Import Restriction, Price Shock, and Local Policy Responses: Evidence from Indonesia

Armand Sim *

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Abstract

This paper uses heterogeneity in the effects of rice import restriction across Indonesian villages to analyze local policy responses to price shocks attributed to a trade protection policy. Rice import restriction imposed sharp increase and considerable variation in domestic rice price. I exploit within village variation by combining agroclimatic conditions to grow rice with provincial rice price over time. Using a comprehensive longitudinal dataset of more than 53,000 villages spanning from 2000 to 2014, I find evidence that rice price hike harmed villages less suited for growing rice in terms of aggregate income and nutrition. District governments distributed more health facilities toward those villages, but only for those that did not already have one. Adversely affected villages empowered themselves by launching more small-scale development projects, particularly capital assistance. Heterogeneity analysis suggests the effects on health facilities (development projects) are significant only in high (low)-inequality villages. This contrasting result can probably be explained by combination of two factors: 1) villages having more control over projects and 2) higher social capital in low-inequality villages. Finally, I show that the presence of public health facilities mitigated adverse effects on presence of infant mortality in low-suitability villages. Overall, these results have important implications for the design of public safety net and risk mitigating strategies to address adverse economic effects at the local level.

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1 Introduction

Millions of households in developing countries have been lifted from poverty due to increased international trade (Goldberg and Pavcnik, 2007, 2016).[1] However, trade also has adverse consequences that are unevenly distributed within countries depending on the degree of local exposure to trade. Studies have documented evidence of adverse consequences of trade on various outcomes, such as labor market (e.g., Edmonds and Pavcnik, 2005; Topalova, 2010; Kis-Katos and Sparrow, 2015) and health (e.g., Anukriti and Kumler, 2019). Governments have implemented schemes, either implicitly or explicitly designed, to help adversely affected individuals or households through social transfers (Autor et al., 2013) or active labor market programs such as vocational training (McKenzie, 2017).

Schemes to help adversely affected communities, such as investment in social infrastructure and provision of public goods, are relatively unknown. These schemes are crucial in developing countries because levels of public social safety nets are low and insurance markets are imperfect. However, tax revenues in adversely affected communities are more likely to shrink due to decreased local income, and thus, limiting local governments' capacity to provide such schemes. The adverse effects on communities may be amplified when local governments have high dependence on local tax revenues (Feler and Senses, 2017).[2] In this paper, I contribute to this topic by exploring local policy responses to adverse consequences of a trade protection policy in a developing country where local government does not rely heavily on local tax revenues. This setting allows me to examine responses to instead of consequences of that protection policy. Understanding local policy responses is important for the design of public social safety nets and risk-mitigating strategies to help alleviate adverse economic shocks at the local level.

I study the effects of local price shocks attributed to rice import restriction on provision of health public goods and small-scale development projects across villages in Indonesia.[3] In 2004, the Indonesian government banned rice import with the purported goal of protecting farmers by increasing return to farming.[4] Studies estimate that the policy contributed to a significant increase in domestic price of rice as much as 37 % in 2006 (Fane and Warr, 2008) and 64 % in 2015 (Marks, 2017).[5] This has important welfare implication. Existing studies attribute increased

[1]The benefits of international trade on aggregate income growth have been established in the literature (Pascali, 2017; Feyrer, 2019).

[2]Feler and Senses (2017) find that localities in the US more heavily hit by import competition from China have lower public goods, such as policing, because import competition reduces property and sales tax revenues. Reduction in policing leads to increased property crime amplifying the economic costs of trade shock.

[3]Health public goods are allocated across villages by district governments, while small-scale development projects are mostly determined by village governments.

[4]The Indonesian government has always protected rice sector regardless of the state of Indonesian economy. Despite many failures, self-sufficiency in rice has always been a main policy objective in agricultural sector up to the point of being considered as a policy emotionally driven by a sense of nationalism (Fane and Warr, 2008).

[5]Rice price change after the import ban in 2004 cannot be fully accounted by tariffs and transportation cost alone. Non-tariff barriers, i.e., import ban, played a significant role (Patunru, 2018).

poverty rate to increased price of rice driven by import restriction (e.g., McCulloch, 2008; Warr and Yusuf, 2014). However, rice import restriction did not have significant impacts on Indonesia's GDP (Warr and Yusuf, 2014).

Studying rice import restriction provides an ideal context to address my research questions for two main reasons. First, it generates price and income shocks to a large proportion of Indonesian population because rice is a staple food. Second, the policy was implemented during the decentralization era. This policy environment is ideal because in this era, district governments rely heavily on transfer grants from the central government in the forms of General Allocation Fund (*Dana Alokasi Umum, DAU*) and Shared Natural Resource Revenue (*Dana Bagi Hasil Sumber Daya Alam, DBH SDA*) especially from oil and gas production. Income shocks resulting from rice import restriction did not have significant impacts on district revenue or the economy in general. Thus, this allows me to examine whether and how local governments respond to the consequences of price shocks at village level. Decentralization also alters mechanisms and allocation decision of public goods provision at the village level. Once centralized, district governments now have the authorities to allocate public goods to villages. Village governments, once suppressed, also have more freedom to express their political aspiration and request for more public goods even though districts hold the final decision.

