Global prices and internal migration: Evidence from the palm oil boom in Indonesia*

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Abstract

I study how regions respond to price shocks in the presence of internal migration. I examine Indonesia in the 2000s as it faced a commodity boom for palm oil, which became one of its main export commodities. I exploit the variation in the land shares and crop suitability to compute the potential contribution of main crops across district economies as a measure of local exposure to shocks. I find that the commodity boom increased the purchasing power of palm oil-producing districts. These districts also received more migration, providing evidence that palm oil price shocks were no longer localized. Indeed, internal migration spread the windfall. I also find spillover to neighboring districts. However, these relatively higher levels of purchasing power did not last after the commodity boom ended in 2014. I show that the palm-oil sector grew through extensification as a response to the price shocks, with no indication of growth through intensification. I estimate the overall welfare gains in Indonesia between 2005 and 2010 and find substantial gains from migration.

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1 Introduction

Many developing economies are primary-commodities producers that face trade shocks from global price fluctuations. International macro literatures have shown that the impact of these fluctuations is not trivial. For example, Fernández et al. (2017) show that 30% of domestic output fluctuations are driven by world shocks that stem from commodity prices. In theory, labor market can respond directly to these fluctuations by moving to booming sector or regions. However, many empirical studies show that trade shocks are usually localized, i.e., labor does not response by moving. Meanwhile, Lucas (2015) documents that one out of ten people in the world is an internal migrant. In developing countries, the intensity of internal migration ranges from as low as 6% in India to as high as almost 50% in Chile. Therefore, understanding how labor responds through mobility in the face of price shocks in international trade is an important question for many developing countries.

The goal of this paper is to study how a multi-region economy responds to price shocks stemming from commodity prices in the presence of internal migration. I take the context of Indonesia as it faced a commodity boom in the 2000s. I fill the gap in the literature by providing evidence of trade shocks that are no longer localized, especially when these trade shocks are advantageous to local income. Many studies on the impact of trade shocks use import shocks that deteriorate income.[1] If there are fixed migration costs or cash-in-advance constraints in migration, then we may not see much response through migration in the face of trade shocks that hurt income. Specifically, I show that internal migration diffuses trade shocks stemming from the commodity boom as people move to palm oil-producing districts.

This paper also contributes to the development policy discourse. I show that the windfall from the commodity boom was short-lived. This paper is the first to document the impact of fluctuations in global prices on welfare indicators over time. It is important to emphasize that this temporary windfall stands in contrast to the longer-run cost imposed by the well-documented deforestation driven by palm oil expansion.[2] This evidence can inform policymakers, including local leaders who have substantial decision-making power over land concessions. The findings also suggest cautions about exchange rate management for the monetary authority, given the importance of primary commodities, including palm oil, as a source of foreign reserves.

Indonesia is an excellent context for studying the impact of price shocks in developing economies for at least three reasons. First, Indonesia is a large country, in terms of population, size and area, but it is mostly a price-taker in the world market. Thus, Indonesia shares with most developing

[1]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.

[2]Hansen et al. (2013) show that Indonesia experienced the world's largest increase in forest loss in 2000-2012. Meanwhile, Austin et al. (2019) show that palm oil plantation was the largest single driver of deforestation in Indonesia for the period from 2001 to 2016. Globally, commodity-driven deforestation has been rampant, accounting for an estimated 27% of the world's forest loss (Curtis et al., 2018).

economies the feature of being a small-open economy. Second, there is a wide heterogeneity in comparative advantage across regions in Indonesia. Hence, Indonesia provides the opportunity to study variation in the exposure to shocks in the face of uniform price shocks. Indeed, Indonesia's regionally representative data makes it possible to study the country as a multi-region economy. Third, there are no legal-restrictions on moving from one region to another in Indonesia. Regions do vary in terms of their level of amenities level, and people have heterogeneous preferences to live in certain regions. Nevertheless, it is plausible to regard residential choices as market-driven choices.[3]

To answer the research question, I perform a set of empirical and quantitative analyses guided by a theoretical framework that matches the context of Indonesia from 2000 to 2015. In particular, I collect three stylized facts that motivate the environment of the model. First, I choose the agriculture sector as the sector of interest, because farmers can adjust crop choices as they face changes in crop prices.[4] Districts with high shares of the agriculture sector also tend to be poorer, which means that districts have different starts before the exposure to price shocks. Second, I choose palm oil and rice as the main crops of interest because they share around half of the agricultural land in Indonesia. Third, the gravity equation on migration flows reveals that regions face upward-sloping labor supply. This result implies that labor moves to regions with higher earnings.

Armed with the three stylized facts, I build two theoretical frameworks as the foundation for the empirical and quantitative analysis. First, I combine a two-sector Specific Factor Model with the multi-region economy as in Redding (2016). I show that the impact of price shocks on regional wages depends on the share of the sector that experiences the increase in relative price. This result guides the measurement of local shocks in the empirical analysis. Second, I decompose the welfare changes in the multi-region economy model as in Redding (2016) into gains from migration and gains from trade. This result guides the quantitative analysis in estimating the overall changes in welfare in Indonesia between 2005 to 2010.

Defining districts as unit of regions, I construct a measure of exposure to price shocks for palm oil and rice based on the result of the theoretical framework. I compute local exposure to shocks using the potential share of palm oil and rice in district economies. In particular, I exploit the variation in crop suitability and pre-shocks harvested area. Armed with the computed local shocks, I employ the difference-in-difference method to estimate the impact of exposure to palm oil price shocks on two main outcome variables: real expenditure per capita as the main proxy for welfare and net-inward migration rate for labor-mobility outcome. I study the impact of the exposure to

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

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

price shocks on three margins: between exposed and non-exposed, heterogeneity in exposure and spillover to non-exposed districts. In addition, I discuss the mechanisms that drive the results. Specifically, I analyze the responses of factors of production, i.e., labor and land, toward the price shocks. Lastly, applying the framework of asymmetric location and labor mobility as in Redding (2016), I estimate the welfare changes in the Indonesian economy between 2005 and 2010. I decompose the welfare changes into gains from migration and gains from trade.

I present three main findings. First, districts exposed to palm oil shocks had significantly higher real expenditure per capita compared to the non-exposed ones. I find that labor responded to the incentives from higher real expenditure per capita in districts exposed to palm oil price shocks. Accordingly, these districts attracted more net-inward migration. Since I follow districts' performance over time, I find evidence that the impact of the shocks was temporary. As the commodity boom ended, the difference between exposed and non-exposed districts also dissipated.

In an analysis of the mechanisms that drive the result, I find that the growth in the palm oil sector was spurred by land expansion (extensification) and not by an increase in actual yield (intensification). Meanwhile, analyzing district premia using the two-step method introduced by Dix-Carneiro and Kovak (2017), I find results that contrast with their results for trade liberalization in Brazil. In this paper, 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 from diffusing through internal migration. Indeed, as the palm oil sector grew through land expansion, they may have increased labor demand in palm oil-producing districts. This increase in labor demand materialized as higher real expenditure per capita and net-inward migration.

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

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

This paper contributes to three strands of literature. First, I contribute to the broad literature on the impact of international trade on labor markets in domestic economies. There are two main channels through which the trade shocks materialize: the price channel and the quantity channel. In the former, trade shocks can stem from trade liberalization as in Topalova (2010) and Kovak (2013), world price changes as in Adão (2015), trade cost changes as in Donaldson (2018), or a combination, such as in Sotelo (2015).[5] I complement this literature by studying trade shocks

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

through the price channel and their relationship with internal migration.[6] I contribute to this literature by showing evidence of how local labor markets adjust and diffuse trade shocks that are advantegous to local income through internal migration.

Second, I contribute to the literature on trade, internal migration and regional dynamics by showing that the impact of the commodity boom has been short-lived. I emphasize the need for caution in taking cyclical factors such as global prices as a sustainable source of growth for regional development. I show that districts with direct exposure to the commodity boom in palm oil received more net-inward migration at the peak of the boom. This mechanism allowed other districts to benefit through outmigration to the booming regions. However, as the global palm oil prices decreased after the boom, these palm-oil producing districts may no longer have provided such spillover to other districts. Meanwhile, using trade liberalization in Brazil, Dix-Carneiro and Kovak (2017) show that regions facing larger liberalization experienced increasingly lower growth in wages and employment. They show that a lack of internal migration and slow capital adjustment amplify the local effects of trade liberalization. Using the accession of China to the WTO, Fan (2019) shows the importance of taking into account internal migration when estimating the impact of trade liberalization on interregional inequality and wage inequality. Méndez-Chacón and Van Patten (2019) study the regional dynamics in Costa Rica due to foreign direct investment flows. They show that the ease of internal migration dampens a monopsonist's market power to push down local wages.

Lastly, this paper contributes to the literature on the palm-oil economy. Qaim et al. (2020) provide the most recent survey of literature on the impact of the palm oil boom. This present paper has much in common with Edwards' (2018) study of the impact of palm-oil expansion in Indonesia on local poverty and deforestation, but I am the first to show the cyclicality of the impact of global palm oil prices on the sub-national level. In particular, I show that districts exposed to the palm-oil boom experienced a temporary windfall.

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

[6] Recent papers show evidence of the importance of taking into account internal migration. For example, Tombe and Zhu (2019) quantify the welfare impacts of reduction in internal trade costs, international trade costs, and internal migration costs in China and show that most of the welfare gain stems from a reduction in internal migration costs instead of the more commonly credited reduction in international trade costs as China joined the WTO. Meanwhile, Pellegrina and Sotelo (2020) use the case of Brazil to show that internal migration can shape regions' and ultimately countries' comparative advantage.

In Section 7, I present the conclusions that can be drawn from the analysis.

2 Indonesia in the 2000s

2.1 Overview

Indonesia is the biggest economy in Southeast Asia. It is the largest archipelagic state in the world, with more than 16 thousand islands[7], spanning over 3000 miles from the west to the east, i.e., approximately the distance from Seattle, Washington to Orlando, Florida. It is an emerging economy and also home to the fourth-largest population in the world, with more than 260 million people in 2018.

Indonesia is rich in natural resources. Such natural comparative advantages make Indonesia an important producer of primary commodities, including agricultural and mining commodities. The contributions of the agriculture sector and mining sector were around 10% and 7% of GDP from 2000 to 2010.[8] Despite the relatively small contribution to the size of the economy, the agriculture sector has the biggest contribution to employment in the economy. It accounted for 45% and 38% of employment in 2000 and 2010, respectively.[9]

At the end of the 1990s, Indonesia experienced a deep economic crisis as part of the Asian Financial Crisis (AFC). In the trough of the crisis in 1998, GDP growth plunged by -13%. The crisis propelled not only economic but also political reform. The economy took some time to benefit from the reform. It started to recover in 2000. Given the significant differences in economic and political institutions before and after the AFC, I take the start of the period of interest as 2000 or 2001.

In the second half of the 2000s, the Indonesian economy was characterized by high GDP growth fueled by high export growth. This period coincides with the commodity boom, i.e., a period of high prices in the world commodity markets. Indonesia experienced double-digit export growth with an average of 12.9% in this period. As shown in Table 1, nominal and real expenditure per capita also grew by 15.8% and 7.4% between 2005 and 2010. I use the real expenditure per capita as proxy for the standard of living in this paper.[10] In general, various economic indicators indicate higher growth in the second half of the 2000s compared to the prior and subsequent periods.

Table 1 also shows statistics on recent migration in Indonesia. Recent migration is defined as changes of residence between the survey year and five years prior to the survey year.[11] Because

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

[8] Ibid.

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

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

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

I focus on internal migration, I include changes in residence at the 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, as shown in Table 2, there is high variation in the prevalence of migration across districts. I use recent migration to show the responses of labor markets in terms of mobility.

2.2 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.[12] During the Global Financial Crisis of 2008 to 2009, commodity prices also plummeted but quickly rose again in 2010. Indonesia's main export commodities, such as palm oil, rubber and coal, follow this overall trend in the world commodity market.[13] To illustrate the extent of the boom for Indonesia as exporters, the world palm oil prices and rubber prices increased by more than fourfold and ninefold at the peak of the boom compared to their levels in January 2000.

The extraordinary magnitude and length of the commodity boom provoked two key changes in Indonesia's export profile in that period. First, as shown in Table 1, exports grew faster than the GDP. Second, Indonesia's exports composition transformed during this period. Indonesia's main primary commodities for exports gained greater shares in Indonesia's export profile. Meanwhile, the shares of non-commodity exports, such as textiles and electronics, shrank as shown in Figure 3.

In addition, Figure 4 shows that most of the increase in exports of Indonesia's main export commodities, such as palm oil, was price-driven. For example, exports of palm oil increased fourfold in quantity but twelvefold in values between 2000 and 2010. This fact supports the assumption used in this paper that world price fluctuations in general and price shocks in the commodity boom period in particular are exogenous to Indonesia.

One may argue that as one of the biggest exporters of palm oil, Indonesia is not a price taker in the world market of palm oil.[14] However, various studies on the commodity boom show that the 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 argue that there is a strong

[12] 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) show that the peak for Indonesia's commodity basket occurred in February 2011.

[13] See Figure 1 for the trend of main price indices constructed by the IMF and Figure 2 for the trend in Indonesia's main commodities.

[14] 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 was around one-third of the world export market.

link between energy commodity prices and non-energy commodity prices. Palm oil is used widely in both categories: in biofuel as an energy commodity as well as cooking oil and in numerous consumer goods as a non-energy commodity. Hence, it is plausible to treat Indonesia as a small-open economy in the world market for palm oil. In addition, exports have generally been greater than imports, making Indonesia a net exporter of palm oil. Thus, increases of palm oil price in the world market improve Indonesia's terms-of-trade.

2.3 Three stylized facts

I document three stylized facts that guide me in building the theoretical framework and running empirical exercises to identify the impacts of the price shocks from the commodity boom and import restrictions on Indonesian economy. 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 the labor response, i.e., spatial labor mobility as a response to the varying degree of exposure to the commodity boom.

Fact 1: The agriculture sector had higher importance in districts that were poorer before the commodity boom.

Figure 5 compares the shares of the agriculture sector and the mining sector in districts' gross domestic products against their level of expenditure per capita in the period prior to the commodity boom and the import restriction on rice. Poorer districts, having a lower average expenditure per capita, tend to have a greater share of the agriculture sector. This fact is not surprising given the relatively small share of the agriculture sector's contribution to GDP compared to its large contribution to employment. Meanwhile, there is no clear pattern in the distribution of districts with a higher-importance mining sector among poorer or richer districts. In addition, the mining sector depends on natural endowments that are not as easily substituted as they are in the agriculture sector. Given the importance of the agriculture sector to the labor force in the economy, I focus on the exposure of price shocks in that sector. This fact also implies that there may exist some structural differences in less developed districts. In reduced-form analysis, I include several control variables to capture these potential structural differences.

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 the aggregate land for crops. One million hectares of rice agricultural land were added between 2000 to 2010, but rice's shares of the aggregate land decreased from 37% to 33%. Meanwhile, palm oil has grown to occupy the second-largest share of agricultural land. At the beginning of the boom, there were 2 million hectares of palm oil plantations. Over a decade later, palm oil has increased threefold to 6 million hectares. As a result, its share of land for crops increased from 6% to 14% from 2000 to 2010. In contrast, other main crops have not increased as much and hence decreased in terms of shares.

