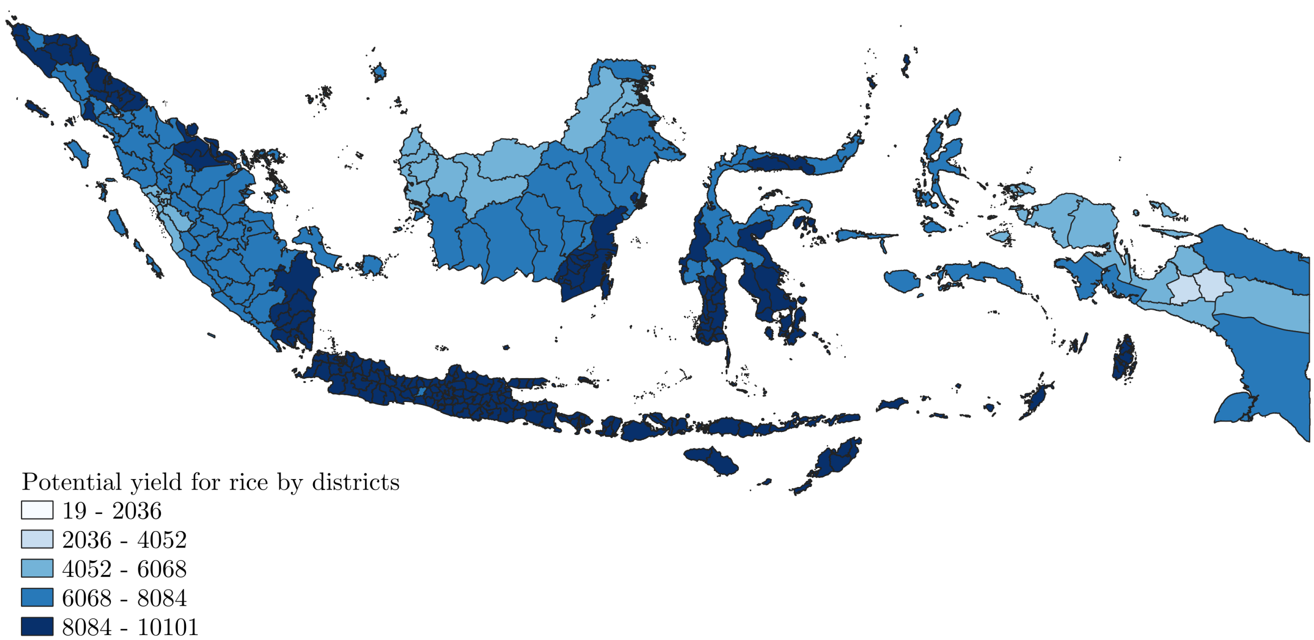
[40] Data can be dowloaded here : http://www.fao.org/nr/gaez/en/.

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



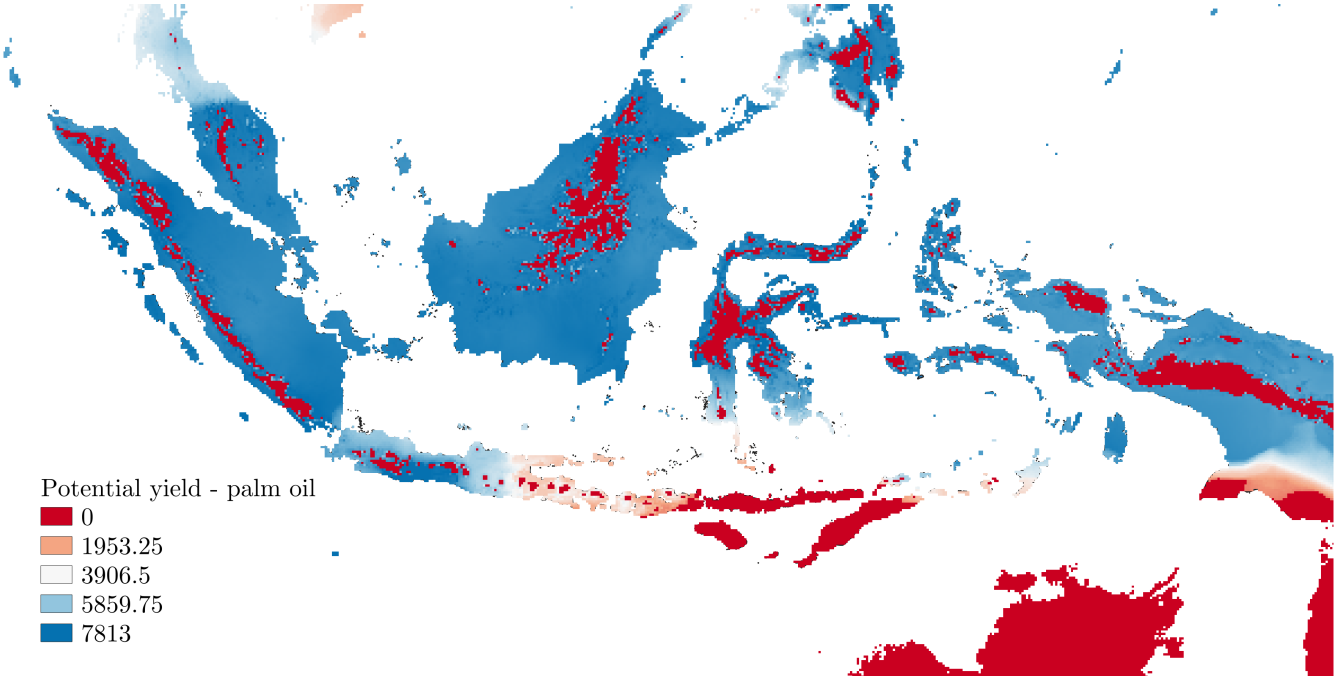
Source: FAO GAEZ.
Notes: Potential yield is in kg DW/ha.