To generate exogenous price shocks at the village level, I use two plausibly exogenous variations. First, I use considerable increase and variation in rice price across provinces and years. Villages of the same province are assumed to be exposed to the same price. The effect of increased rice price on income, for example, is not direct and clear. Rice price hike is likely to benefit net sellers but harm net buyers (Deaton, 1997). To help address this problem I interact provincial price variation with plausibly exogenous geographic variation in agroclimatic condition for growing rice at village level, which provides a measure of price shock. This approach relies on the assumptions that villages more suited to grow rice are more likely to benefit from the rice price hike because they have higher elasticity of supply and higher proportion of net-sellers farmers. Differential effect arises from comparing high with low suitability villages.[6]

To implement my empirical design, I assemble a comprehensive longitudinal village-level dataset covering more than 53,000 villages spanning from 2000 to 2014 drawing on a variety of sources. I use six waves of village census *Podes* (2000, 2003, 2005, 2008, and 2014) to obtain information on public goods and development projects. Time-invariant village-level rice suitability data that measures potential rice yields comes from FAO-GAEZ project. Monthly domestic price of rice across provinces from 2000 to 2014 comes from the Central Bureau of Statistics (BPS). In addition, I use complete records of various census data (i.e., the 2003 and 2013 Agricultural Census as well as the 2000 and 2010 Population Census) to construct other village characteristics, such

[6] Throughout this paper, villages in the 10^{th} percentile of rice suitability distribution are considered low-suitability villages, while those in the 90^{th} percentile are considered high-suitability villages.

as land ownership, proportion of net seller rice farmers, and ethnic diversity. Finally, to complement analysis at the less aggregate level, I use nationally representative household survey, the National Socioeconomic Survey (*Susenas*). Overall, the longitudinal nature of the dataset allows me to associate changes in public goods and projects with differential price shocks induced by changes in price of rice and variation in rice suitability.

The main results show evidence that villages adversely affected by rice import restriction were more likely to receive health public goods from the district government in the forms of health facilities but not health personnels. The effects are economically meaningful. Low suitability villages were 4 % and 5.4 % more likely to receive the overall and support health facilities than high suitability villages. The results from intensive margin analysis suggest that the effects do not extend to villages that already had a health facility. These results imply that district governments attempted to distribute resources evenly to adversely affected villages.

I find evidence of adversely affected communities empowering themselves by launching more development projects. Low suitability villages were 14 % more likely to launch a capital assistance project.[7] I also find significant increases in intensive margin: 8.6 %, 9.1%, and 17 % for all types of project, infrastructure, and capital assistance project, respectively. These significant results on the intensive margin analyses are in contrast to the null results on public goods (intensive margin). The difference in the degree of influence villages have on public goods and projects provision can probably explain the difference. While villages can put pressure on district governments for public goods, provision, districts hold the final decision. On the other hand, villages traditionally hold more power in projects implementation through some forms of democratic system.

I identify several plausible pathways to better understand why rice price hike led to larger increase in public health facilities and development projects in low suitability villages. I explore demand-side mechanism by examining two outcomes: aggregate income and nutrition. The results lend supports for this mechanism. Rice price hike led to higher aggregate income for villages more suited for growing rice, as indicated by the increased presence and intensity of nighttime lights and smaller number of people eligible for health insurance program for the poor. I find that households in high suitability villages enjoyed better nutrition, as measured by higher calories and protein consumption per capita.

I complement the analysis on mechanisms by investigating treatment effects heterogeneity by landholding inequality. Two things motivate this heterogeneity analysis. First, while changes in aggregate income and nutrition help understand the demand-side story of the main results, it is incomplete given the large variation of landholding inequality across villages, Gini coefficient of 0.54 in 2003. Second, a large literature has documented the role of land or wealth inequality in determining provision of public goods and local projects. The evidence is mixed. High inequality

[7]Unlike information on public goods, information on development projects was only available starting in the 2008 *Podes*. Thus, the study period here refers to 2008-2014.

can contribute to higher level of public goods received from higher-tier governments (Banerjee and Somanathan, 2007; Dell, 2010), but it can also lead to lower local public goods and projects (e.g., Alesina and La Ferrara, 2000).

My findings are in line with the mixed evidence in the literature. I find significant effects on the probability of receiving support health facilities but only among villages with high land inequality. On the other hand, significant effects on capital assistance projects (at extensive and intensive margins) are only found among villages with low inequality. These contrasting results suggest that high inequality helps in lobbying for public goods from higher tier-governments but low inequality helps reach decision in launching development projects. One potential explanation is the negative relationship between inequality and collective action (e.g., Bardhan, 2000; Dayton-Johnson, 2000; Khwaja, 2004). Collective action can lead to higher provision of local projects by increasing community participation, but it is more likely to have stronger influence when it matters. This is the case for development projects, where villages hold final decision over types and number of projects to launch than that of public goods, where district governments hold the final decision.

Finally, I identify social capital as another plausible channel. An increase in social capital, a variety of collective action measure, has been documented to strengthen social cohesion and cooperation which can lead to higher provision of public goods and development projects. I find that individuals in adversely affected villages express higher social capital, especially trust level.[8] The effects are significant only in villages with low land inequality. This finding lends support to why adversely affected villages with more equal landholding distribution were more likely to launch development projects.

Having shown that health facilities are distributed more heavily towards the low-suitability villages, I investigate whether those villages benefited more from the presence of health facilities. I focus on two health outcomes: infant (IMR) and maternal mortality rates (MMR). I find that negative income shocks increased the presence of both IMR and MMR by 5.2 % and 15.5 %, respectively, but health facilities mitigated some of it. The presence of IMR, but not MMR, is lower in a village that has a public health facility.