The substantial increase in the land share for palm oil occurred mostly in districts with high potential yield in producing palm oil. Comparing the ratio of palm oil plantations relative to each district's total area in 2001 and 2011 in Figure 7a, the increase in these shares tends to be larger where the potential yield is higher. Meanwhile, Figure 7b shows that land shares for rice have not increased as widely as those for palm oil. In contrast, some districts have reduced their shares for rice. This pattern goes hand-in-hand with the fact that there has been little increase in rice fields nationally, as shown in Table 3.[15]

The changes in crop mix and in particular the increase in land dedicated to palm oil as a booming crop may imply increases in labor demand in districts suitable for this crop. Figure 7a shows that suitability, represented by potential yield as estimated by FAO, also needs to be taken into account and that these yields are heterogeneous across districts.[16] Hence, in this study, I include changes in the prices of both palm oil and rice as price shocks. In addition, rice also faced exogenous price shocks stemming from import restrictions that started in 2004. McCulloch and Timmer (2008) provide a summary of the political economy of rice in Indonesia from the 1970s to 2008. Few changes in policy occurred between 2008 and the period of study of this paper.

Fact 3: Districts faced upward-sloping labor supply.

The period of high palm oil and rice prices did not only present large changes in prices but also it lasted for a relatively substantial period of time. This meant that some people had the opportunity to maximize their welfare by changing their residency. Table 4 shows the results of the running gravity equation on recent migration flows across districts from 2011 to 2014. This period captures internal migration during the high commodity prices period.

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

In order to see the variation of net-inward migration rates across regions, Table 5 above tabulates the net-inward migration rates by the percentiles of potential yield in growing palm oil and rice. Between 2000 and 2010, the median district increased its net-inward migration rates.

[15] One may wonder why there are districts with low suitability but a high land share for rice. The explanation is that rice is a staple food for most of the Indonesian population. People grow rice for their own household to eat. Also, because most farmers have a relatively low area of rice field per household, scaling up may not be easy.

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

Districts with high suitability for growing palm oil tend to have higher net-inward migration rates in 2010 compared to 2000. Meanwhile, districts with high suitability for growing rice tend to have lower net-inward migration rates in 2010 compared to 2000.[17]

3 Theoretical framework

The commodities or industries of interest in this study are crops. Data on employment from crops, unlike employment data in the manufacturing sector, is rarely available. Hence, we cannot use an 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 a guide for measuring the exposure to price shocks and predicting how the shocks affect wages across regions. Guided by the stylized facts presented above, I construct a theoretical framework that combines the classical specific factor model and the spatial economy set-up as in Redding (2016). This framework allows for the local labor market to face an upward-sloping labor supply. The main difference from Redding (2016) is that I assume a small-open economy that engages in trade with no iceberg trade cost, for both for international trade and interregional domestic trade. Meanwhile, labor can move across regions, taking into account asymmetric for preference on amenities in these regions.[18] In addition, I 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 a two-sector economy in order to match the actual economy more realistically. 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 consisting 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 sectors use 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). The total endowment of labor in the economy is

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

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

fixed at the amount $\bar{L}$. Meanwhile, the 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 as p_2.

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

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

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

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

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

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 the price index is the same in all regions due to the small-open economy assumption and the lack of trade costs. 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 the commodity sector in region n is:

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

The labor demand for sector 1 in each region n is $L_{n1}^D = \frac{\alpha Y_{n1}}{w_n}$ for sector 1. Meanwhile, the labor demand for sector 2 in region n is $L_{n2}^D = \frac{\beta p_2 Y_{n2}}{w_n}$. Thus, the total labor demand in region n is the sum of the 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 that he or she supplies inelastically. Each worker receives wages for the labor services he or she provides by working in region n. Moreover, I assume that the rent for capital and land in the whole economy is distributed in a lump sum to all the population. I use this assumption because the focus of this study is medium-run changes. In this regard, I do not take a stance on how non-labor inputs are endowed. Hence, for a worker in region n, her or his income equals:

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

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

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

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

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

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

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

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

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

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

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

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

3.1.2 Exogenous Price Shock

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

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

A Simple Case: $\alpha = \beta$

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

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

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

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

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

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

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

Armed with the changes in labor demand in (14) and the changes in labor supply in (16), we can use the population-mobility condition in (13) to solve for 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 $\theta_n \equiv \epsilon B_n (w_n+\varphi)^{\epsilon-1} w_n$.

Furthermore, using the labor-market clearing condition in each region $n \in N$ from (11), we have $\hat{L_n^D} = \hat{L_n^S}$, thus

$$\Leftrightarrow \hat{w_n} = \left(\frac{\lambda_n}{\lambda_n+\theta_n}\right)\left[\gamma_{n2}\hat{p} + \frac{\hat{D}}{\lambda_n}\right] \tag{20}$$

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

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

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

where $\lambda_n \equiv \frac{L_n}{\bar{L}}$ as labor shares in region n, $\theta_n \equiv \epsilon B_n (w_n+\varphi)^{\epsilon-1} w_n$ represents relative amenities and initial wages, $\gamma_{n2} \equiv \frac{\alpha p_2 Y_{n2}}{\alpha(Y_{n1}+p_2 Y_{n2})}$ as the share of the sector experiencing the increase of the relative price in the economy of region n.

Proposition 1 shows that in the presence of a uniform price shock, the impacts on wages across regions vary. The changes in wages in each region depend on the region's share of the population, amenity level, and sectoral composition. Intuitively, an increase in the relative price of sector 2, the commodity sector, increases the demand for labor in sector 2. This mechanism allows a uniform price shock to be exposed to regions differently because each region has different sectoral composition. Meanwhile, the increase in the demand for labor in sector 2 in each region pushes up the wages in the region, which simultaneously attracts workers to move to the region with the booming sector. The movement of workers, then, effects changes in wages as more workers move to the region and increase the labor supply. 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 a higher amenity level attracts more workers or retains more workers. Thus, for a given price shock and sectoral composition, the higher the amenity level of a region, the less price shocks affect region's wages.

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

The goal of the quantitative analysis is to estimate the welfare changes for the set of the whole economy. Thus, I use the general framework of Redding (2016) to guide the quantitative analysis. The main environment of the multi-region economy includes: preferences as in (1) over amenities provided by location of residence, a set of tradable goods with share α and housing with share $1-\alpha$. Agents draw idiosyncratic amenities from the Fréchet distribution with shape parameter ϵ as in (2). Meanwhile, tradeable goods are produced in monopolistic competition with many firms. Each region has productivity drawn from the Fréchet distribution with shape parameter θ.

The welfare gains from trade in this setup are shown in Equation 21 below. The equation shows the proportional changes in the 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 the changes in population shares. The parameters include α as the share of tradeable goods and services, θ as the shape parameter of the distribution of productivity and ϵ as the shape parameter of the distribution of amenities across districts.

$$\frac{U_n^1}{U_n^0} = \frac{U^1}{U^0} = \left(\frac{\pi_{nn}^0}{\pi_{nn}^1}\right)^{\frac{\alpha}{\theta}} \left(\frac{L_n^0}{L_n^1}\right)^{\frac{1}{\epsilon}+(1-\alpha)} \tag{21}$$

3.3 Decomposition

Consider the formula for the welfare gains from trade shown in Equation 21. Take the relative changes for each region n, where $\hat{x} \equiv \frac{dx}{x}$.

$$\hat{\pi}_{nn} = \frac{\theta}{\alpha}\left[\left(\frac{1}{\epsilon}+(1-\alpha)\right)\hat{L_n}\right] - \frac{\theta}{\alpha}\hat{U} \tag{22}$$

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,[19] 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 $\sum_n \varphi_n = 1$,

$$\frac{\theta}{\alpha}\hat{U} = \sum_n \left[\frac{\theta}{\alpha}\left(\frac{1}{\epsilon} + (1-\alpha)\right)\hat{L_n}\right]\varphi_n - \hat{\pi} \tag{23}$$

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 and multiply by $\frac{L_n}{L_n}\bar{L}$:

$$\sum_n \hat{L}_n \frac{L_n}{\bar{L}} = \frac{d\bar{L}}{\bar{L}} \tag{24}$$

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 as shown above.

To simplify, assume that there is no change in total labor endowment in the whole economy, i.e., $\frac{d\bar{L}}{\bar{L}} = 0$, and subtract Equation 23 from the right-hand side of Equation 24:

$$\hat{U} = \underbrace{\left(\frac{1}{\epsilon} + (1-\alpha)\right)\sum_n \hat{L}_n\left(\varphi_n - \frac{L_n}{\bar{L}}\right)}_{\text{gains from migration}} - \underbrace{\frac{\alpha}{\theta}\sum_n \hat{\pi}_{nn}\varphi_n}_{\text{gains from trade}} \tag{25}$$

Proposition 2. *Assumming there is no change in total labor endowment in the whole economy,*

[19] 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 production relative to its total expenditures, the weighted sum of regional domestic trade shares using these regional expenditure shares is the aggregate domestic trade shares.

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

i.e., $\frac{d\bar{L}}{\bar{L}} = 0$ *and using* φ_n *as the district's share of the national expenditure and* λ_n *as the district's population share, the welfare change can be decomposed as the following equation. The first term represents gains from migration, while the second term represents gains from trade.*

$$\hat{U} = \underbrace{\left(\frac{1}{\epsilon} + (1-\alpha)\right)\sum_n \hat{L}_n\left(\varphi_n - \lambda_n\right)}_{\textit{gains from migration}} - \underbrace{\frac{\alpha}{\theta}\sum_n \hat{\pi}_{nn}\varphi_n}_{\textit{gains from trade}} \tag{26}$$

Proposition 2 shows that the welfare gains have two components. The first 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 the domestic trade share, π_{nn}, decreases.

4 Data and measurement of exposure to shocks

Armed with the guidance in measuring regional exposure to price shocks as shown by Proposition 1, I compute the exposure of price shocks of the two main crops: palm oil and 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.[20] The heads of districts, like members of parliament at the district level, are elected directly by residents of the districts every five years. Local governments have some income from local taxes but also receive transfers from the central government. In addition, the minimum wage is set at the district level.[21] Over the course of the period studied here, there have been numerous district and province proliferations. I use the administrative district definition in 2000 to maintain the same set of districts over time: 321 districts.[22]

4.1 Data

I combine several sources of data that can capture the determinants of regional welfare and regional exposure to price shocks as guided by the theoretical framework. Indonesian datasets allow me to do this because they contain regionally representative data. Below, I describe the main variables and datasets I use.

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

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

[22] The complete set has 342 districts. In most empirical exercises, I use a panel of 321 districts. A lack of data availability is the reason the full dataset is not used.

Real expenditure per capita The main outcome variable is real expenditure per capita. I use expenditure per capita because in the case of Indonesia, data on expenditure has been better recorded than data on income. Expenditure can capture well-being better than labor income can, because we also want to take into account any income from land rent.[23] Furthermore, the households savings rate is relatively small. Vibrianti (2014) tabulates the Indonesian Family Life Survey (IFLS) 2007 and shows that only 26% of households have savings. Hence, household expenditure data is a good representation of income.[24]

I obtain data on household expenditure per capita from the Social and Economic Household Survey (*Susenas*) directly and the from the survey published in the World Bank's INDO DAPOER database computed from *Susenas*. I use several district averages of expenditure per capita. First, I use the total district average, which includes the whole sample for each district. I also extract district premia from the 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 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 the survey years and five years prior to the survey years. For the years 2011 to 2016, I extract data on migration flows across districts from *Susenas*. Meanwhile, for earlier years, I obtain migration flow data from a sample of the Population Census and Inter-Census Population Surveys provided by IPUMS. From the constructed matrix of migration flows, I compute the net migration rate for each district.

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

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

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

I choose assumptions about the most relevant use of technology for each crop. I then take the district average of the yield for each crop.

I obtain data for harvested areas by district and by crop from the Ministry of Agriculture's statistics website.[25] The data on harvested areas include all types of plantations, i.e., both large and small plantation holders. For the national aggregate crop area, I use the FAO database. The total area for each district is obtained from the World Bank's INDO DAPOER.

Prices All data on prices are converted into rupiah. World palm oil price data is obtained from the IMF Commodity Price Series. These price series are in US dollars.To take into account the rupiah's depreciation over the same period, I calculate the rupiah prices using exchange rate data from the FRED Database. Because Indonesia's small-open economy, the rupiah prices are the relevant prices. Hence, the price shocks measured in this paper are inclusive of this depreciation. Meanwhile, the retail domestic rice price data by province is obtained from *BPS*. The 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.

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

4.2 Exposure to price shocks

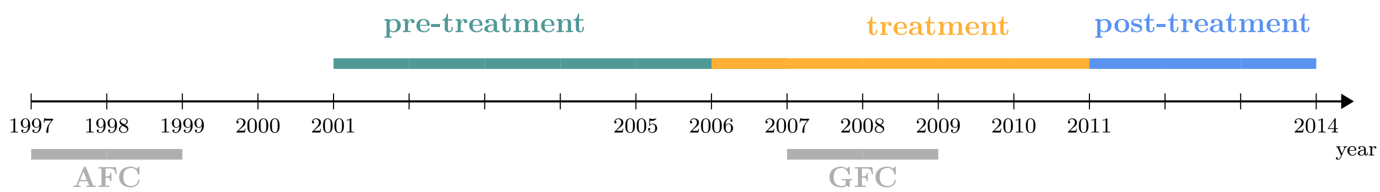
As we learn from Fact 1 and Fact 2, districts vary in their comparative advantage in agricultural products, especially in growing palm oil and rice. Hence, districts are not uniformly exposed to the increase in crop prices. In order to embody this exposure heterogeneity, I construct a measure of exposure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

First, to capture the price changes, it is useful to define the timeline that I am using. I illustrate this timeline below. Figure 7 shows the trend in real palm oil prices and real rice prices as the basis for the timeline. I define the treatment period as the onset of the commodity boom for palm oil prices and as the import ban started to have an impact on rice prices. For palm oil prices, I take 2010 as the end of the treatment period, because prices started to decline in 2011 even though the average price was still quite high. Meanwhile, as we can see from the figure below, the real prices of rices have been fairly stagnant since 2011. Hence, I also take 2010 as the end

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

of the treatment period for rice price shocks. The post-treatment period of interest, then, is the subsequent the three to five years after the treatment period, i.e., from 2011 to 2014 or longer when data is available.

I define the pre-treatment period price as the average price between January 2001 and 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. To measure price changes, I take the long difference in log between the treatment period and the pre-treatment period.