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



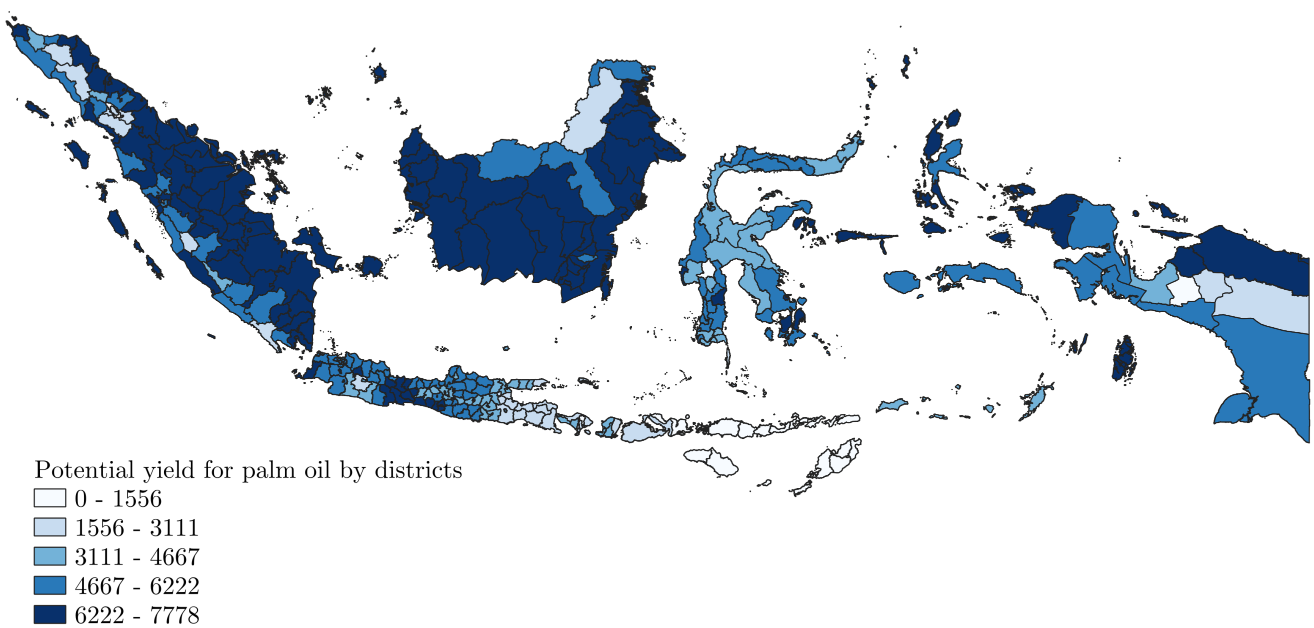
Source: FAO GAEZ, author's calculation.
Notes: Potential yield is in kg DW/ha. Districts use the district definition in 2000.

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)



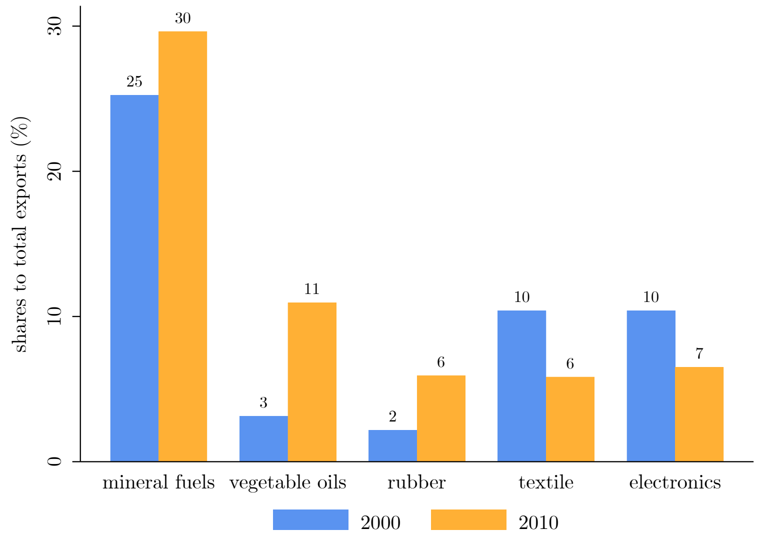
Source: FAO GAEZ, author's calculation.
Notes: Potential yield is in kg DW/ha. Districts use the district definition in 2000.