This paper connects to several strands of literature. First, this paper contributes to the literature studying policies or compensation schemes in response to adverse effects of international trade or globalization. Studies mostly evaluate the effects of policies for individuals or households, such as social transfers (e.g., Autor et al., 2013) and active labor market policies (Crépon and Van Den Berg, 2016; McKenzie, 2017). I contribute to this literature by providing the first evidence on policy responses and the effects of those policies at village level in a developing country

[8] An increased social capital or cooperation after adverse shocks has been observed, especially in the context of natural disasters, either in developing (e.g., Cassar et al., 2017) and developed countries (e.g., Whitt and Wilson, 2007).

context. Understanding policy responses is crucial because adverse effects on communities can be amplified in the setting with low investment in social infrastructure or public goods provision.

Second, this paper contributes to the literature studying the role of wealth or land inequality in provision of public goods or local development projects (e.g., Galasso and Ravallion, 2005; Banerjee and Somanathan, 2007; Banerjee et al., 2007; Araujo et al., 2008). Much of the studies in the literature take land or wealth inequality as relatively constant due to absence of exogenous shocks. In this paper, I find that when the relative values of land change due to rice price shocks it can amplify the role of inequality in public goods and development projects.

Third, this study is also related to the literature on decentralization, targeting performance, and public goods provision by local governments (Bardhan, 2002; Besley and Coate, 2003; Gadenne and Singhal, 2014). Decentralization is considered relatively better than centralized system in terms of accountability and knowledge on the local communities. These factors are likely to improve targeting performance either in government programs or public goods provision. I complement this literature by showing that local price and income shocks help local governments identify problem and distribute public goods when they have legitimate authorities.

Finally, this paper complements the literature studying the impacts of policies fueled by nationalism and protectionism sentiments (Becker et al., 2016; Fisman et al., 2014; Barwick et al., 2019; Bloom et al., 2019; Fetzer and Schwarz, 2019). Studies in this literature have examined how nationalism and protectionism sentiments shape policies and its consequences, but specific topic on local governments' responses to those policies has not been explored. This paper provides the first causal evidence on that topic in a developing country context.

The remainder of this paper is organized as follows. Section 2 discusses the context: rice import restriction and village institutional settings. Section 3 discusses data and measurement. Section 4 discusses estimation framework. Section 5 discusses main results. Section 6 discusses the mechanisms. Section 7 discusses the mitigating effects of public health facilities on infant and maternal mortality rates. Section 8 concludes.

2 Context

2.1 Rice Import Restrictions

Rice is the most important agricultural commodity in terms of its proportion to expenditure, income, and employment. First, rice is the staple food for the majority of Indonesian population, and it constitutes more than 20% of the food expenditure of the poorest 40% of the population (McCulloch, 2008).[9] Second, rice is an important source of income and employment among farm-

[9]As in many developing countries, food constitutes a large share of total expenditure in Indonesia: well above 60% for more than half of the Indonesian population (McCulloch, 2008)

ers. The 2003 agricultural census reveals that 55% of agricultural households are rice farmers, more than any other commodities. Out of those rice growing households, more than 70% are net producers (McCulloch, 2008).[10]

Given the importance of rice, the government has long been concerned with policies to increase domestic production and limit its dependency on international market through various rice intensification programs (e.g., mass guidance program or *Bimas*) or other protection measures like tariff or non-tariff measures (Timmer, 2005). Despite those policies, Indonesia has regularly been a net importer, as seen in Figure A.1.[11]

Before the 1997/1998 economic crisis, the state logistic agency, *Bulog* (Badan Urusan Logistik), was the sole importer.[12] Following financial agreement with the IMF in 1998, the government was forced to abolish *Bulog*'s monopoly role and allow private sectors to participate in rice import business. However, the policy only lasted for less than two years. The growing influence of pro-farmers groups purportedly pressured the government to implement a series of rice import restriction policies aiming to protect farmers.

In 1999, the government introduced a 20% tariff for imported rice, which was sharply raised to approximately 75% in 2003 (Warr, 2005; Fane and Warr, 2008). In 2004, importing rice was effectively banned. While private sectors were completely prohibited to import rice, *Bulog* could import limited quantities of rice only during certain periods with the goal to secure rice supply (Warr, 2005, 2011). The ban was originally intended to be a seasonal policy to protect rice farmers,[13] but the policy had been repeatedly extended and had not been completely revoked (Warr and Yusuf, 2014).[14] Figure A.1 shows that Indonesia's net rice import fell sharply following the ban, but it appears that domestic production increased in response to higher domestic price. Specifically, between 2004 to 2014 domestic production and yield increased by about 31 % and 13 %, respectively.

Indonesia had rarely imported rice exceeding 5% of total national consumption, but the import managed to stabilize domestic price (Dawe, 2008). It is, thus, unsurprising that the domestic rice price increased significantly following the ban. Figure 1 shows that domestic price started to climb in 2005 as the stocks of rice from previous year were starting to thin.[15] Between 2000 and

[10] The proportion of farmers in urban areas is nonzero. The 2004 National Socioeconomic Survey (*Susenas*) records that 16 % of urban population work as farmers, where 50 % of them are rice farmers. The proportion of the urban poor that work as farmers is higher, 37 %, where 50 % of them are rice farmers.