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

Applying Proposition 1 in the theoretical framework, which states that the impact of exogeneous price changes on income depends on the output share of the sector whose price changes, I construct a measure of exposure to price shocks in palm oil and rice for each district, S_{id}. Equation 27 below shows the construction of this measure. The measure allows districts to be exposed differently to uniform price shocks. The price of palm oil is exogeneously determined in the world market. Hence, all districts in the sample face the same prices and price changes for palm oil. Meanwhile, the prices of rice clear at the provincial level. I assume that farmers in each district are price takers to these provincial rice prices. This assumption is plausible given the size of each farmer relative to the province aggregate.

$$S_{id} = \hat{p}_i \frac{Y_{id0}}{GDP_{d0}} = \hat{p}_i \frac{p_{i0} \cdot T_{id0} \cdot \psi_{id}}{GDP_{d0}} \tag{27}$$

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

Variations across districts in the estimated production of palm oil and rice are determined by variation in harvested area in the pre-treatment period and variation in crop suitability from the FAO GAEZ data. In the pre-treatment period, there was no indication that farmers predicted that the commodity boom would occur. As Fact 2 suggests, even in districts that are very suitable for palm oil, the harvested areas were relatively low, similar to those in districts that are less suitable. Furthermore, the importance of each crop across districts is also determined by the size of the economy of the district. I use district GDP excluding the oil and gas sector, because I assume that this measure represents the pie of the economy that are distributed locally in each district.

Figure 8 and 9 display the computed exposures of palm oil price shocks and rice price shocks across districts. The districts with the highest exposure to palm oil price shocks are concentrated in Sumatra, the main island on the west end of the country, and Borneo, the main island east of Sumatra. Meanwhile, the districts with the highest exposure to rice price shocks are spread out across all of the main islands of Indonesia. Table 6 exhibits the summary statistics of the computed exposure to price shocks.

Defining exposed districts

I group districts into a set of exposed districts and a set of non-exposed districts for each crop. As we can observe from the distribution of exposure to shocks in Figure 8, Figure 9 and Table 6, more than half of the districts are not exposed to palm oil price shocks. Meanwhile, most districts have some degree of exposure to rice price shocks. The latter fact is not surprising because rice is the staple food for most of Indonesia's population. Many districts produce some amount of rice even if they are not net producers.

For palm oil, I define exposed districts as districts with positive values of exposure to shocks and non-exposed districts as those with zero exposure to palm oil price shocks. For rice, I define exposed districts as districts with an exposure value higher than the 40th percentile. The final set of these exposed and non-exposed districts is summarized in Table 7 and illustrated in Figures 10 and 11. Out of 321 districts, 81 districts are categorized as exposed to palm oil price shocks and 129 districts are exposed to rice price shocks.

5 Empirical results

I use the constructed exposure to price shocks to study how it affects districts on two fronts: a comparison between exposed districts and non-exposed districts and spillovers to non-exposed districts. I also show some mechanisms that can explain the results by analysing the responses in factors of production, especially labor and land.

5.1 Specification

I use the difference-in-difference method for econometrics specification to study the impact of palm oil price shocks and rice price shocks on districts' economies. Specifically, I perform an event study as in Equation 28 to show the average differences between exposed and non-exposed districts over time. Meanwhile, I use Equation 29 to show any heterogeneity in the impact of the shocks.

$$y_{dt} = \alpha + \sum_{i} \sum_{r \neq 2005} \beta_{ir} \left(I_{di} \cdot \mathbb{1} \left(year_r = t \right) \right) + \boldsymbol{X_d} \cdot t\gamma \cdot + \delta_d + \delta_t + \epsilon_{dt} \tag{28}$$

$$y_{dt} = \alpha + \sum_{r \neq 2005} \beta_{i=palm,gr} \left(I_{i=palm,dg} \cdot \mathbb{1} \left(year_r = t \right) \right) + \lambda_t S_{i=rice,d} \cdot t + \boldsymbol{X_d} \cdot t\gamma + \delta_d + \delta_t + \epsilon_{dt} \tag{29}$$

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

Furthermore, as Fact 3 in Section 2 reveals, districts with a high share of the agriculture sector in their economies can be structurally different because they tend to be poorer compared to those that rely less on the agriculture sector. Hence, I include a matrix of control variables to take this fact into account. These controls include the percentage of the rural population in 2000, the share of villages with asphalt roads in 2000 and the length of district roads in bad condition. These variables represent structural conditions that may matter in terms of supporting growth, such as inherent trade costs. I also include the size of a district's output in the mining sector in 2000 to control for the impact of the commodity boom on mining commodities. Meanwhile, I control for the district's output in the manufacturing sector in order to control for what could be a Dutch disease channel, in which a non-exposed sector may experience lower investment and growth or increasing costs from non-tradables. All of the control variables are interacted with year fixed effects. In addition, I include district fixed effects and year fixed effects. Thus the coefficients of interest capture the within-district changes in the outcome variables.

The difference-in-difference specification can establish the causal impact of exposure to the price shocks if it fulfills three assumptions. First, there is a parallel trend between the exposed districts and the non-exposed districts. Second, the price shocks are exogenous shocks to districts. In addition to the fact that exogenous components were used to construct the exposure to shocks, exogeneity is fulfilled because there is no uptick in the coefficients of interest during pre-treatment period. The plots of the coefficients of interest confirm that the first and second assumptions are fulfilled. Third, there is no change in crop productivity. If crop productivity increased due to the price shocks, then the coefficients are biased because they also capture the impact of the increase in productivity. Tables 8 and 9 confirm that there are no changes in actual yield for either palm oil or rice in the period of study. Hence, the third assumption is also fulfilled. Thus, the coefficients of interest reflect the impact of exposure to palm oil price shocks and exposure to rice price shocks.

5.2 Impact of the exposure to palm oil price shocks

Districts exposed to palm oil price shocks had higher (ln) real expenditure per capita during the peak of the boom in 2011 and 2012. Figure 12 plots the estimated β_{ir}s for palm oil price shocks and their respective 95% confidence obtained from running Equation 28. This result shows that income shocks from palm oil prices were translated as an increase in purchasing power.

Figure 12 also shows that the exposed and non-exposed districts were not significantly different in the pre-treatment period of 2000 to 2004 relative to the base year 2005. One exception is that districts exposed to palm oil price shocks had significantly lower (ln) real expenditure per capita in 2002. However, the difference is negligible in other years. Hence, the results shown by the coefficients of interest, β_{ir}s, establish the valid causal impact of the palm oil price shocks.

The palm oil price shocks increased the real expenditure per capita in the exposed districts by 6 log points or approximately 6% relative to the base year at its peak in 2011 and 2012. This effect corresponds to 37% of one standard deviation in the proportional change of real expenditure per capita in 2011 and 2012 relative to 2005. The impact of the commodity boom decays afterward, with coefficients not different from zero. The cycle seems to directly follow the global commodity prices, which started to decline in 2013 and 2014 as well. This result fills a gap in the literature by providing the first evidence that the commodity boom affected subnational regions differently and that these regions experienced a temporary windfall.

Among districts exposed to palm oil price shocks, I find heteregeneity in the impact of palm oil price shocks. Figure 13 plots the estimated coefficient for three terciles of palm oil price shocks over time. Districts in the bottom two terciles of palm oil price shocks had a significantly higher (ln) real expenditure per capita during the post-treatment period compared to the non-exposed districts. Following the trend in the overall impact of palm oil price shocks, the impact of the commodity boom dissipates as the boom ended in 2013.

Because districts exposed to palm oil price shocks had higher expenditure per capita, they might have attracted labor to move to them. To test whether districts exposed to the shocks received more migration, I run Equation 28 on net-inward migration and share of net-inward migration relative to district population. Figure 14 plots the estimated β_{ir}s for net-inward migration as the outcome variable, while Figure 15 plots the coefficients for share of net-inward migration as the outcome variable.

Before I continue with the analysis of the results, I would like to describe some of its limitations. Because recent migration data was not collected annually before 2011, I combine several datasets to construct recent migration flows data over time. For the years 2000 and 2010, I use the Census Population that is provided by IPUMS. For year 2005, I extract recent migration flows from the Inter-Census Population Survey provided by IPUMS. For the years 2011 to 2014, I use the Socio-Economic Household Survey(*Susenas*) datasets. Hence, there may exist some structural differences in the sampling of these datasets.[26] For this reason, in the analysis of migration as the outcome variable, I include the year 2010 as part of the post-treatment period.

Both Figures 14 and 15 show 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 afterward. These results support the previous findings that districts exposed to palm oil price shocks become more attractive to labor to move to these regions. Because we find that labor responds to incentives to move to booming regions, the price shocks too are no longer fully localized.

Confirming the heterogeneous findings about the impact to real expenditure per capita, I also find that the districts exposed to palm oil price shocks in the bottom tercile are the ones that receive significantly more net-inward migration. Figures 16 and 17, respectively, show the impact of the commodity boom on net-inward migration and the share of net-inward migration across terciles.

The empirical results here show that once the positive windfall has a significant effect, we see that labor responds by moving as these booming districts became more attractive. This finding adds to the understanding of how trade shocks affect labor mobility. Many studies in this field find that trade shocks tend to be localized; see, for example, Autor et al. (2013) for the case of the US, Dix-Carneiro and Kovak (2017) for the case of Brazil, and Topalova (2010) for the case of India. However, most such studies explores trade shocks that are disadvantegous to local incomes. Hence, if there is a cash-in-advance constraint on migration costs, we may not see labor mobility responses to such trade shocks. The fact that I find a contrasting result does not necessarily mean that Indonesia is a special case. Instead, the result here provides some evidence that the labor mobility margin can be active when trade shocks are advantegous to local income. One possible explanation is that such trade shocks can help labor overcome the cash-in-advance constraint on migration costs.

5.3 Spillover to non-exposed districts

Booming districts may also demand more goods and services from nearby districts because it is cheaper to purchase from nearer districts than from more distant districts, due to lower transportation and transaction costs. To assess whether there is any spillover of impacts of exposure to palm oil price shocks to non-exposed districts, I run the following specification.

$$y_{dt} = \alpha + \sum_{g \in 1,2,3,4} \sum_{r \neq 2005} \beta_{gr} \left(I^g_{dt} \cdot \mathbb{1} \left(year_r = t \right) \right) + \psi_{palm,d} + \delta_{rice,d} + \boldsymbol{\gamma} \boldsymbol{X_d} + \delta_d + \delta_t + \nu_{dt} \tag{30}$$

In Equation 30, the outcome variables are real expenditures per capita and migration flows.

[26] Table 2 tabulates the main statistics across sources of recent migration data.

As in the previous specifications, I include a set of control variables, district fixed effects and year fixed effects. First, I control for the potential yield in growing palm oil, $\psi_{palm,d}$, to purge the effect from the impact of the districts changing status from palm-oil non-grower to grower. I also add the status of exposure to rice price shocks, $\delta_{rice,d}$. I run the specification on a panel of districts that are not exposed to the palm oil price shocks. To capture heterogeneity due to proximity to exposed districts, I create four dummy variables. Each dummy variable indicates four of the lowest centiles of minimum distance to exposed districts.[27] Hence, the coefficients of interest are β_{gr}s. These coefficients capture the difference of district of centile g in year r compared to districts in the 5th to 10th centiles (the control group) relative to the base year 2005.

First, I find that the nearest non-exposed districts to districts exposed to palm oil price shocks also had higher real expenditure per capita. Figure 18 plots the coefficients of interest with (ln) real expenditure per capita as the outcome variable for the distriicts in the two lowest centiles in distance. These coefficients are positive and statistically significant from zero for the nearest non-exposed districts. Following the trend in the impact to the exposed districts, these coefficients also shrink over the outcome period.

In response to the spillover indicated by higher expenditure per capita in the neighboring districts of booming regions, I find also that the same non-exposed districts that are close to districts exposed to palm oil price shocks also receive more net-inward migration. Figure 19 plots the estimated β_{gr}s for net-inward migration as the outcome variable. Supporting the result above, labor seems to respond to the higher purchasing power provided by these nearest districts. These districts receive more net-inward migration compared to the control group, which is further away from the districts exposed to palm oil price shocks.[28]

5.4 Mechanisms

I provide several mechanisms, focusing on the response of factors of production. The idea is that the shocks may have lasted long enough and were big enough that the factors of production also responded to the shocks. First, I provide justification that labor responds through internal migration by analyzing the impact of the price shocks on district premia. Second, because I focus on agricultural commodities, I analyze two possible methods through which the agriculture sector expands: extensification by land expansion and intensification by increasing yield.

5.4.1 District premia: the role of internal migration

One may argue that, structurally, districts exposed to palm oil price shocks have a different labor and sectoral composition that may drive their higher expenditure per capita at the peak of the

[27] The distance between two districts is computed as the distance between their centroids.

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

boom. Another argument is that there exist frictions in labor mobility that prevent welfare from equalizing across districts. I follow the two-step method used by Dix-Carneiro and Kovak (2017) to analyse the evolution of district premia over the period of study. First, to control for labor and sectoral characteristics, I run a Mincerian-type regression on household-level expenditure per capita by controlling household heads' economic and demographic variables. To avoid selection bias due to labor market biases, I follow Bryan and Morten (2019) in imposing some selection criteria. That is, I include households with male heads of households between the ages of 15 and 61. I also take only those who report having had an income in the three months prior to the survey. Equation 31 below shows the Mincerian equation.

$$y_{\omega dt} = \alpha + \boldsymbol{\beta X_{\omega dt}} + \delta_{dt} + \delta_{it} + \delta_{st} + \epsilon_{\omega dt} \tag{31}$$

The outcome variable is individual ω's real expenditure per capita in year t, living in district d. I include the vector of the household heads' controls, such as years of education, years of experience and years of experience squared. I run this regression separately for each year $t \in [2002, 2005, 2011, 2012, 2013, 2014]$[29] and take the estimated district fixed effects, δ_d, as the district premia. Note that I also add fixed effects for sector of employment, δ_i, and status of employment (self-employed, employee, etc.), δ_s. The fixed-effects on sector of employment are particularly important to purge any premium from working in a particular sector, including the agriculture sector that faced the price shocks. Thus, the district premia explain the premium on real expenditure per capita by simply living in a particular district.

Second, I run Equation 28 with the estimated district premia as the outcome variable. Figure 20 shows the estimated coefficients of interest that show the difference in district premia between exposed and nonexposed districts. Neither set of coeffecents on exposure to palm oil and rice price shocks is statistically different from zero. This result implies that after controlling for labor composition and sectoral premium, there is no significant difference between the exposed and non-exposed districts. It also implies that the positive impact of palm oil price shocks on exposed districts is not driven by labor market friction.

This result stands in contrast to what Dix-Carneiro and Kovak (2017) find in the case of the impact of trade liberalization in Brazil, where frictions to labor mobility amplified the impact of trade shocks locally. In the Brazilian case, the district premia grew more negative over time, because affected labor could move out of the regions where trade liberalization hit industries worse. Meanwhile, in this study, the fact there is no significant impact on district premia due to exposure to palm oil price shocks also implies that there are no frictions that are significant enough to prevent people from moving in order for the district premia to equalize across districts. In regard to the positive impact of the palm oil price shocks to real expenditure in palm oil districts, the

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

finding on district premia shows that labor is mobile enough to diffuse the income-enhancing shocks from the exposure to palm oil price shocks.

5.4.2 Extensification versus intensification

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

The palm oil crop expanded through extensification. Table 10 shows that especially for the bottom tercile of exposed districts, the coefficients for the post-treatment period on the harvested area are positive and significant. Given that there was more land to work on, demand for labor may have increased. This increase in demand is consistent with the increase in real expenditure per capita and net-inward migration in exposed districts, as discussed above.