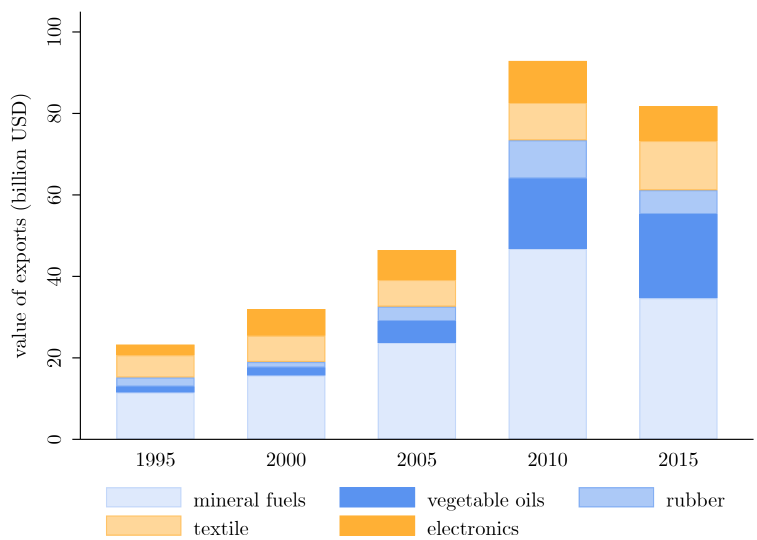
A.7 Village Census (*Podes*)

Podes is a triannual census covering information of social, economic and geographic condition of all villages in Indonesia. It includes questions on demography, 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 5-year 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

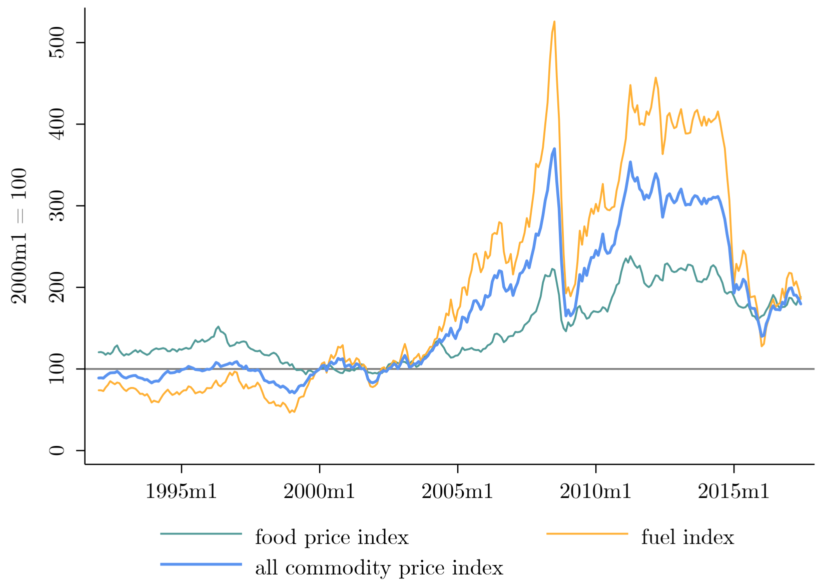




Source: UNCOMTRADE, authors calculation.
Notes: Mineral fuels refer to HS 27, vegetable oils refer to HS 15, rubber refers to HS 40, textile etc. refer to HS 61 to HS 64, electronics refer to HS 85. These figures show selected export goods. Hence their shares do not add up to 100 percent.

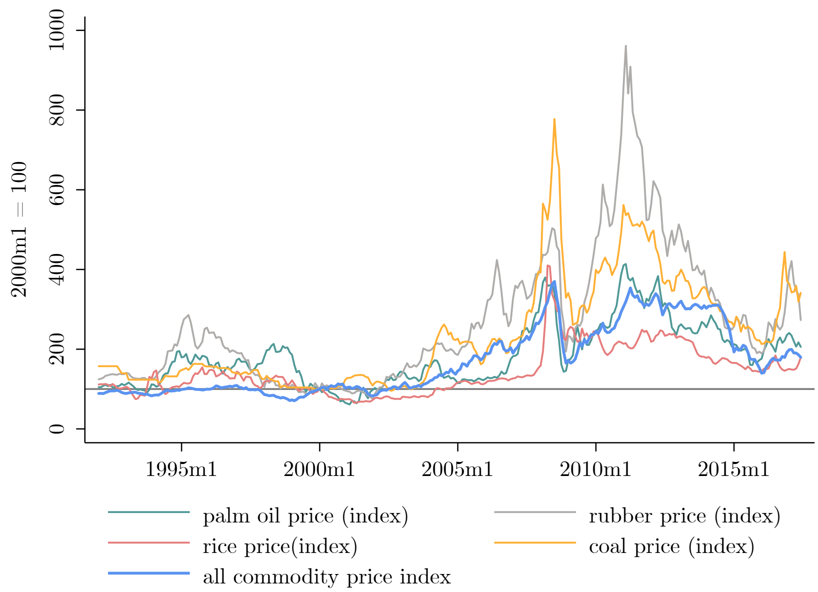
C The Commodity Boom in the 2000s and Rice Import-Restriction Era in Indonesia