[11] For a comprehensive overview on historical Indonesian rice cultivation and related policies, see Mears (1984) and Simatupang and Peter Timmer (2008).

[12] In addition to rice, *Bulog* controlled other commodities, such as sugar, maize, and soybeans.

[13] The Ministry of Trade and Industry regulation No.9/MPP/Kep/1/2004 stipulates that rice import was prohibited one month prior to, during, and two months after the harvest season.

[14] Instead of lifting the ban, the government has been imposing import quotas which vary over time depending on, for example, domestic rice supply and demand.

[15] Due to heavy reliance on domestic supply, the increasing trend in domestic price appears unaffected by the brief period of sharp increase of the global rice price between 2008-2011.

2014, domestic rice price increased annually by 0.1 log points, as shown in Panel B of Table 1. Some estimates suggest that import ban contributed to the price hike by 37% and 64% in 2006 and 2015, respectively (Fane and Warr, 2008; Marks, 2017).[16]

In addition, import ban also imposed substantial price variation across provinces, as shown in Figure 4. There was relatively negligible variation in domestic rice price pre-ban in contrast to that of the post-ban, which indicates a lack of arbitration by domestic traders in the post-ban era.[17] There are three plausible explanations. First, a weaker role of the state logistic agency, *Bulog*, in stabilizing domestic price. Second, a disruption to the thriving relationship between the private and international traders during the more liberal trade regime prior to 2004 (Bazzi, 2017).[18] Third, the overall low elasticity of supply (0.2-0.4); it varies across regions depending on soil characteristics and land types. As a comparison, the elasticity of demand for Thailand's rice exports varies between -2.5 to -5 (Warr, 2005).

2.2 Institutional Setting

2.2.1 Decentralization

The political context during the period of this study corresponds to the decentralization reform period that started in 1999. Following the fall of the President Seoharto's authoritarian regime (1967-1998) — known as the New Order —, there was a massive urge to decentralize responsibilities to local government. Fiscal decentralization to provincial and district governments increased the share of total expenditures managed by subnational governments to 36 % in 2011, a 50 % increase from the mid-1990s (World Bank, 2003). Decentralization of political power allows districts and villages to merge or proliferate to form a new district or village. This resulted in a significant increase in the number of the new governments at all level.[19] By 2014, Indonesia is divided into 34 provinces and 511 districts. Each district is divided into subdistricts that are further divided into villages. There are two types of villages based on observable characteristics: *desa*, which is more rural, and *kelurahan*, which is more urban.[20] Following the decentralization reform in 1999,

[16]The estimates in both studies are measured in terms of nominal rate of protection (NRP), which measures the effect of the government trade policy at any given nominal exchange rate compared to a situation in absence of said policy. See Fane and Warr (2008) and Marks (2017) for details.

[17]The price variation post-ban is persistent and follows random walk as suggested by test results that fail to reject the null hypothesis of unit root (p-value > 0.85 for all cities). This alleviates some concerns that the significant effects of price are false positive.The results come from the two unit root tests. First, the augmented Dickey-Fuller test. Second, acknowledging the fact that rice prices across cities are less likely to be independent, I apply heterogeneous panel unit root tests suggested by Im et al. (2003).

[18]Bazzi (2017) demonstrates that areas closer to domestic ports and shipping distance to Bangkok and Ho Chi Minh experienced higher increases in price suggesting high dependency to import rice.

[19]See Fitrani et al. (2005) for more details on decentralization.

[20]While the head of *desa* is decided through local election, the head of *kelurahan* is directly appointed by district mayor. The categorization of villages into *desa* and *kelurahan* were initiated after the passage of the Village Law No.5 of 1979. The law stipulates that all villages were *desa*, and some of them were categorized as *kelurahan* by the

the number of villages increased significantly from more than 66,000 in 2000 to more than 80,000 in 2014, where well above 85% of them are *desa*.[21]

Decentralization has significant impacts on villages because it alters the decision process on the allocation of public goods and development projects as well as the financial resources for villages.

Public Goods The decision-making process for the provision of public goods in Indonesian villages has evolved since the fall of the New Order era. Prior to decentralization, the main source of funding for village public goods came from the national budget and was highly centralized. Virtually every important decision regarding village budget and public goods provision required approval from the district mayors (Antlöv, 2003; Tajima et al., 2018). In addition to budget allocation from the central government, villages could submit a proposal to the National Development Planning Process (*P5D*) for public goods provision. However, village officials were mainly unaware of this mechanism hampering them to submit high-quality proposals that led to undesirable outcomes for their village (Evers, 2000).

Decentralization changed the process for public goods provision in villages, especially concerning the roles of district and village governments. While district governments remains central in funding and allocating public goods, village governments also play an important role in initiating and leading maintenance of the public goods, especially infrastructure, such as roads and bridges (World Bank, 2010). Overall, to some degree, villages still relied on higher-tier governments for public goods provision both before and after decentralization. However, this does not rule out the influence of village governments in improving the level of public goods provision. This has been documented even before decentralization.