Meanwhile, there is no indication that the palm oil crop expanded through intensification. Table 8 shows that the coefficients for the post-treatment period on actual yield are not significantly different from zero. Furthermore, it is worth noting that because the commodity boom did not last forever, the impact of the price shocks due to the boom also lowered as commodity prices started to decline. This finding may provide a warning to policy-makers that the palm oil sector may not provide a sustainable source of growth if the sector continues to rely on growth from land expansion.

5.4.3 Discussion of deforestation

Globally, commodity-driven deforestation is rampant.[30] In a meta-analysis of drivers of deforestation, Busch and Ferretti-Gallon (2017) mention that agricultural price as one of the drivers associated with higher deforestation. Indonesia also is also special in this regard because it experienced the largest increase in forest loss.[31] In the case of Indonesia, various studies show that palm oil expansion was the main driver of deforestation, at least until 2014. Figure 21 shows the trend of annual forest loss driven by palm oil plantation in Indonesia and real palm oil prices. We can see that there is still a fairly strong positive correlation.

The main finding on the impact of palm oil price shocks is that palm oil-producing districts benefited for several years. In line with what Edwards (2018) find, palm oil-producing districts experienced faster poverty reduction. He also shows that this gain comes with some costs, these districts also experienced more deforestation. The finding in this paper emphasizes that the gain did not last permanently. As world prices started to decline in 2013-2014 without an increase in

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

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

actual productivity, the return to palm oil for these districts dissipated. This evidence can help policy-makers and the public to understand the impact of the commodity boom in palm oil while taking into account the potential social cost that deforestation imposes over a long period. In this regard, I echo the concern emphasized by Wheeler et al. (2013) that the success of forest conservation efforts need to acknowlege the fluctuations in world markets and decisions made by financial authorities on the exchange rate and the interest rate. Monetary authorities should be cautious when relying on the primary commodity as the backbone of exports and hence the source of foreign reserves. As shown in Section 2, Indonesia's export profile has become more commodity-intensive since the commodity boom in the mid-2000s. Meanwhile, because local leaders have the power in land concession as shown by Burgess et al. (2012), this evidence offers a realistic assessment of the opportunity cost of forests. A recent study on the spillover impact of cash transfers on deforestation by Ferraro and Simorangkir (2020) sheds lights on the importance of creating an outside option as a source of income in regions that are prone to deforestation. Lastly, the fact that there is no lingering benefit enjoyed by palm oil-producing districts highlights the possibility that new palm oil concessions may not provide more benefit than costs to the people there.

6 Quantitative estimation

Lastly, I quantify the welfare changes in Indonesia that occurred in the period between 2005 and 2010. I use the decomposition of welfare changes that I derived in the section on the theoretical framework. Specifically, I decompose the source of the welfare changes into gains from trade and gains from migration. To quantify both gains, I use internal migration flows data and the Inter-Provincial Input Output Table. 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 indicates the importance of taking into account internal migration in welfare analysis.

6.1 Data and parameters

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

$$\hat{U} = \underbrace{\left(\frac{1}{\epsilon} + (1-\alpha)\right)\sum_{n} \hat{L}_n \left(\varphi_n - \lambda_n\right)}_{\text{gains from migration}} - \underbrace{\frac{\alpha}{\theta}\sum_{n} \hat{\pi}_{nn}\varphi_n}_{\text{gains from trade}} \tag{32}$$

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

Next, I assume the value of parameters as shown in Table 11. I use conservative values as assumptions for parameters, as in Redding (2016) and Bryan and Morten (2017). Armed with data on expenditure shares, population shares, domestic trade shares and the parameters, I compute the gains from migration for each district and gains from trade for each province.

6.2 Results

The total welfare gain over the period from 2005 to 2010 is a welfare increase of 0.39% (proportional change to the initial state in 2005) welfare increase. When I decompose the welfare gains, gains from migrations account for one-third of the gains, while gains from trade account for two-thirds of the gains. The overall size of the welfare gains is in line with the welfare estimation in the literature. For example, Broda and Weinstein (2006) estimate that US consumers experienced 2.6% of GDP welfare gains from expanded import varieties between 1972 and 2001.

Gains from migration Gains from migration in this paper are quantified from two variables: districts' population shares and the difference between districts' expenditure shares and population shares. Figure 22 compares these two variables according to exposure to palm oil price shocks. The color of each hexagon on the graphs represents the share of exposed districts in that particular bin of population shares and the difference between expenditure shares and population shares.

We can see that many districts exposed to palm oil price shocks gain through migration, because they have a positive value for the difference in expenditure shares and population shares, i.e., the districts are richer. These districts received positive net-inward migration. Some portion of the districts have around zero or negative net-inward migration, but their values for the difference of expenditure shares and population shares are also negative. Such districts gain by experiencing outmigration.

Gains from trade Meanwhile, given that there are no data for district-level domestic trade shares, I use provincial-level (a more aggregated level than the district level) domestic trade shares to compute gains from trade. The result for each province is presented in Table 12. Several palm oil producers are the main contributors to the gains, such as Kalimantan Selatan, Kalimantan Timur, Kalimantan Barat and Sumatera Utara. Others, however, experienced losses, such as Jambi and Riau. These results are driven by changes in (provincial) domestic trade shares. Palm oil-producing provinces tend to have lower domestic trade shares in 2010 compared to 2005 as their export shares in their economy roared due to the commodity boom.

7 Conclusion

Developing economies are vulnerable to changes in the world commodity markets. This paper studies the impact of price shocks on Indonesia in the mid-2000s. Given the magnitude and the length of the commodity boom that exposed Indonesia as one of the main palm oil producers, factors of production, including labor, may have responded to these shocks by moving to districts directly exposed to the shocks. In particular, I study the impact of price shocks on different districts in the presence of internal migration.

I present three main findings. First, palm oil price shocks benefitted producing districts with higher real expenditure per capita. However, the impact of the palm oil price shocks was temporary. I find that the palm oil sector grew through land expansion without any significant growth in actual yield. The increase in land that needed to be cultivated was met by more inward migration and higher real expenditure per capita.

The second main result is that there is evidence of spillover of the shocks to non-exposed districts. In particular, the non-exposed districts nearest to districts exposed to palm oil price shocks also experienced higher real expenditure per capita and net-inward migration. The intuition behind this result 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, because trade and migration costs are lower if they buy from nearby sources.

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

These results provide policy-relevant lessons. First, I provide evidence of the impact of global prices' cyclicality at the sub-national level. The result then questions the sustainability of relying on cash crops through land expansion. The concern about sustainability is even more critical if we take into account the social costs of land expansion that causes deforestation. This evidence can inform not only local governments who hold the authority to make land concessions and who may have an interest in creating local development strategy, but also national-level fiscal and monetary authorities who are interested in sustaining sources of foreign reserves and growth in general. In addition, the concern about commodity-driven deforestation is not exclusive to Indonesia; we can see the same pattern in other crop-exporting regions.

References

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

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

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

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

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

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

Broda, C. and D. E. Weinstein (2006): "Globalization and the Gains from Variety," *The Quarterly journal of economics*, 121, 541–585.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Qaim, M., K. T. Sibhatu, H. Siregar, and I. Grass (2020): "Environmental, economic, and social consequences of the oil palm boom," *Annual Review of Resource Economics*, 12, 321–344.

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

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

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

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

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

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

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

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

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

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

Tables

Table 1: Summary Statistics

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

Sources:World Development Indicator for GDP and exports. Population Census for migration rate in 2000 and 2010, Social-Economic Household Survey (*Susenas*) for the average of recent migration rate in 2011-2014. INDO DAPOER dataset by the World Bank for expenditure per capita. IMF Commodity Price Series for price of palm oil. BPS for price of rice. All growth figures and averages are the author's calculations.
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 the nominal price in the world market in each period. Price of rice is the average of the nominal domestic price of rice in each period. Domestic price of rice is the average of provincial prices.

Table 2: 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 at the district level as as defined in 2000. Inter-Census Population Survey 2005 does not include districts in the Nanggroe Aceh Darussalam Province.

Table 3: Land shares of main crops

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

Sources: FAO, author's calculation.

Notes: Shares of each crop refers to their shares relative to total land for crops.

Table 4: Gravity of 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 from 2011 to 2014. Estimated amenities are predicted first components from running principle component analysis (PCA) on selected variables from the Village Census (PODES) 2005 and 2008.

Table 5: Net-inward migration rates by crop suitability

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

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

Table 6: 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

Table 7: Number of exposed and non-exposed districts

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

Table 8: Crop intensification: Actual yield for palm oil

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

Standard errors in parentheses

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

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

Table 9: Crop intensification: Actual yield for rice

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

Standard errors in parentheses

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

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

Table 10: Crop extensification: Palm oil

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

Standard errors in parentheses

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

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

Table 11: Assumption for parameters

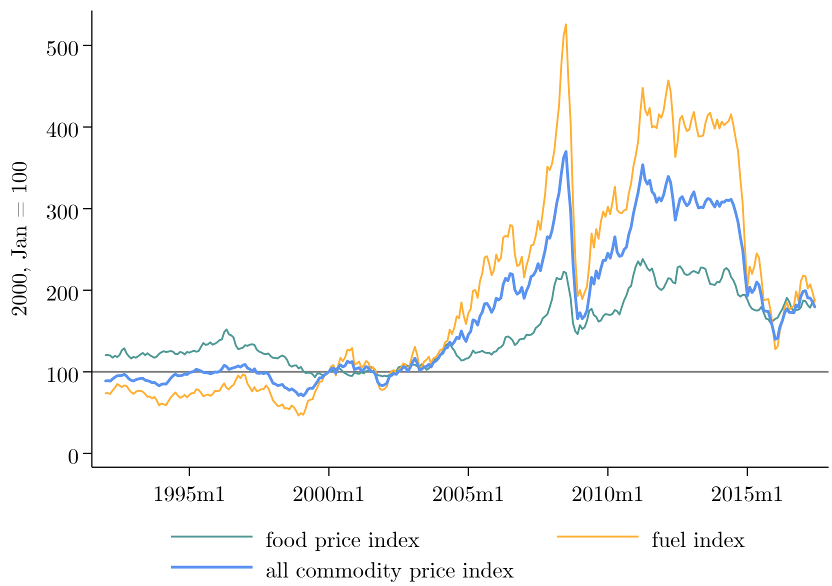
parameter	description	value
α	share of tradable goods in consumption basket	0.75
θ	Fréchet parameter for productivity	4
ϵ	Fréchet parameter for amenity	3

Table 12: 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

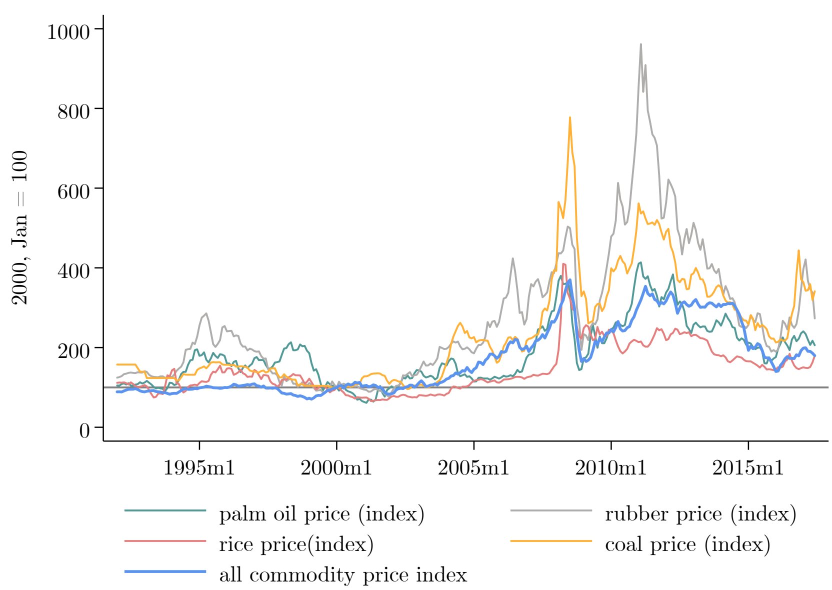
Figures

Figure 1: Trends in main world price indices



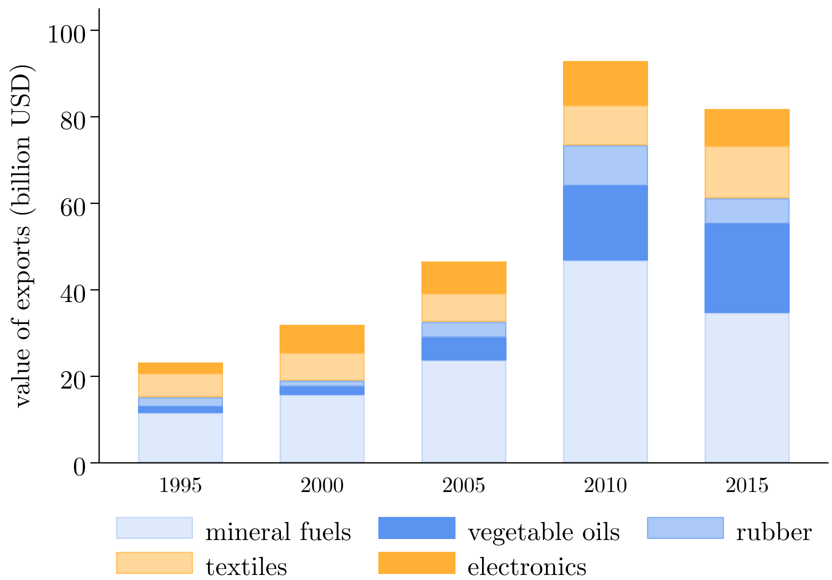
Source: IMF Commodity Price Series.

Figure 2: Trends in world price indices of Indonesia's main commodities



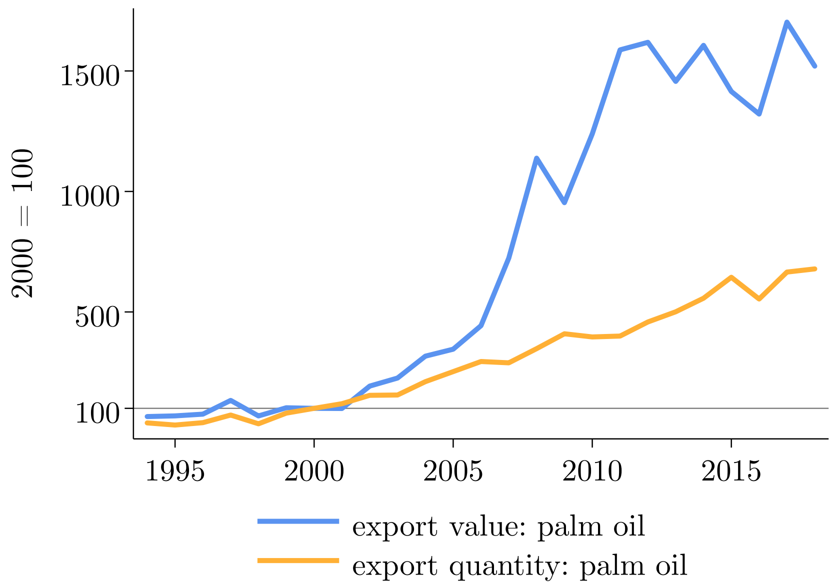
Source: IMF Commodity Price Series, author's calculation.