Figure A.6: Trend of main world price indices



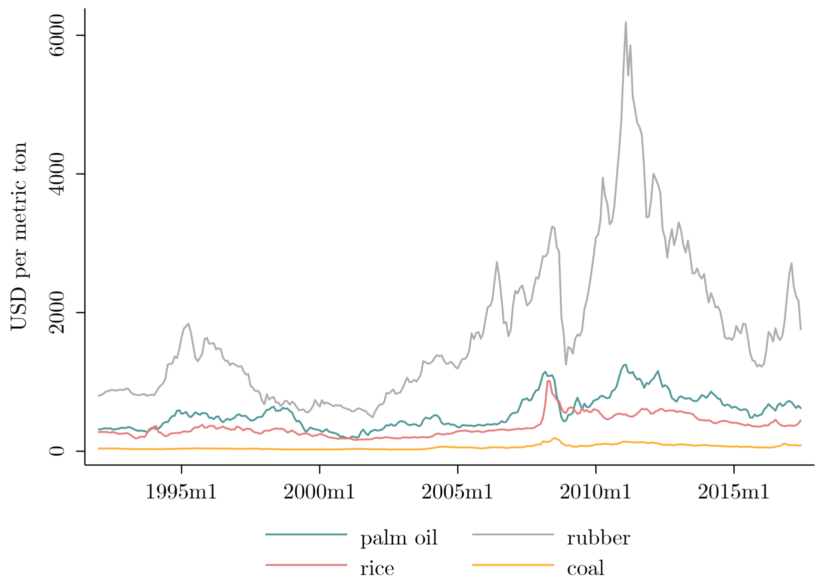
Source: IMF Commodity Price Series.

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

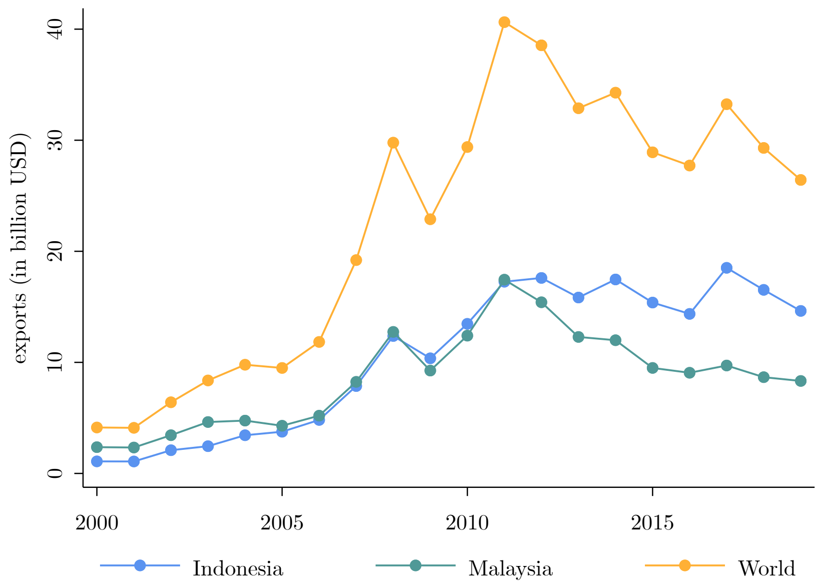


Source: IMF Commodity Price Series.

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

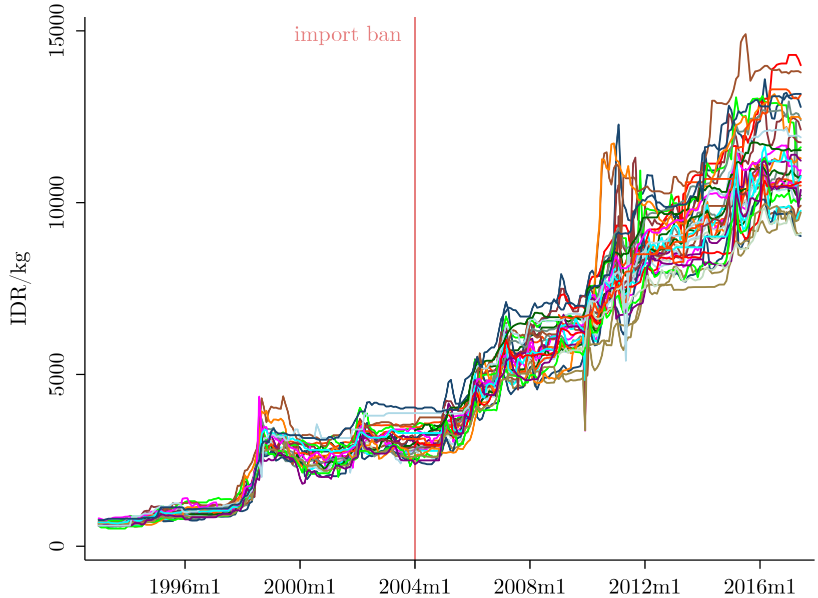
Source: UNCOMTRADE, author's calculation.
Notes: Rubber refers to HS 4001. Coal refers to HS 2701.

Figure A.10: Trend of palm-oil exports



Source: UNCOMTRADE.