Despite top-down and centralized approach in the New Order era, recent studies find that villages could influence public goods provision through the roles of educated heads (Martinez-Bravo, 2017) and inter-village competition indirectly induced by the level of ethnic segregation (Tajima et al., 2018). The influence of villages is theoretically larger after decentralization due to more freedom in the expression of political aspiration and collective actions. This has been documented in an extensive longitudinal local level institutions study covering 40 villages over more than a decade (Wetterberg et al., 2014).[22] The study finds that, among other factors, income shocks, shifts in sources of income, and distribution of power and assets within a village con-

central government. The conversion of *desa* into *kelurahan* stopped in 1992 mainly due to financial reasons (Niessen, 1999). See Martinez-Bravo (2014) for more detailed explanation on the historical formation and differences between *desa* and *kelurahan*.

[21] Decentralization reform, which marked the end of Soeharto government in 1998, provided massive far-reaching autonomy to local governments, including fiscal responsibility and splitting or forming new local government.

[22] Local-level Institution study is a study on the relationship between local institutions, poverty, and village governance in rural areas in Indonesia combining descriptive and quantitative methods. The study was conducted in 3 provinces, 6 districts, 40 villages, and 1,200 households. It has been conducted three times: 1996/1997, 2000/2001, and 2012.

tribute to the collective capacity of villagers that can affect level and choice of public goods and development projects.

Public Healthcare Public health system providing basic primary health care consists of hospitals, clinics, and smaller facilities. The main health centers or clinics, *Puskesmas*, are staffed by at least one physician and roughly five nurses providing primary care. The smaller supporting facilities, *Pustu*, are staffed by one to three nurses and received monthly visit from a physician. *Pustu* helps provide basic services to villages or areas that are out of reach by *Puskesmas*.[23]

Development Projects The main goals of development projects are to empower village communities in the forms of infrastructure, capital assistance, and employment-related assistance projects. There are several mechanisms for a village to launch projects. First, villages obtain financial resources from central government programs, such as the National Community Empowerment Program (*PNPM*, formerly known as the *Kecamatan (subdistrict) Development Program or KDP*). Every year, each village within a participating subdistrict writes a proposal for small-scale projects in, for instance, infrastructure and capital assistance (Olken, 2007). Each proposal is ranked in an intervillage forum within subdistrict according to predetermined criteria such as the number of beneficiaries and project cost. All projects are funded until block grants are exhausted, with the top ranked project receives priority. Second, villages write proposals to district governments through *P5D*. Third, villages receive irregular grants from district governments or from other parties, such as NGOs. Those grants are then allocated to projects of their choice. While it is useful to be able to distinguish financial source for each project, the data unfortunately does not allow me to do it. Overall, villages have relatively more control over the allocation of development projects than that of public goods controlled by district governments.

Financial Resources Village financial sources have been evolving over time. Following the first major political reform concerning village governance, Law 5/1979 stipulated that each village received block grant from district government. The massive decentralization reform provided more financial sources to villages. Law 22/1999 stipulated that each village had the autonomy to raise its own revenues in addition to receiving block grants from district government. In 2004, each village was set to receive additional grants from the central government, as mandated by Law 32/2004.

In summary, there are two broad sources of village financial resources: village own-source revenues and transfer grants (from district and central governments). Villages raise own incomes through the following sources: own-managed traditional markets, charges on small scale public

[23] Other facilities include village health posts (poskesdes), village maternity posts (polindes), and neighborhood health posts (posyandu). These facilities are usually run by communities and volunteers and may not even have permanent locations.

transportation vehicles that pass through their jurisdictions, and other fees related to administrative services (Antlöv et al., 2016). Most of village revenue comes from transfer grants from higher-level government, especially district government. Unfortunately, there are many missing observations and inconsistent structures in data collection of village revenues information in *Podes* preventing me to conduct further analysis on types of revenues.

3 Data and Measurement

This section presents information on data sets and measurement, construction of the study sample, descriptive statistics, and estimation framework. I combine multiple data sets that include population and village census as well as gridded data to form the basis of the main empirical analysis. The unit of analysis is at village-year level.

3.1 Public Goods and Development Projects

The data on the main outcomes, public goods and development projects, come from the village census (*Podes*). This dataset has been collected roughly three times every decade starting in 1980.[24] In each wave *Podes* collects rich information on village characteristics, such as the land size, geographic location, population, existing infrastructure projects, public goods, and development projects.[25] The information comes from the official village documentation and interviews with the village head. The *Podes* sample size has increased over time following the decentralization reform that allow villages to split and merge to form a new village. The 2000 wave covers more than 66,000 villages, but it has expanded to 82,000 in 2014. For the purpose of this study, I use the 2000, 2003, 2005, 2008, 2011, and 2014 waves.

The main outcomes include sets of health public goods and development projects.[26] I focus on health public goods that are consistently collected across waves. These include health care personnels (medical doctors) and health care facilities. I examine two types of facilities: the main facilities (*Puskesmas*) and the supporting facilities (*Pustu*).

[24]The latest wave was recently completed in 2018. *Podes* has three main themes which alternate every wave: agriculture, economy, and population. For example, the 2003 wave focuses on agriculture. In that year, *Podes* collects detailed information on village agriculture, such as production yields of cash crops and land plots allocated for each crop. The agriculture module was not collected in the 2006 wave, for example, because in that year *Podes* focuses on village economy and collects more detailed information on the small enterprises, for instance.

[25]There are some information that are not consistently collected every wave. For example, detailed information on village budget allocation, such as for construction or maintenance of infrastructure, and development projects were only available starting in 2008. The number of health facilities and officials were not collected in 2008.