Figure 3: Indonesia's exports transformation



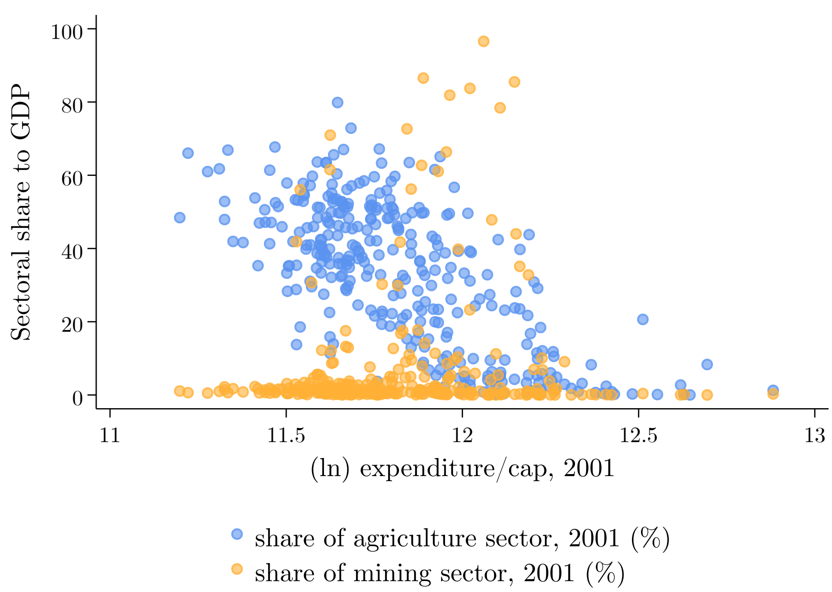
Source: UNCOMTRADE, author's calculation.
Notes: Mineral fuels refer to HS 27. Vegetable oils refer to HS 15, rubber refers to HS 40, textiles refers to HS 61 to HS 64. Electronics refers to HS 85. This figure shows selected export goods. Bars in blue represent primary-commodity exports, while bars in yellow represent manufacture exports.

Figure 4: Indonesia's palm oil exports



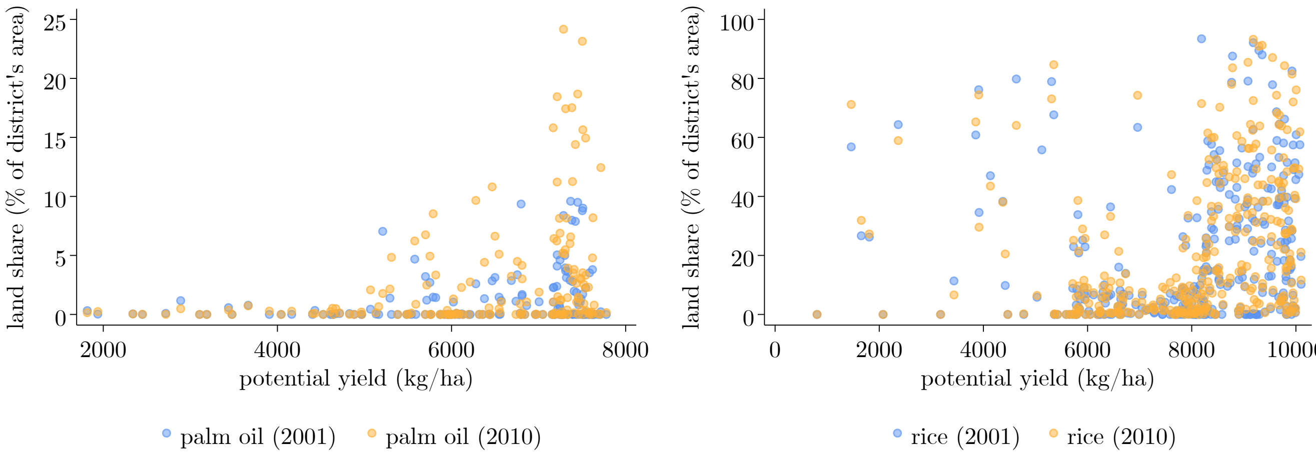
Source: UNCOMTRADE, author's calculation.
Notes: This figure compares the value and volume of exports of palm oil, defined as HS 1511.

Figure 5: Importance of the agriculture sector and mining sector across districts



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

Figure 6: Land shares of palm oil and rice by potential yield.

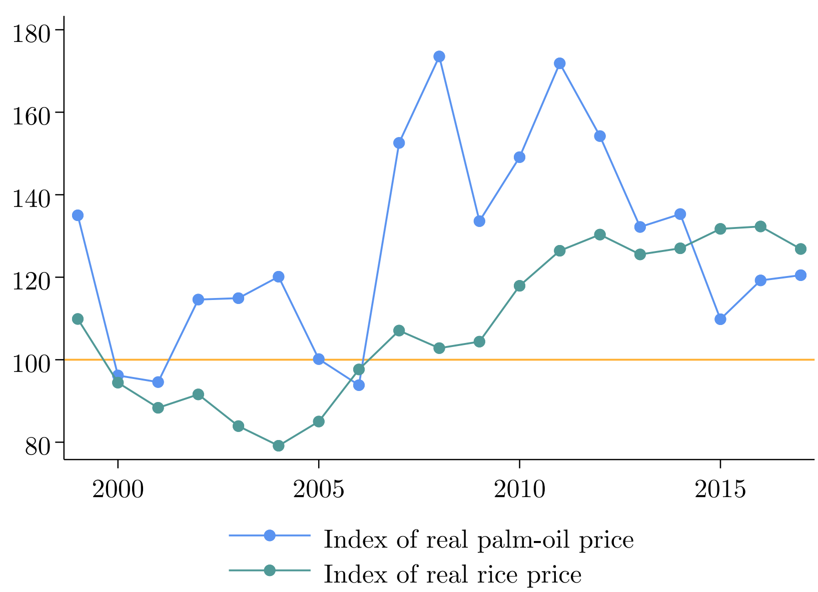


(a) palm oil

(b) rice

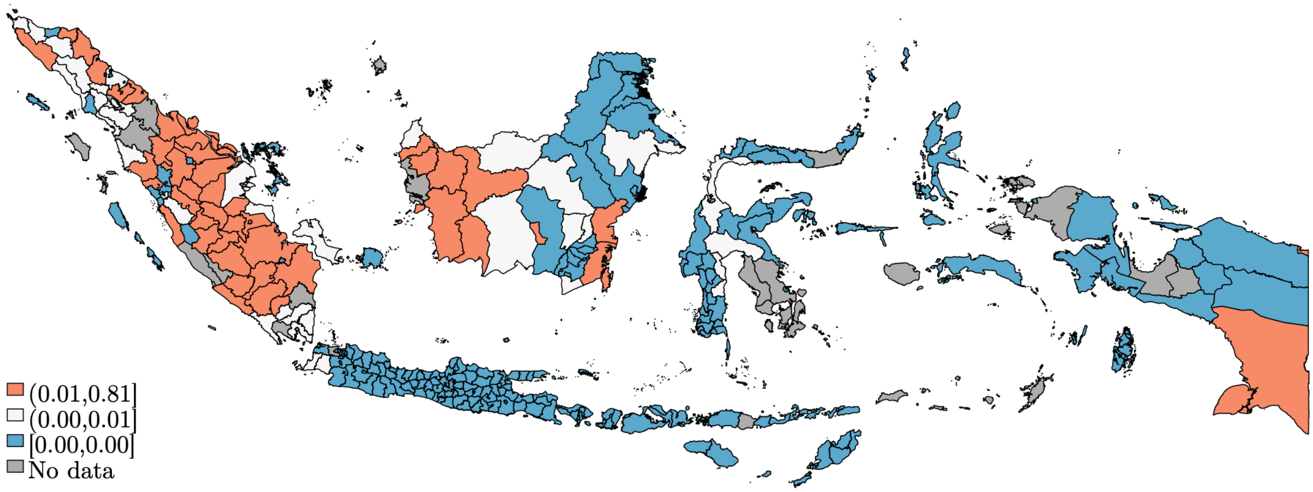
Source: Area for each crop is from Tree-Crops Statistics, Ministry of Agriculture. District total area is from World Bank's INDO DAPOER. Potential yield data is from FAO GAEZ dataset. Land shares are the author's calculation. District's potential yield is the average of potential yield in the district.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

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



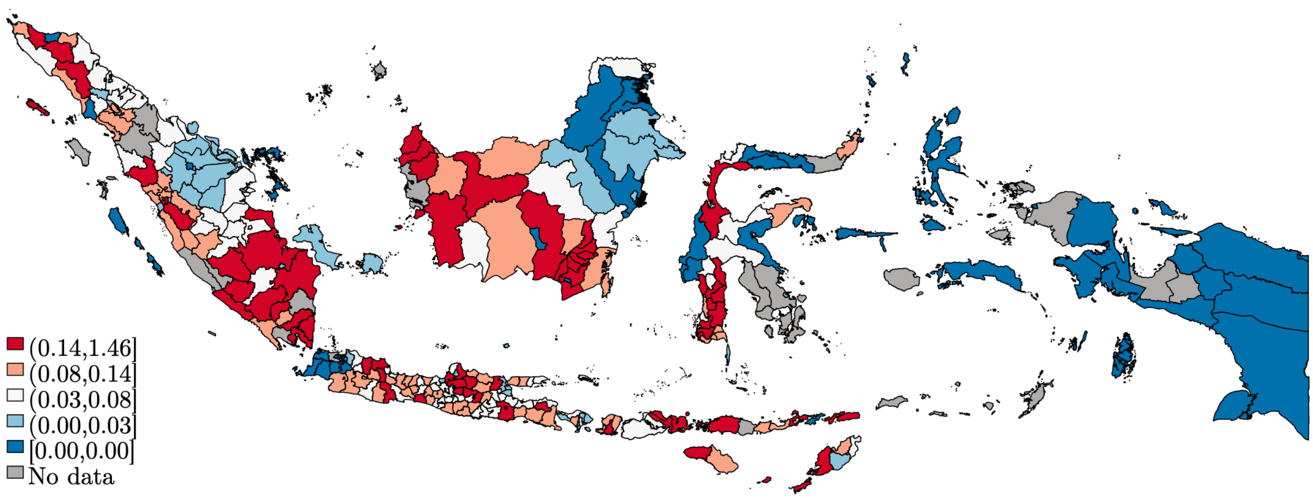
Source: IMF Commodity price series for world palm oil prices, FRED Database for exchange rates, BPS for provincial rice prices and Indonesian CPI. Author's calculation.
Notes: National rice prices are the simple average of provincial rice prices.

Figure 8: Exposure to palm oil price shocks



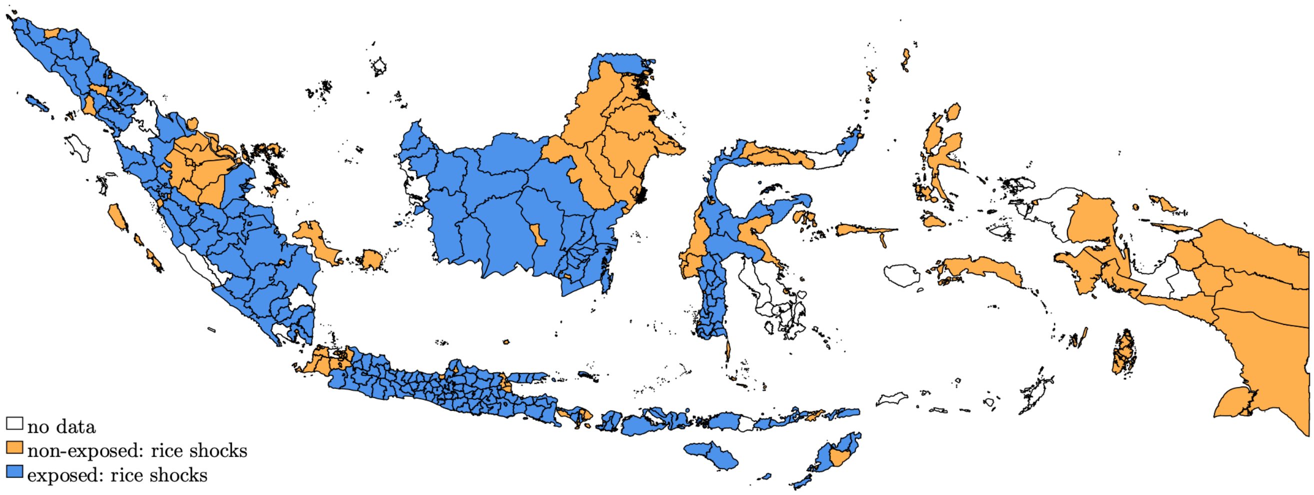
Notes: The definition of districts uses district boundaries in 2000. Exposure to price shocks is calculated using Equation (27).

Figure 9: Exposure to rice price shocks



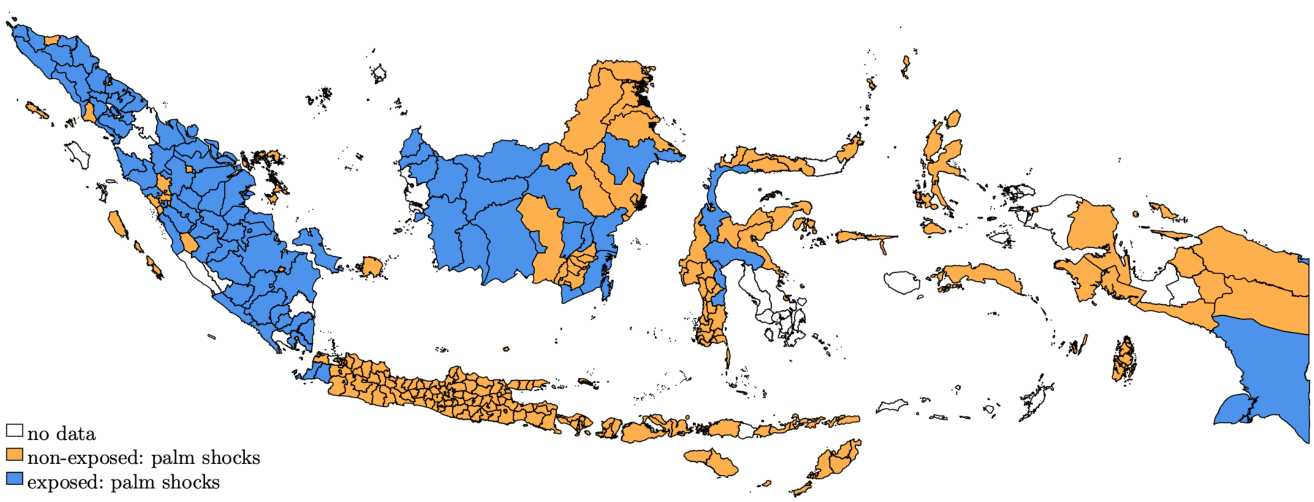
Notes: The definition of districts uses district boundaries in 2000. Exposure to price shocks is calculated using Equation (27).