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



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

D Exposure to price shocks

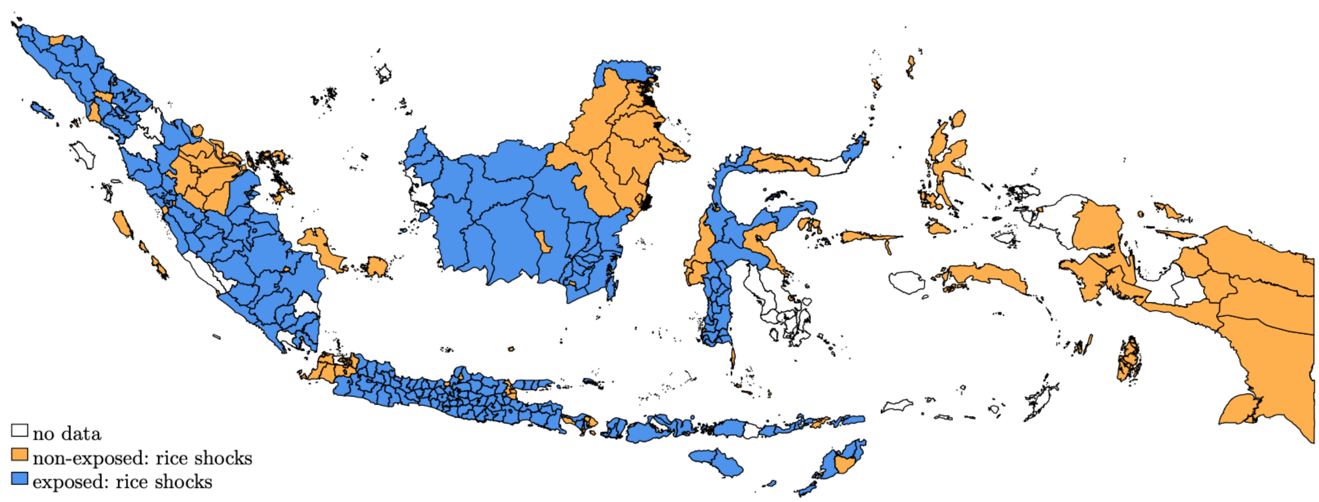
D.1 Summary statistics

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

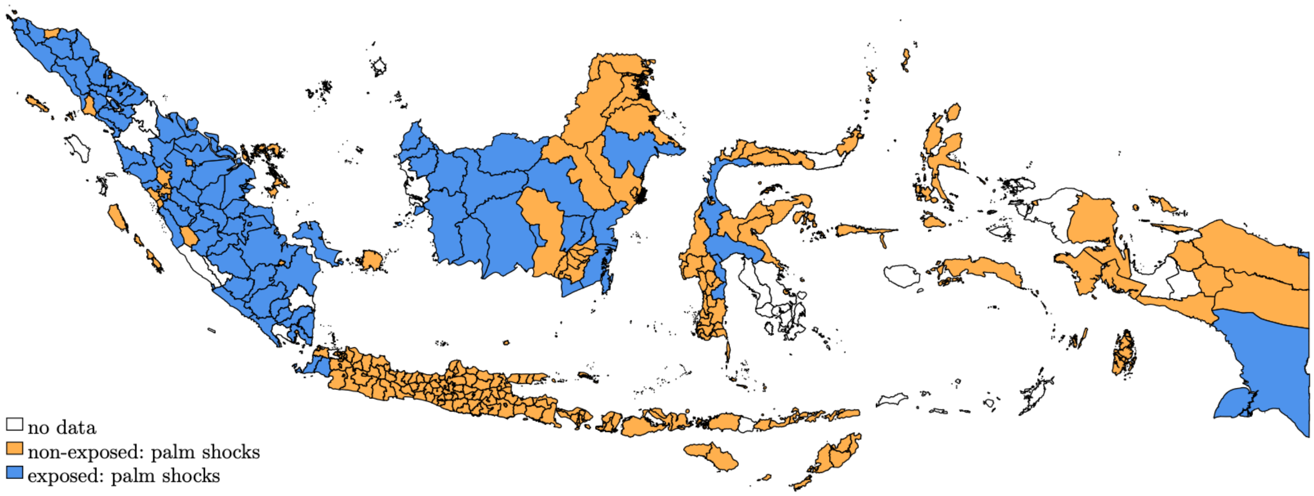
D.2 Exposed and non-exposed districts

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.