[26]In general, development projects can include both public and excludable goods (Chavis, 2010; Araujo et al., 2008). As documented in *Podes*, the projects include public goods, such as maintenance or building road infrastructure, and excludable goods, such as capital assistance to the eligible villagers. To avoid confusion, I separate these two outcomes in the analysis even though some products of the development projects are public goods.

The development project consists of three broad sets of outcomes. First, infrastructure project. This project includes maintenance or construction of the following public infrastructures: road, bridge, schools, sanitation, traditional market, irrigation, and other economic support facilities. Second, capital assistance project. This project aims to increase village economic capacity by providing loans for agriculture, non-agriculture, and other types of enterprises. Third, employment assistance project This project includes training program to increase production and marketing capacity as well as enhancement of civic engagement. To be consistent across waves, I restrict my analysis to projects that are not funded by *PNPM*.[27]

Flow and Stock Variables Changes in public goods and development projects are examined in its extensive and intensive margin.[28] For intensive margin analyses, I follow Cassidy (2019) by dividing the outcomes into stock and flow variables. Flow variables include variables that are probably only present for limited time, such as development project and health personnel outcomes. For example, the funds for development projects or contracts for medical doctors might not be perpetually renewed. In contrast, stock variables, such as school buildings or health care center, might remain indefinitely. Thus, by definition, both variables are constructed differently to reflect changes between periods. The outcome flow variables Y_{vpt} at village v and province p at the end of period t reflects the number of the variable at that period. On the other hand, the annual change in stock variables in period t must take into account the stock of that variable in the previous period, t_0, which is calculated as follows:

$$Y_{vpt} = \frac{1}{t_1 - t_0}\left(Y_{vpt_1} - Y_{vpt_0}\right) \tag{1}$$

3.2 Rice Price and Suitability

Rice Price The monthly domestic rice price data is collected by the central bureau of statistics (BPS) from a major representative city in each province. This practice is common in many developing countries (Deaton, 1997). Because data on commodity and food crop prices at village level is not available and observable, I assume that villages within the same province are exposed to the same price. I further assume that provincial price is exogenous to each village. This assumption is not too stringent because a village is less likely to determine the price of rice at the province level.

I use the monthly retail price data that spans from January 2000 to March 2014 to construct a key independent variable, price change.[29] The variable is defined as the annualized growth in

[27] Information on development projects was only introduced in 2008.

[28] In addition to the three broad measures of development project, I also create two additional variables: 1) an indicator variable for whether a village receives any kind of project in particular year (extensive margin) and 2) a continuous variable that sums up all projects that are available in a village (intensive margin).

[29] While it is probably more ideal to use farmgate than retail price, regional farmgate price data is not avail-

the log rice price between *Podes* waves. For example, to examine the effects on village outcomes in 2003, the price change measures growth January 2000 to March 2003. For outcomes in 2005, price change is constructed from April 2003 to March 2005. Price changes for subsequent waves follow the same construction method.[30] Figure A.3 illustrates the distribution of annual price changes from 2000 to 2014, where the darker shade implies higher price change than the lighter shade. The annual price change does not seem to be permanently attributed to certain provinces, whether rice producing or not.

Rice Suitability Data for rice suitability, which measures potential or maximum attainable yields (ton/hectare) of rice, comes from the FAO-GAEZ project.[31] This measure is arguably exogenous as it is climate-driven productivity, not observed by the actual pattern of production. The climatic record is based on daily weather records observed in each year from 1961 to 1990, which provides good approximation for historical condition (Nunn and Qian, 2011; Costinot et al., 2016; Fiszbein, 2017). To obtain rice suitability information at the village level, I aggregate the suitability information across grids using area weights, i.e., the total area of the grid overlapping with the village, divided by the total village area. Figure 2 describes geographic variation of rice suitability in Indonesia, where darker shades indicate higher values. Rice suitability appears to be a good proxy for rice production (ton/hectare), at least for Indonesian villages, as illustrated by Figure 3.

3.3 Other Variables

To measure the differential impacts of rice price change on aggregate income, I use two proxy variables. First, I follow the standard approach in the literature by analyzing nighttime lights, which has been increasingly shown to be a reliable indicator for economic development, especially in areas with shortage of quality data (Henderson et al., 2012). I measure extensive margin — indicator for presence of lights — and intensive margin — intensity of lights — of nighttime lights. The data comes from the National Oceanic and Atmospheric Administration (NOAA) Defense Meteorological Satellite Program. The data used in this paper spans from 2000 to 2011.[32]

Second, the number of health card (*Kartu Sehat*) issued in the last year. The health card program was launched in 1998 as part of the social safety net program (*Jaringan Pengaman Sosial*) intended to protect the poor during the economic crisis. The benefits of health card beneficiaries include various free services at public health care providers, such as outpatient and inpatient care

able. Figure A.2 shows that it might not pose an estimation problem because the movement of retail price is highly correlated with that of farmgate price.

[30] Data collection for *Podes* generally commenced in the first quarter of the year, around March or April.

[31] The FAO-GAEZ project provides worldwide grid cells information on predicted yields on various crops by combining various high-resolution geographic data with agronomic models, described in detail by Costinot et al. (2016).

[32] The latest available data is 2013, but to allow comparability with the *Podes* waves, I only use the data up to 2011.

(Sparrow, 2008; Bah et al., 2018). This variable comes from *Podes*.