Figure 10: Exposed and non-exposed districts: Rice price shocks



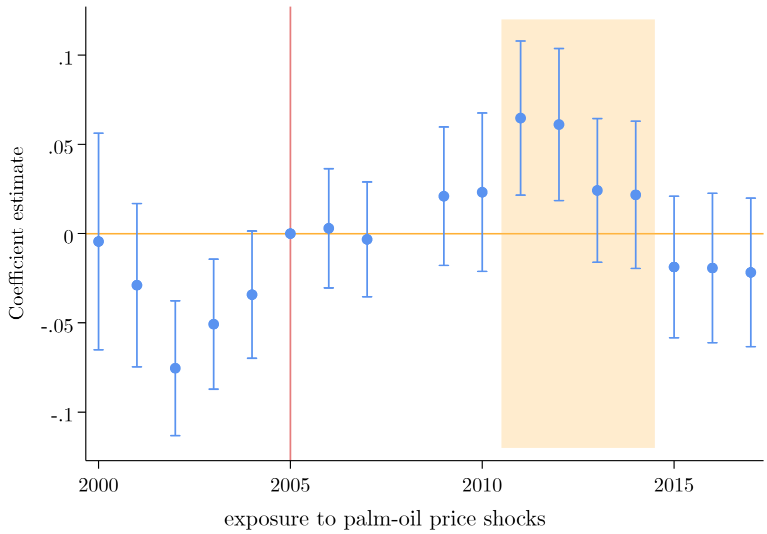
Notes: District definitions and borders use the district definitions in 2000. Exposed districts are defined as districts with exposure to rice price shocks of above 40 percentile.

Figure 11: Exposed and non-exposed districts: Palm oil price shocks



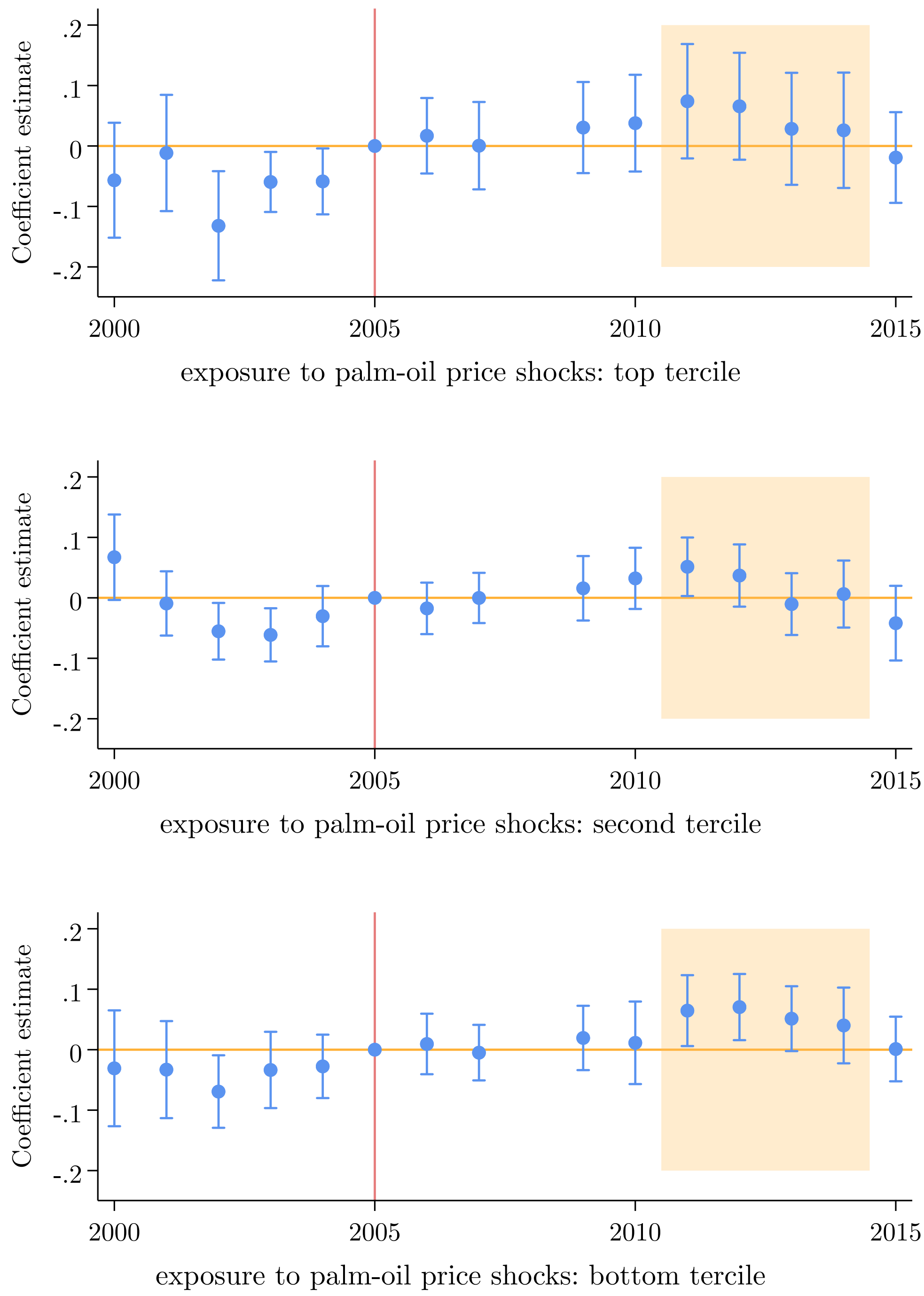
Notes: District definitions and borders use the district definitions in 2000. Exposed districts are defined as districts with a positive value of exposure to palm oil price shocks.

Figure 12: Impact of exposure to palm oil price shocks on real expenditure per capita



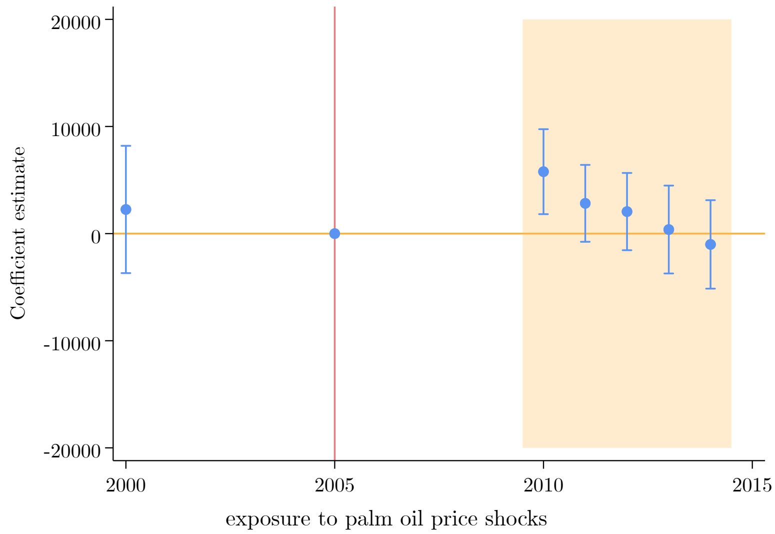
Notes: The dependent variable is the log of (district average) real expenditure per capita. The model includes control variables interacted with year, district fixed effects and year fixed effects. Regression is run on a panel of districts over year. Standard errors are clustered at the district level. Point estimates are relative to the 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: Impact of palm oil price shocks on real expenditure per capita across terciles



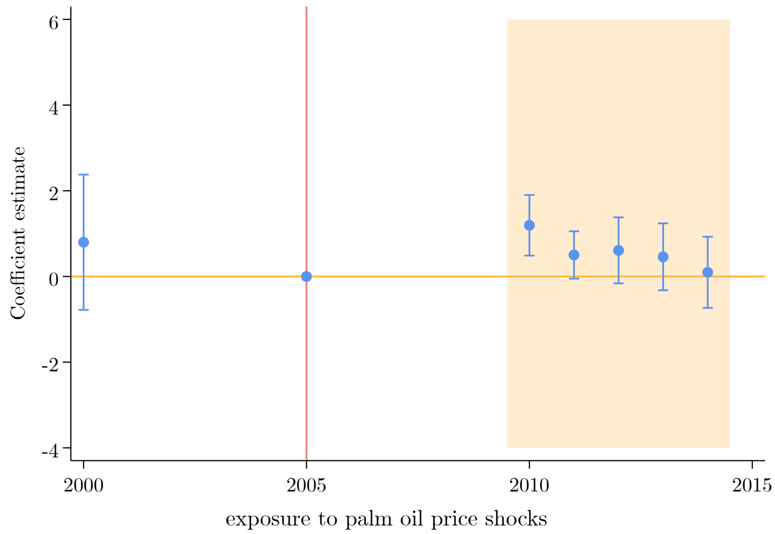
Notes: The dependent variable is (ln) real expenditure per capita. The model includes control variables interacted with year, district fixed effects and year fixed effects. Regression is run on a panel of districts over year. Standard errors are clustered at the district level. Point estimates are relative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

Figure 14: Impact of palm oil price shocks on net-inward migration



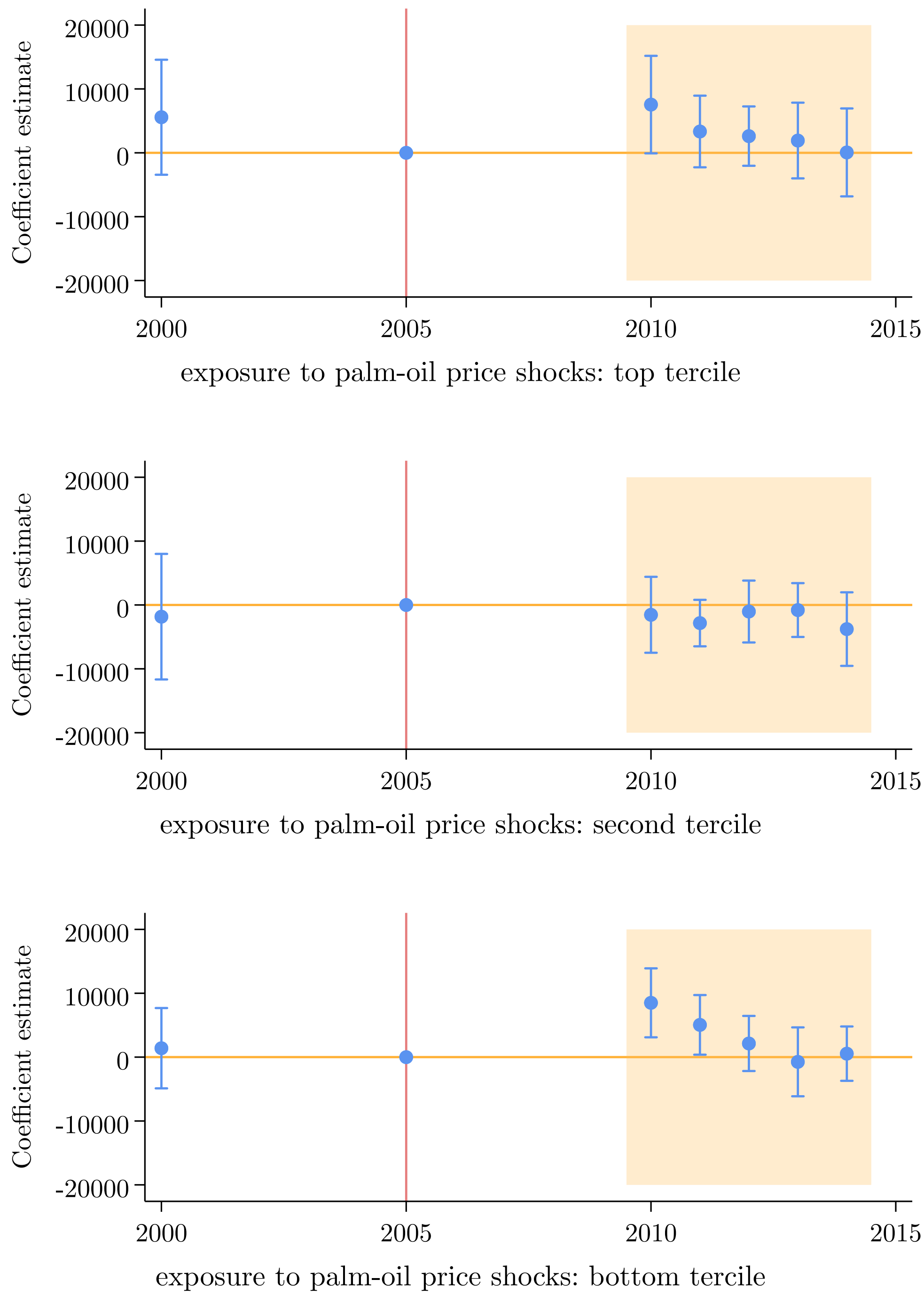
Notes: The dependent variable is the net-inward migration. The model includes control variables interacted with year, district fixed effects and year fixed effects. Regression is run on a panel of districts over year. Standard errors are clustered at the district level. Point estimates are relative to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

Figure 15: Impact of palm oil price shocks on share of net-inward migration



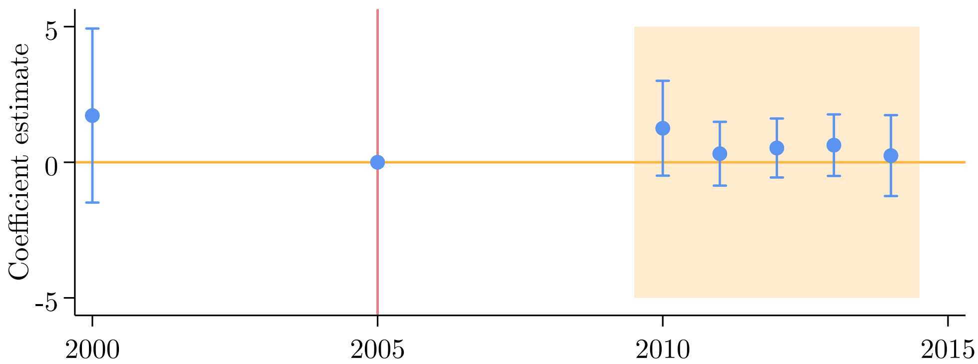
Notes: The dependent variable is the share of net-inward migration. The model includes control variables interacted with year, district fixed effects and year fixed effects. Regression is run on a panel of districts over year. Standard errors are clustered at the district level. Point estimates are relative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

Figure 16: Impact of palm oil price shocks on net-inward migration across terciles