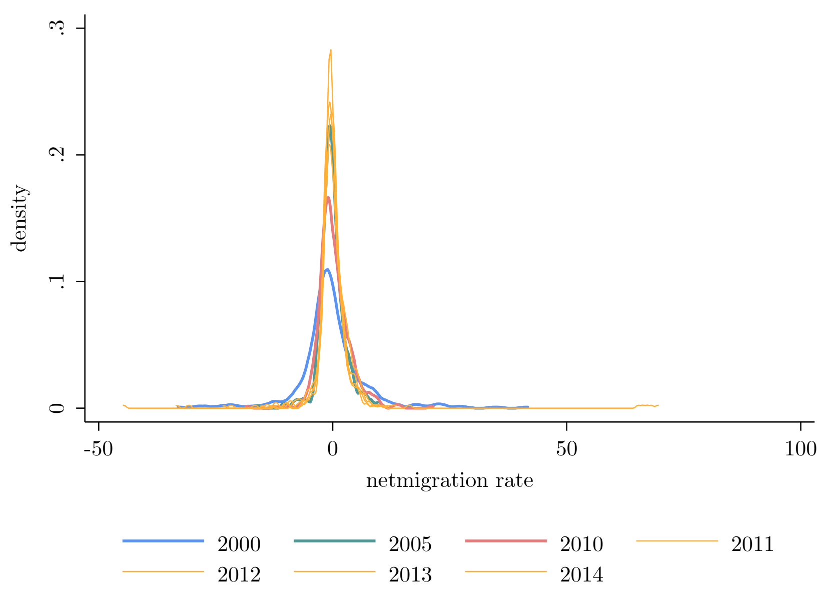
Figure A.13: Exposed and non-exposed districts: palm-oil price shocks



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

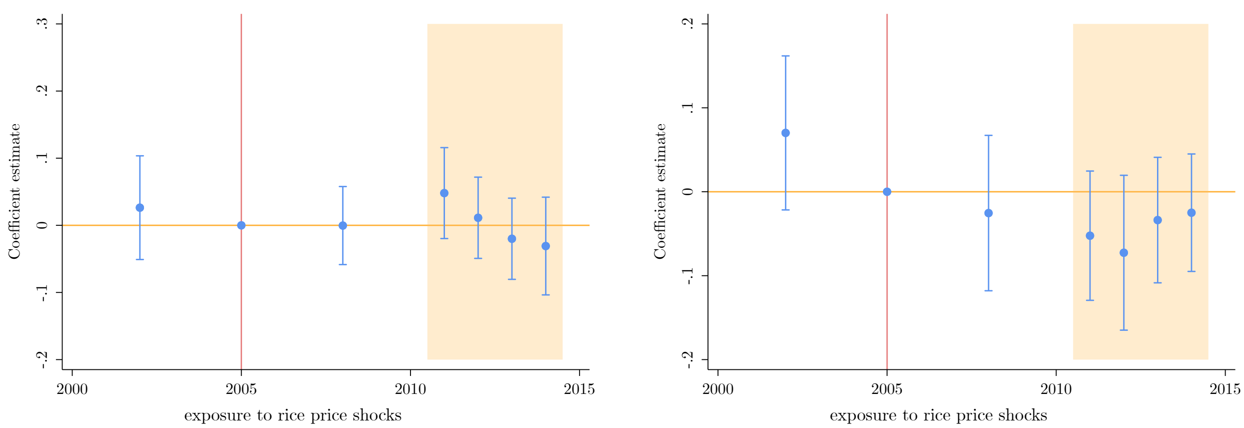
Sources: Population Census 2000 and 2010 from IPUMS for year 2000 and 2010, Inter-census Population Survey 2005 for 2005 from IPUMS, *Susenas* for 2011-2014. Author's calculation.

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

F Econometrics results

F.1 Impact of rice price shocks

Figure A.15: Impact of rice price shocks: agriculture households and nonagriculture household



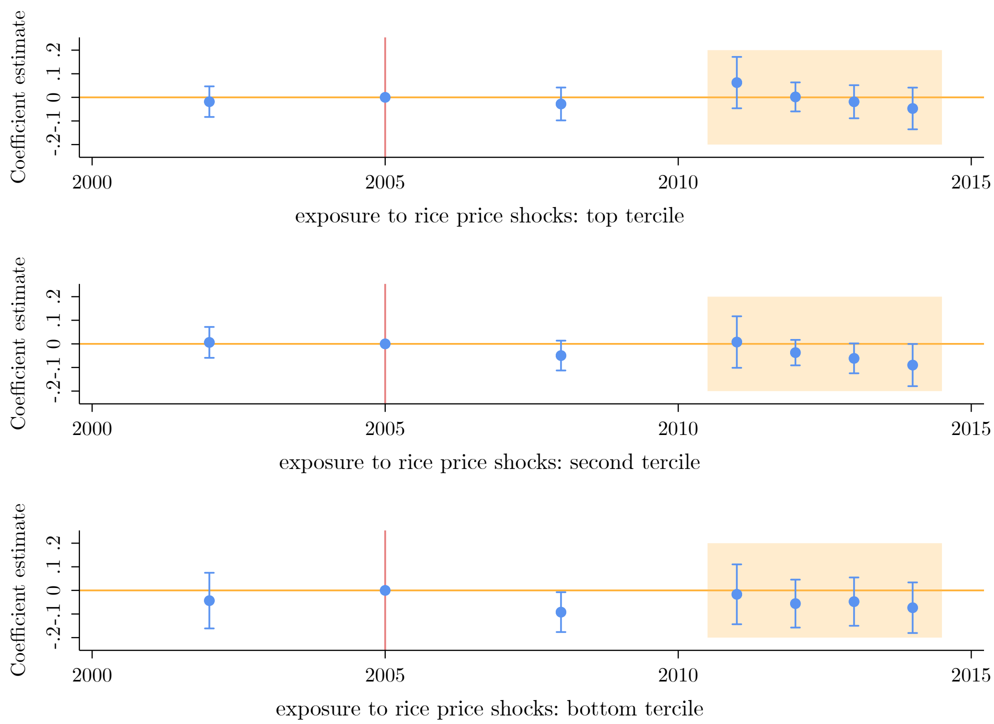
(a) agriculture households

(b) nonagriculture households

Notes: Dependent variable is the log of (district average) expenditure per capita of agriculture households and non-agriculture households. 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.