I use additional complete census records to construct additional village agriculture and demographic characteristics. First, the 2003 agricultural census to construct inequality in land ownership and other agricultural-related variables.[33] Second, the 2000 population census to construct ethnic diversity measures.

3.4 Sample Construction and Summary Statistics

The main analysis is based on a balanced panel of 53,152 villages out of 298 districts and 26 provinces matched across the *Podes* waves. In total, the final sample has 318,912 village-year observations. To improve accuracy and quality of the data I impose some restrictions. First, I exclude Papua and West Papua provinces due to unreliable data. Second, I drop villages that amalgamated within the study period. To maintain comparability of institutions, I exclude provinces with special autonomy status which may affect provision and distribution of public goods and development projects.[34] To maintain a consistent unit of observation, village outcomes are aggregated up to the 2000 borders.

Table 1 displays summary statistics. An average district is divided into more than 270 villages. On average, each village has a total population of more than 3,500. The Gini coefficient of 0.54 in landholding indicates high wealth inequality within a village. The state of public health facilities and personnels is quite worrying. Only 20 % and 44 % of villages have at least one doctor and health care center. However, development projects are well distributed. Almost every village has at least one development project (84 %), where infrastructure maintenance project is the most popular (70 %).

4 Estimation Framework

My empirical strategy is similar in spirit to the standard difference-in-difference method but with continuous treatment intensity.[35] This method estimates whether changes in rice price affect provision of health public goods and development projects disproportionately in villages more suitable for rice production.

This approach requires plausibly exogenous shocks that vary across time and villages. The time variation comes from the movement in annual rice price. I exploit a sudden and major rice import restriction that contributes to substantial rice price variation across provinces, which is

[33]The agricultural census has been conducted every decade since 1963 with the latest wave completed in 2013. The 2003 wave records landholding information on 40 million households.

[34]Provinces with special autonomy status include the capital of Indonesia, DKI Jakarta, Nanggroe Aceh Darussalam, and DI Yogyakarta.

[35]This approach is commonly used to analyze the effects of commodity or food price shocks (Dube and Vargas, 2013; McGuirk and Burke, 2017; Sviatschi, 2018).

arguably exogenous to villages because national rice production and consumption are not driven by a small fraction of villages. The cross-sectional variation comes from geographic variation in rice suitability, which measures potential or maximum attainable rice yields, across villages. I interact both time and spatial variations as an indirect way to measure price shocks at the village level. A large increase in rice price in low (high) suitability villages is considered negative (positive) shock.

Villages with higher rice suitability are assumed to be more likely to benefit from higher rice price. However, this is not guaranteed because an increase in rice price does not necessarily translate to an increase in net income. Theoretically, it depends on whether a household is a net producer or a net consumer. Rice price hike benefits net producers but hurts net consumers (Deaton, 1989). Because variable that informs net-producer status at village level is not available, I use a proxy variable indicating whether the majority of farmers in a village both sell and consume agricultural products. This variable is conditional on a village being an agricultural village.[36] The 2003 and 2005 *Podes* document that eight out of ten villages are mainly agricultural suggesting that the proxy variable is quite representative at the national level. More importantly, Figure A.4 shows that rice suitability is positively correlated with the majority share of farmers selling and consume their products suggesting that my approach is sensible. Furthermore, using complete record of the 2013 Agriculture Census, I verify that the relationship between rice suitability and proportion of net sellers remains positive after adjusting for the proportion in the same village in 2003, as shown in Figure A.5.[37]

Equation 2 presents the estimation specification.

$$Y_{vpt} = \beta_0 + \beta_1 Price_{pt} + \beta_2 Price_{pt} \times RiceSuit_{vp} + \theta X_{vpt} + \gamma_v + \delta_t + \sigma_d t + \epsilon_{vpt} \tag{2}$$

where Y_{vpt} denotes public goods and development projects variables in village v, province p, and year t. $RiceSuit_{vp}$ is time-invariant measure of rice suitability, measured in thousands of tons per hectare. $Price_{pt}$ is the annualized log growth of domestic rice price in province p. $\boldsymbol{X}_{vpt}$ are time-varying covariates that include (log) population to account for scale effects and access to public goods and projects,[38] (log) distance to district capital and (log) distance to sub-district capital to account for political influence of physical distance on local resources (Stasavage, 2010; Campante and Do, 2014; Henn, 2018).[39] I also control for the interaction between the following

[36]This variable comes from the 2005 *Podes*. While it does not have information on specific agricultural products being sold and consumed, it is reasonable to assume that rice drives up the number given that it is the most dominant agricultural product among Indonesian farmers McCulloch (2008).

[37]A household is considered a net seller of rice if it sells some or all of the harvested rice. This variable is not available in the 2003 Agriculture Census, which explains why I use indicator from 2003 *Podes*.

[38]Including (log) population also indirectly controls for migration inflow that might be affected by better economic opportunities induced by increased rice price.

[39]Distances between village and district and sub-district capital vary because village and district splits over time.

time-invariant variables and year fixed effects: (log) village size and (log) harvested lands for rice.[40] These covariates respectively control for changes in the pattern of usage of lands and incentives to plant rice that may affect outcomes.