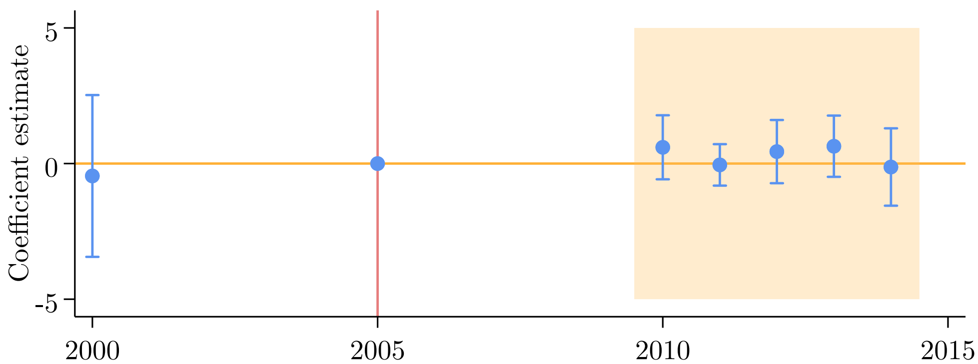


Notes: The dependent variable is net-inward migration. The model includes control variables interacted with year, districts fixed effects and year fixed effects. Regression is run on a panel of districts over year. Standard errors are clustered at the district level. Point estimates are relative to year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

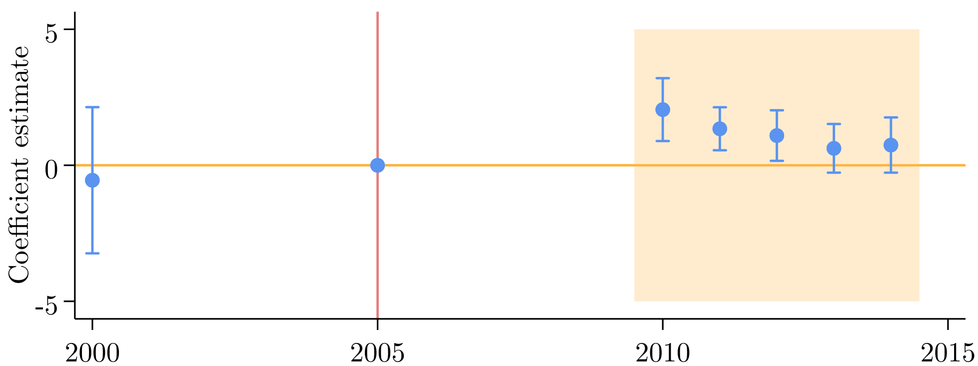
Figure 17: Impact of palm oil price shocks on share of net-inward migration across terciles



exposure to palm-oil price shocks: top tercile



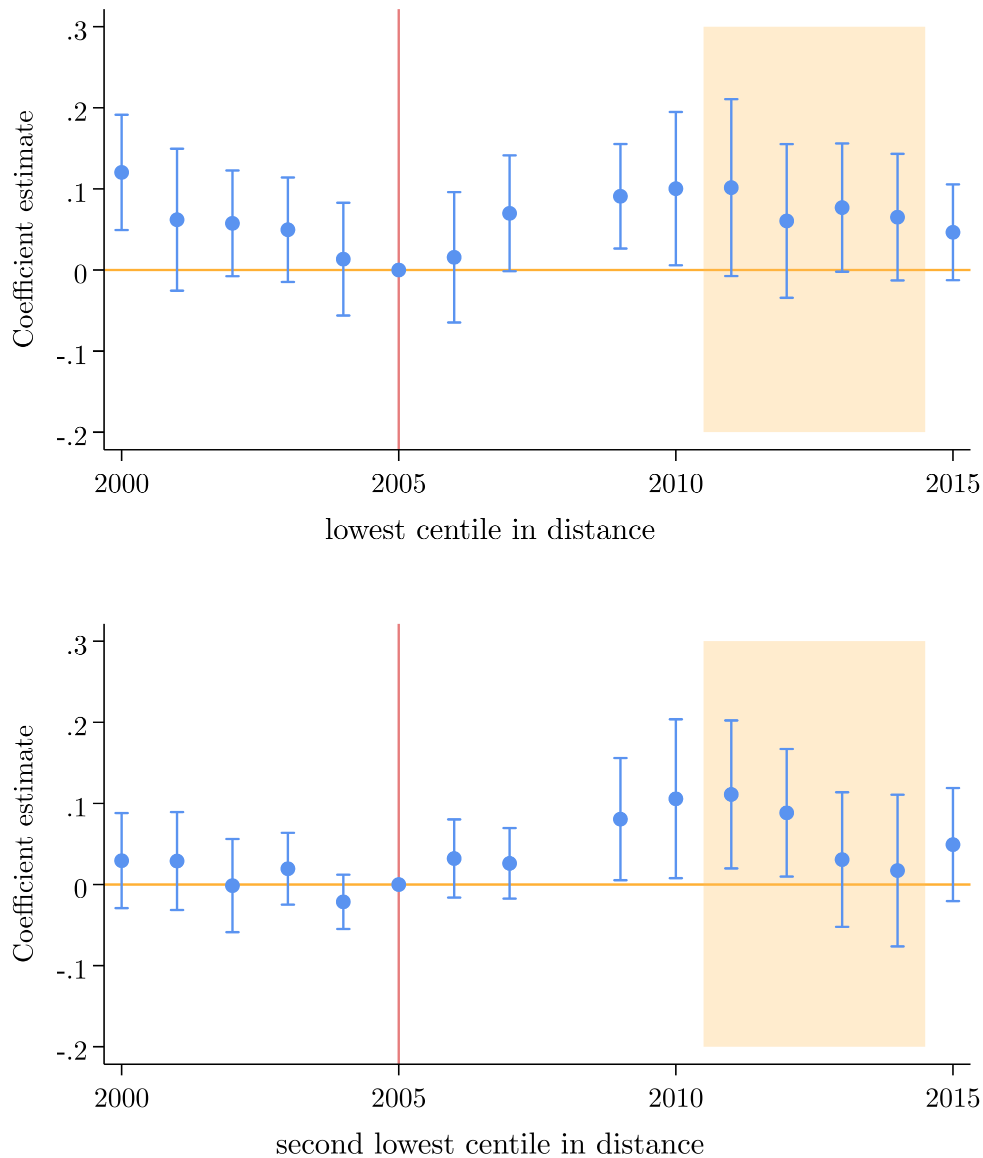
exposure to palm-oil price shocks: second tercile



exposure to palm-oil price shocks: bottom tercile

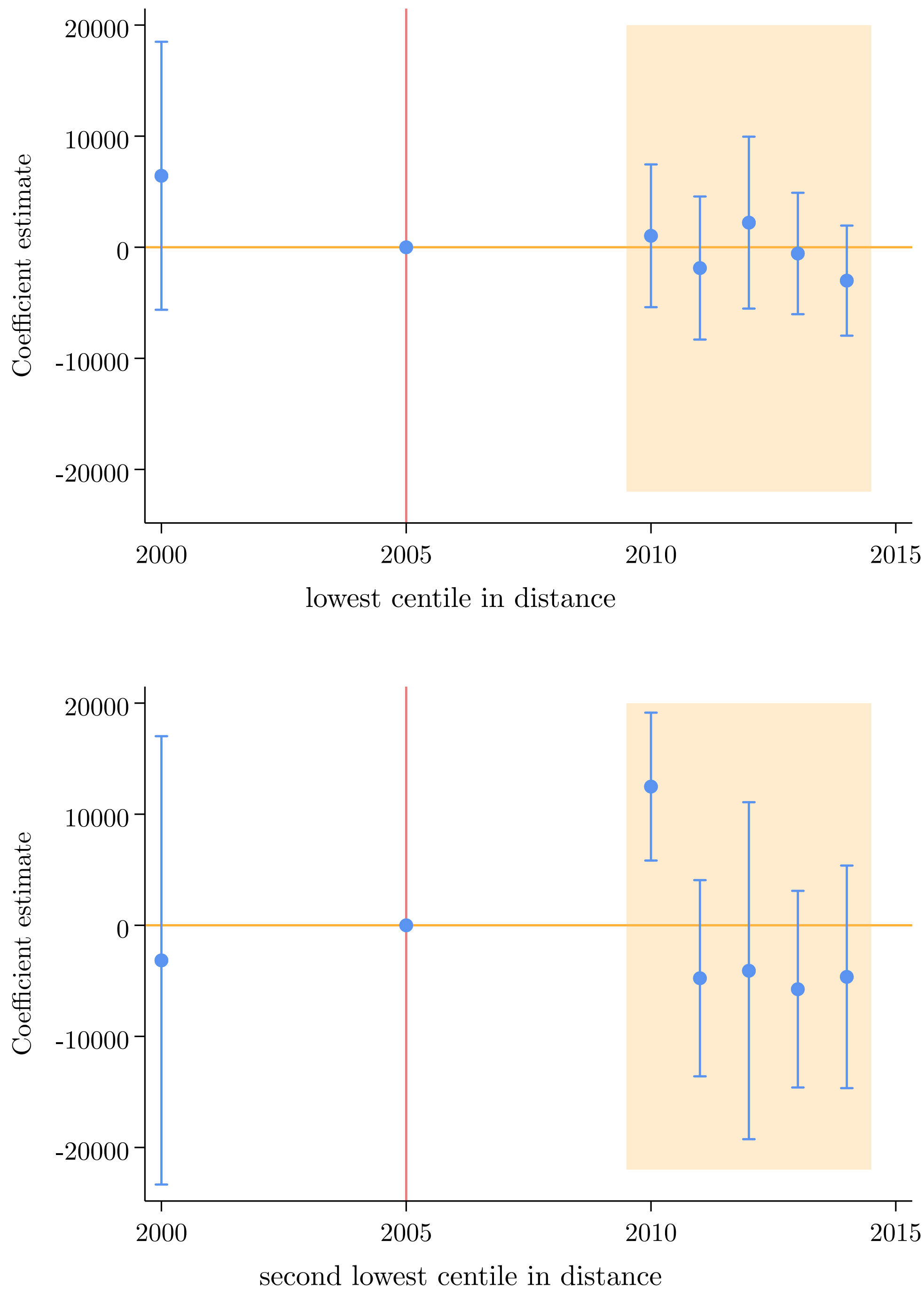
Notes: The dependent variable is share of net-inward migration. The model includes control variables interacted with year, districts fixed effects and year fixed effects. Regression is run on a panel of districts over year. Standard errors are clustered at the district level. Point estimates are relative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

Figure 18: Spillover of palm oil price shocks to nearest non-exposed districts: Real expenditure per capita



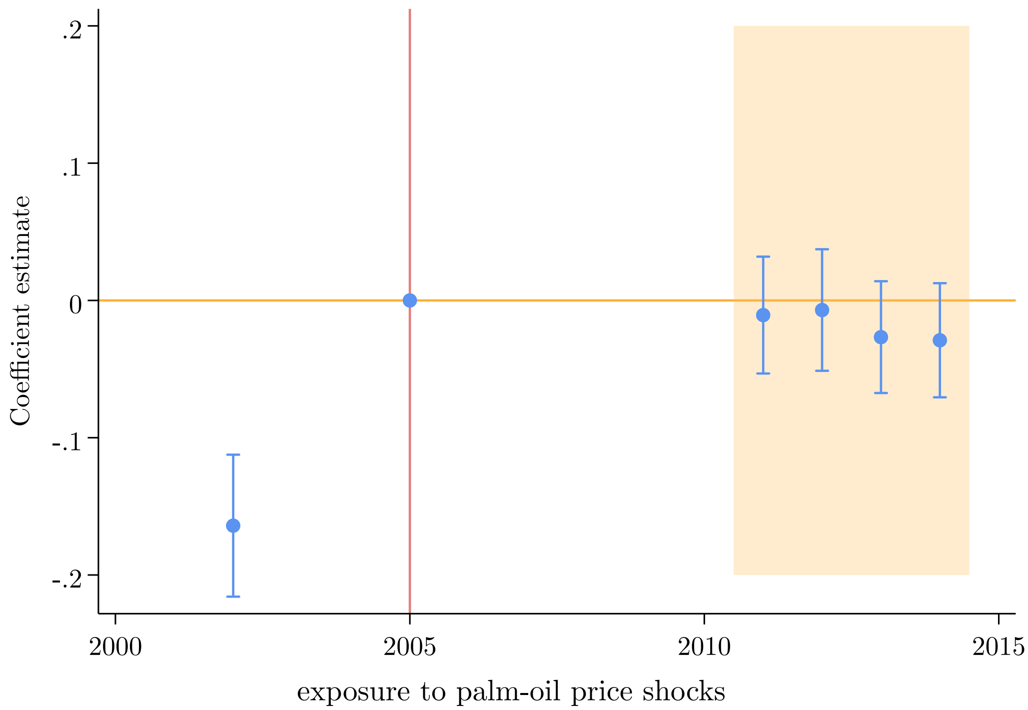
Notes: The dependent variable is (ln) real expenditure per capita. The model includes potential yield of palm oil, status of exposure of rice price shocks, other control variables, districts fixed effects and year fixed effects. Regression is run on a panel of districts that are non-exposed to palm oil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

Figure 19: Spillover of palm oil price shocks to nearest non-exposed districts: Net-inward migration



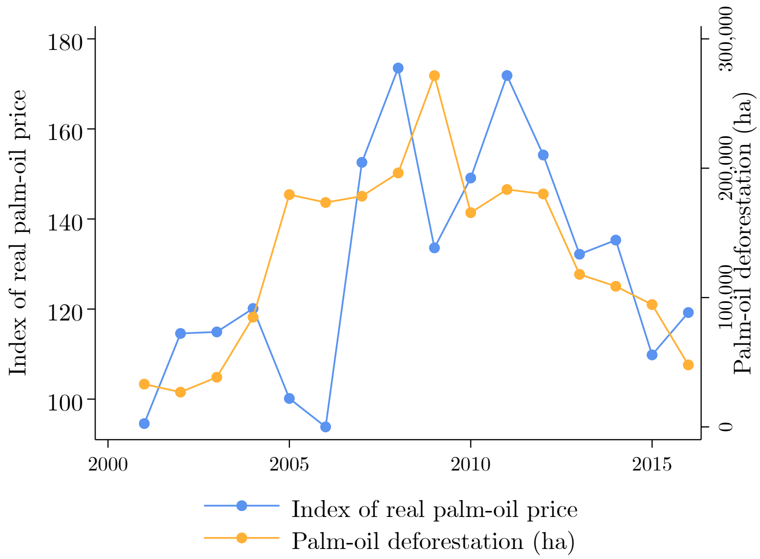
Notes: The dependent variable is the number of net-inward migrations. The model includes potential yield of palm oil, status of exposure of rice price shocks, other control variables, districts fixed effects and year fixed effects. Regression is run on a panel of districts that are non-exposed to palm oil price shocks over year. Standard errors are clustered at the district level. Point estimates are relative to the year 2005, the omitted category. The 95% confidence intervals for coefficients are shown by the range plots. Shaded area shows post-treatment period.