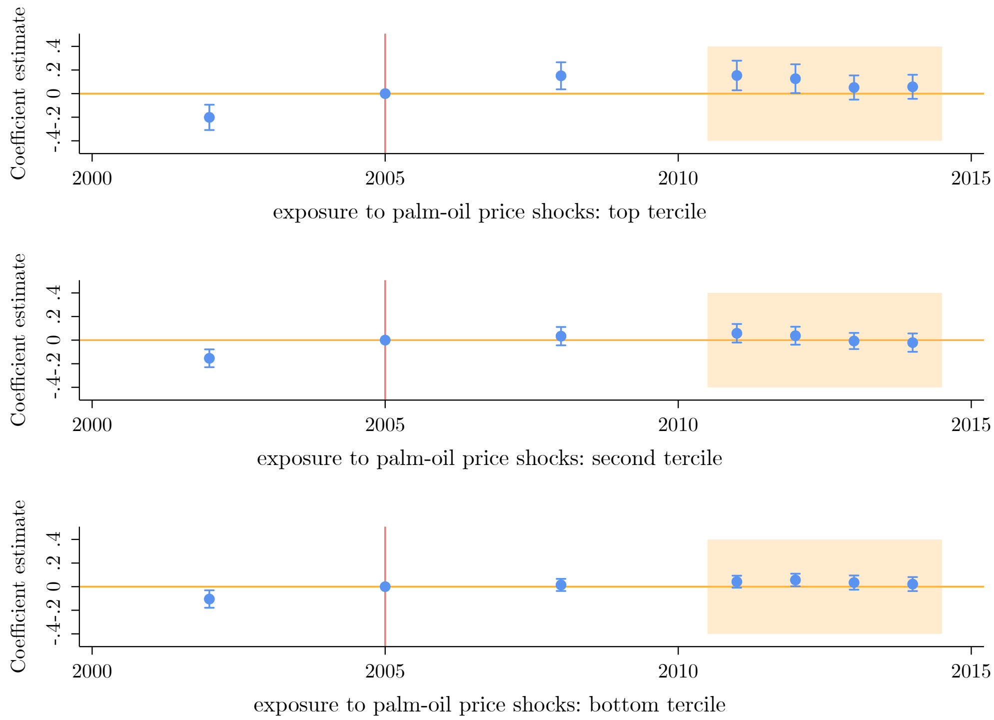
F.2 Results for agriculture households across groups of exposed districts

Figure A.16: Impact of exposure to rice price shocks to real expenditure per capita of agriculture households



Notes: Dependent variable is (ln) real expenditure per capita of agriculture households. 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.

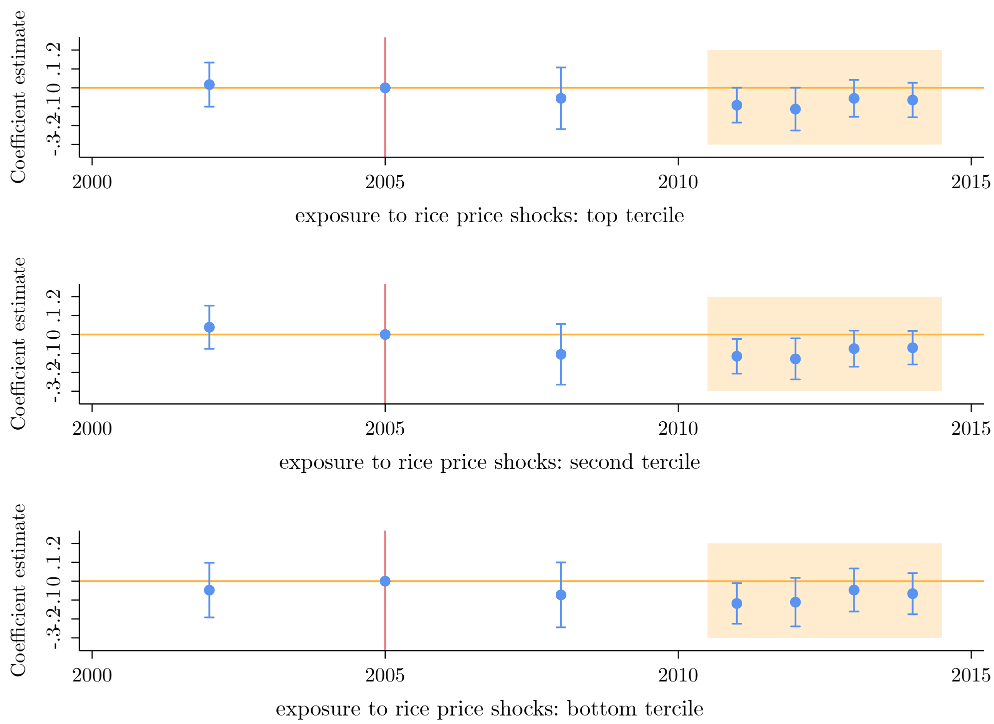
Figure A.17: Impact of exposure to palm-oil price shocks to real expenditure per capita of agriculture households