Figure 20: Impact of palm oil price shocks on district premia



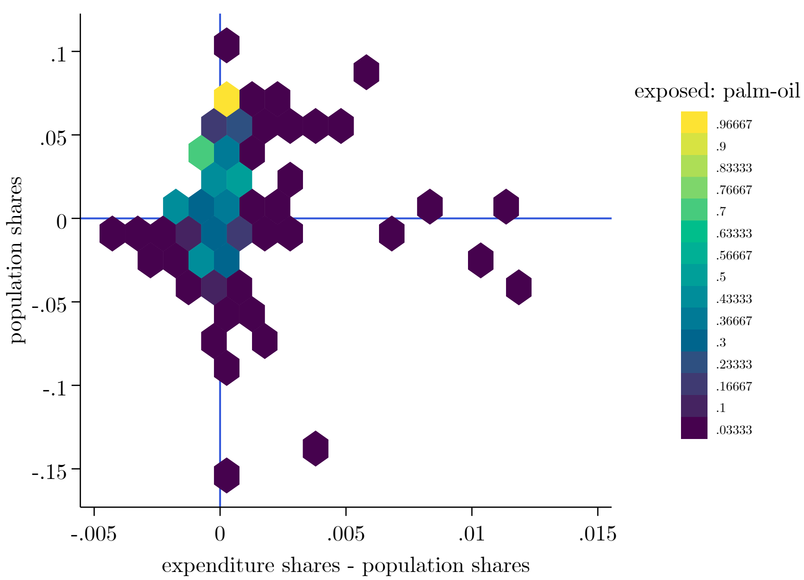
Notes: The dependent variable is the estimated district premia obtained from running Mincerian regressions on real expenditure per capita at the household level. The model includes control variables, districts and year fixed effects. Regression is run on a panel of districts over year. Standard errors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

Figure 21: Deforestation driven by palm oil plantation and palm oil price



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

Figure 22: Distribution of drivers of gains from migration by exposure to palm oil price shocks



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

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 a proxy for regional welfare and local earnings from this dataset. In addition, I also get sectoral GDP, area, and population for each district from this dataset. For each year, I crosswalk districts to the districts defined in 2000.

The 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) Regional GDP in manufacturing sector in 2000
- (ln) Length of district road in bad condition in 2000
- Percentage of villages with asphalt roads in 2000.

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

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

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

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 are provided by IPUMS. This dataset is a 10% sample of the complete census and is representative up to the district level.

A.4 Prices data

A.4.1 IMF Commodity Price Series

I use commodity prices in the IMF Commodity price series as a benchmark for world prices. The benchmark world price for palm oil is the palm oil prices of the Malaysia Palm Oil Futures (first contract forward) 4% to 5% FFA in USD per metric ton. The benchmark world price for rice is the 5% 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) in adding 20 USD per ton for rice shipping and a 10% mark-up in order to translate the world rice price to the retail price for imported rice in Indonesia.

A.4.2 Retail prices data for rice from BPS

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

A.4.3 Exchange Rates from FRED

I retrieve the 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 the 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 on the harvested area for palm oil and rice by district from 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 district published in these datasets as well.

I do not take the yield data directly from this dataset because I want to use the same district 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.[32] For each crop, I take the assumptions on water supply and input level as shown in Table A.1 below. I also take the estimated potential yield for the period 1961-1990.

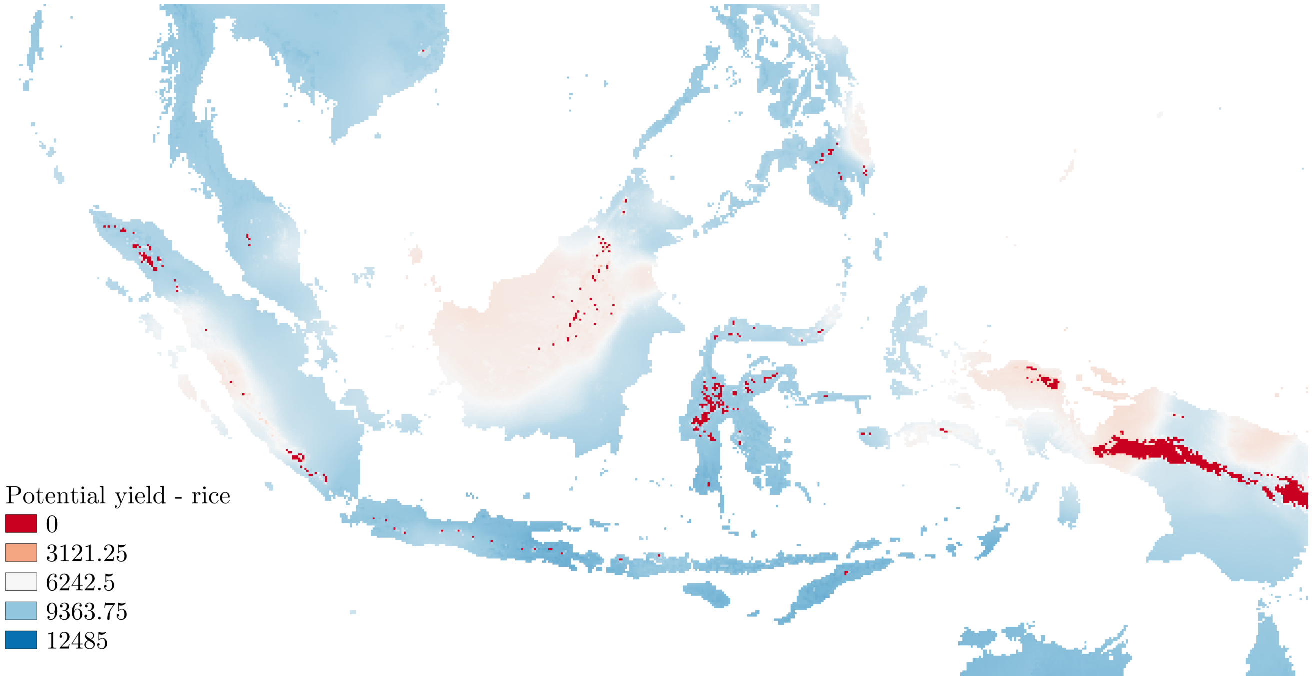
Table A.1: Assumptions about water supply and input level

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

Raw data from FAO GAEZ is presented in a five-grid level raster data. Figure A.3 and Figure A.1 show the raw potential yield data for, respectively, palm oil and rice in Indonesia and the surrounding area. For district-level analysis in this paper, I take the district averages for each crop. The district average is computed by dividing the sum of the potential yield in each district by the count of pixels overlaid on each district. For districts with less than 1 pixel, I divide the sum of the potential yield by 1 pixel. Figure A.2 shows the distribution of the district-average potential yield for rice. Figure A.4 shows the distribution of the district-average potential yield for palm oil.

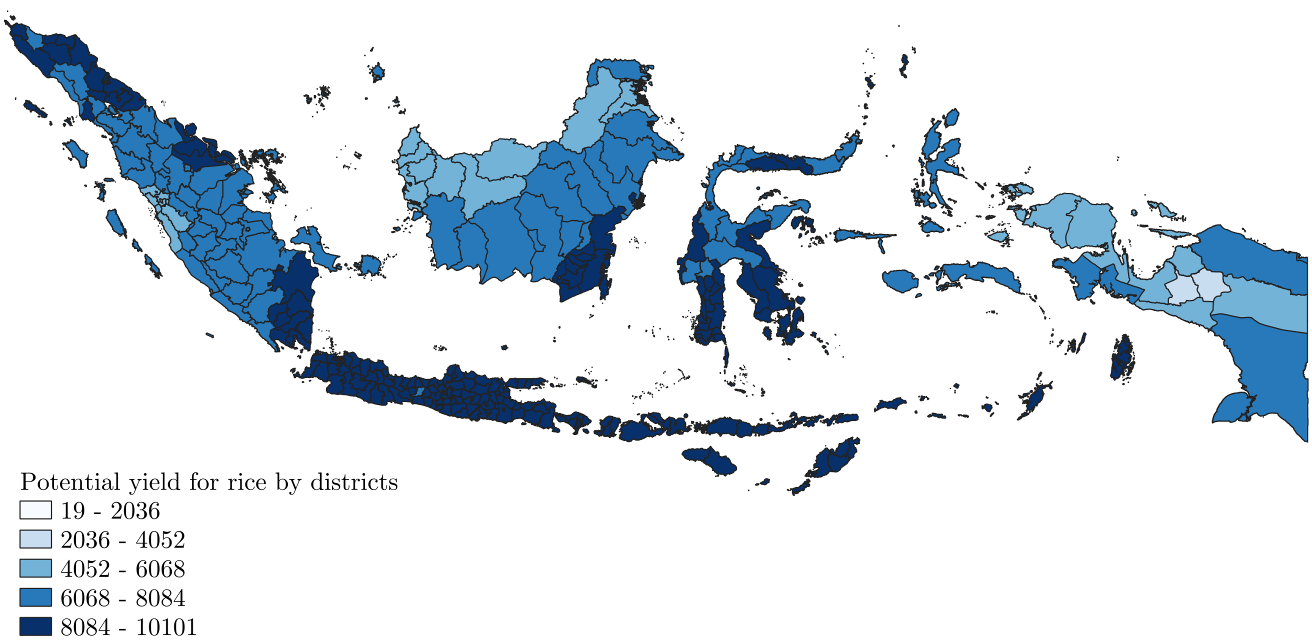
[32] Data can be dowloaded here : http://www.fao.org/nr/gaez/en/.

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



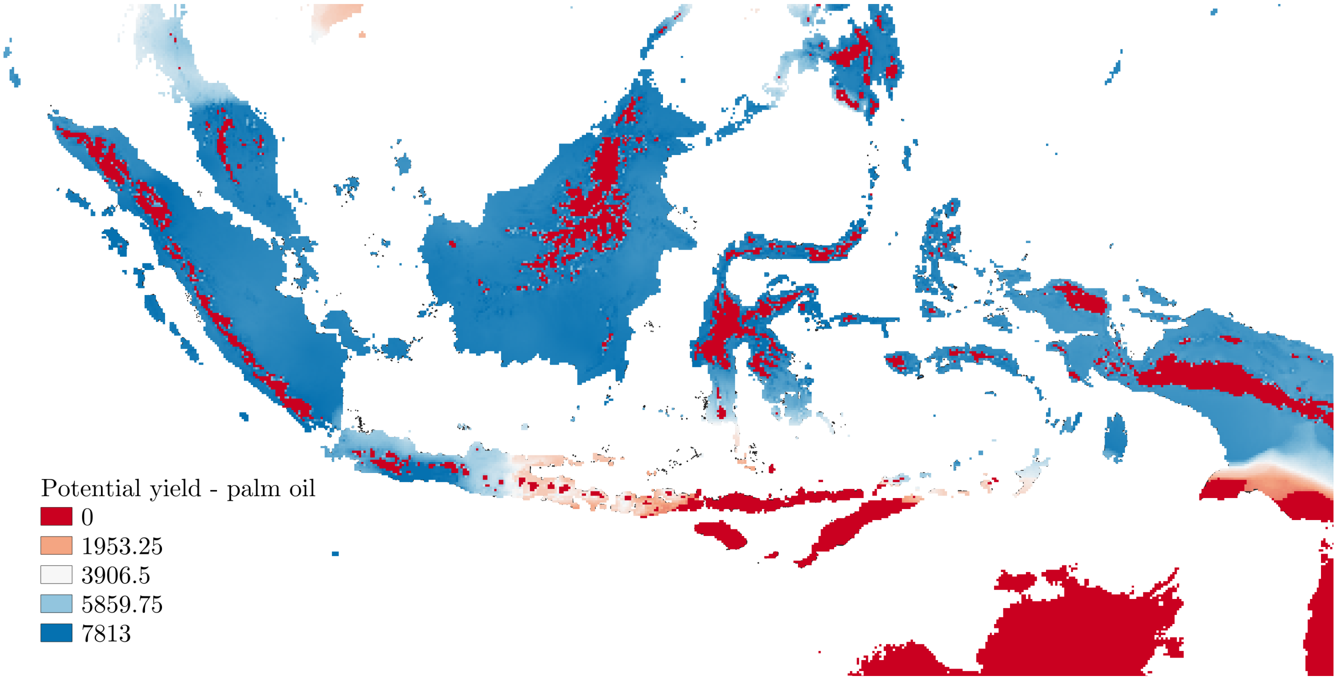
Source: FAO GAEZ.
Notes: Potential yield is in kg DW/ha.

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



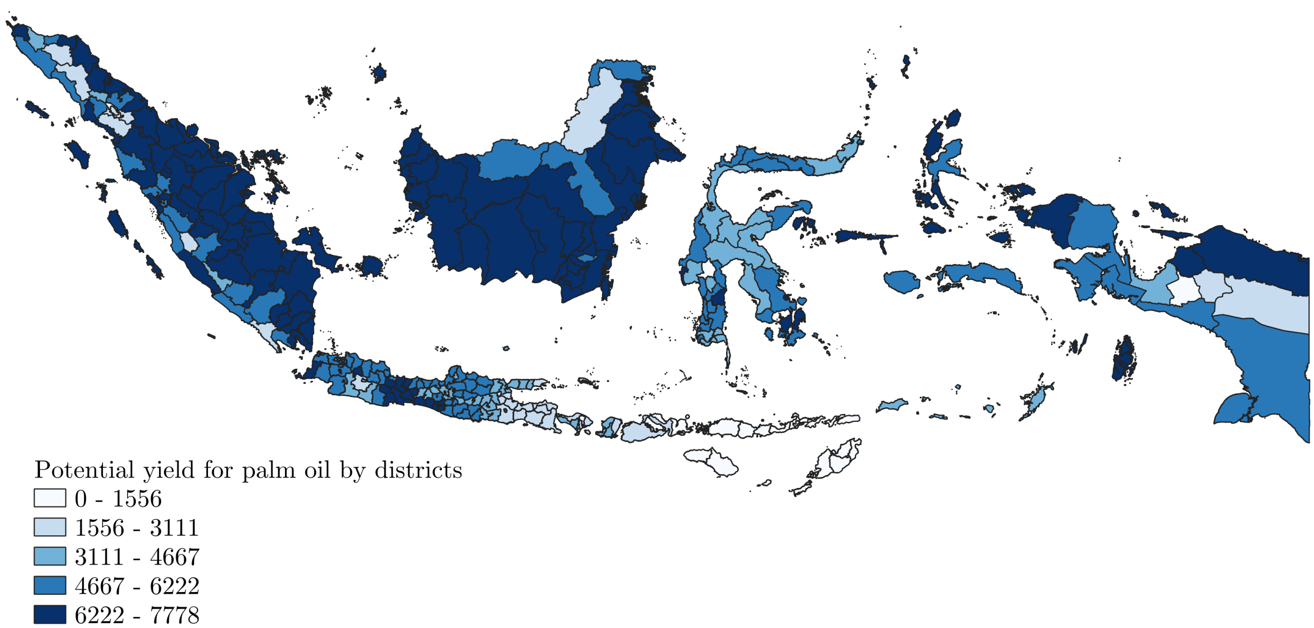
Source: FAO GAEZ, author's calculation.
Notes: Potential yield is in kg DW/ha. Districts use the district definition from 2000.

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



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

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



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

A.7 Village Census (*Podes*)

Podes is a triannual census covering information about the social, economic and geographic condition of all of the villages in Indonesia. It includes questions on demographics, natural resources, quality and quantity of infrastructure, and other economic variables. I use the 2005 and 2008 census to get measures on observed amenities during the period five years prior to *Susenas* 2011-2014. For each variable of observed amenities, I take the district average using population as a weight. Then, following studies 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.