Notes: Dependent variable is (ln) real expenditure per capita of agriculture households. 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.s

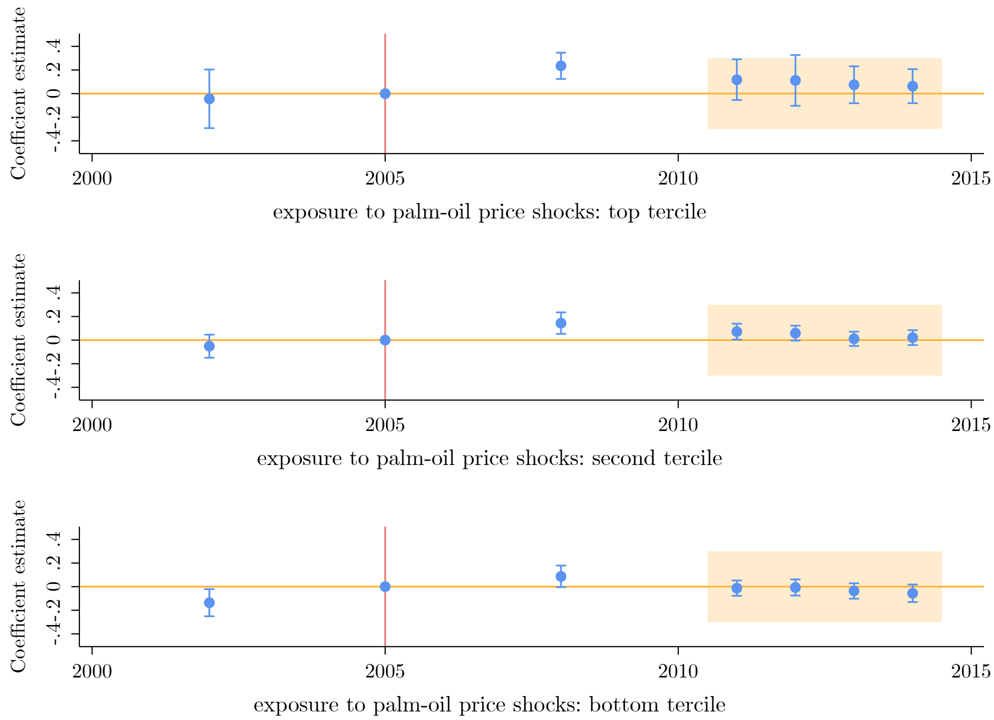
F.3 Results for non-agriculture households across groups of exposed districts

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



Notes: Dependent variable is (ln) real expenditure per capita of non-agriculture households. 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 palm-oil price shocks to real expenditure per capita of non-agriculture households



Notes: Dependent variable is (ln) real expenditure per capita of non-agriculture households. 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.4 Crop extensification: expansion on land for crops

Table A.5: Crop extensification: palm-oil

	Dep. var: harvested area		
	(1)	(2)	(3)
palm shocks, tercile=1 × year=2011	2.195***	2.195***	2.195***
	(0.546)	(0.547)	(0.549)
palm shocks, tercile=2 × year=2011	0.248	0.251	0.251
	(0.273)	(0.274)	(0.275)
palm shocks, tercile=3 × year=2011	0	0	0
	(.)	(.)	(.)
(ln) potential yield		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: 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. I use robust standard error.

Table A.6: Crop extensification: rice

	Dep. var: harvested area		
	(1)	(2)	(3)
rice shocks, tercile=1 × year=2011	0.00268	0.00381	0.00380
	(0.087)	(0.087)	(0.087)
rice shocks, tercile=2 × year=2011	0.0511	0.0511	0.0511
	(0.053)	(0.053)	(0.053)
rice shocks, tercile=3 × year=2011	0	0	0
	(.)	(.)	(.)
(ln) potential yield		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: 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. I use robust standard error.

F.5 Intensification: actual yield of crops

Table A.7: Robustness check: actual yield for palm oil

	Dep. var: actual yield		
	(1)	(2)	(3)
palm oil shocks, tertile=1 × year=2011	0	0	0
	(.)	(.)	(.)
palm oil shocks, tertile=2 × year=2011	-0.197	-0.196	-0.239
	(0.539)	(0.550)	(0.553)
palm oil shocks, tertile=3 × year=2011	-0.513	-0.512	-0.556
	(0.546)	(0.561)	(0.562)
(ln) potential yield		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: 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. I use robust standard error.

Table A.8: Robustness check: actual yield for rice

	Dep. var: actual yield		
	(1)	(2)	(3)
rice shocks, tertile=1 × year=2011	0	0	0
	(.)	(.)	(.)
rice shocks, tertile=2 × year=2011	0.125	0.125	0.125
	(0.163)	(0.163)	(0.163)
rice shocks, tertile=3 × year=2011	-0.100	-0.101	-0.101
	(0.083)	(0.083)	(0.083)
(ln) potential yield		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: 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. I use robust standard error.

G 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