Village fixed effects, γ_v, and year fixed effects, δ_t, account for time-invariant village characteristics and common nationwide shocks, respectively. District-specific time-trends, $\sigma_d t$, account for potential omitted variables at district level that may cause upward trends in the distributive policies (e.g., public goods provision), such as shifts in political preferences.[41] Robust standard errors ϵ_{vpt} are clustered at the district level to control for potential serial correlation over time and across villages within a district. This approach is somewhat stringent given that the cross-sectional variation in the key independent variable is at the village level.[42] The identifying assumption is that, after accounting for time-invariant factors at the village level and common trending factors at the district level, variation in rice price is not correlated with unobserved factors that also affect public goods and development projects.

The key coefficient of interest, β_2, captures differential effects of rice price change on outcomes that arise from comparing villages with varying rice suitability. In all specifications, $\beta_2 < 0$ implies that an increase in rice price leads to a larger increase in health public goods and development projects in villages less suitable for growing rice.[43]

5 Results

5.1 Public Goods

I start by presenting the estimated differential effects of rice price change on health public goods, i.e., the interaction term $Price \times Suitability$, in Equation 2. Figure 6 summarizes the results. While price shock can explain changes in extensive margin (Panel A), it cannot explain changes in intensive margin (Panel B). Villages that were adversely affected by price shock were more likely to receive health facilities but not doctors. Figure 7 confirms that the effects started taking place after the implementation of rice import restriction, especially between 2003 and 2005, illustrating the significance of the policy.

Table 2 presents the regression results from a linear probability model. Panel A reports results on changes in extensive margin, while Panel B reports results on changes in intensive margin. The coefficient of -0.085 (column 4 of Panel A) on any health facility is statistically significant

[40] Total village size (in km^2) and total harvested lands for rice (in thousands of hectare) are constructed from the village map in 2000 and the FAO-GAEZ project, respectively.

[41] As a robustness check, I substitute district-specific time-trends with village-specific time trends. The main results hold.

[42] This approach, however, is useful because the decision for public goods provision varies across districts.

[43] Because most public goods experienced a nationwide increase during decentralization period, a negative coefficient should generally be interpreted as a smaller increase.

($p < 0.01$) and economically meaningful. To measure the magnitude of the estimated coefficient, consider, for example, the rise in health facilities associated with the rise in rice price. I compare high (90^{th} percentile) with low suitability villages (10^{th} percentile). A high suitability village has the mean suitability of 5.93 tons per hectare, while a low suitability village has the mean suitability of 3.86 tons per hectare. During the period of the study, 2000 to 2014, yearly price of rice increased by 0.10 log points. Thus, the coefficient of -0.085 in column 4 implies that the price rise led to an increase of 1.7 percentage points in total health center, which accounts for 4 % relative to the mean.[44] The effect is larger for *Pustu*, i.e., a 1.8 percentage points or 5.4 % relative to the mean.

The effect on *Puskesmas* is insignificant and small (column 2) implying that the effect on any health facility is entirely driven by *Pustu*. This is interesting because *Pustu* is more ubiquitous than *Puskesmas*.[45] The most likely explanation is the lower cost of building *Pustu* than that of *Puskesmas*. Result on column 1 suggests that an increased presence of health center is not necessarily accompanied by an increase in the presence of doctors, which makes sense because doctors are not directly assigned to *Pustu*. An alternative explanation is that district government might have preferred more easily visible public goods (i.e., health facilities) to the less visible ones (i.e., doctors) to gain political supports, which is not uncommon in developing countries (e.g., Williams, 2017). Testing this conjecture requires information on voting data at the village level, which is unfortunately unavailable.

In summary, adversely affected villages were more likely to receive public goods in the forms of health facilities but not health personnels. The results of intensive margins analysis suggest that the effects do not apply to villages that already had a health facility, suggesting that the district government attempted to provide a more equal distribution of health public goods across villages.

5.2 Development Projects

I now turn to discuss the results on development projects, summarized in Figure 8. Panel A plots the effects on the extensive margin, while Panel B on the intensive margin. To reiterate, the intensive margin measures the number of development projects, not the amount of funding. The overall results show a somewhat different pattern than that of public goods. I find evidence on both margins. Panel A indicates that rice price increases led to higher probability of launching a capital assistance project in villages where lands are less suited for rice production. I do not find evidence on the other projects. However, Panel B shows that the coefficients on intensive margin for other projects are negative and significant, except for the employment assistance project.

[44]The magnitude is obtained by the following calculation: $0.017 = (0.1 \times -2.07 \times -0.085)$.

[45]In 2000, prior to decentralization reform, the ratio of villages to the number of facilities for *Pustu* was lower than that of *Puskesmas*, 3 vs. 8 (Tajima et al., 2018). The ubiquity of *Pustu* can be explained by the legacy of Soeharto's *Inpres* program in 1970s which focused on building and funding *Pustu* (Shah et al., 1994).

Table 3 presents the regression results. Columns 1 to 4 report the results on extensive margin, while columns 5 to 8 on intensive margin. The coefficient of -0.357 (column 3) is both statistically and economically significant. Between 2008 and 2014, the period in which data on development projects is available, yearly rice price increased by 0.12 log points. Thus, rice price hike translates to an increase of 8.8 percentage points in likelihood of launching a capital assistance project in less suitable villages, which accounts for 14 % relative to the mean. The effects on the intensive margin are also significant: 8.6 %, 9.1 %, and 17 % for any projects (column 5), infrastructure (column 6), and capital assistance projects (column 7), respectively.

There are two key points that are worth highlighting. First, the largest impact is on the capital assistance project. This reveals that villages that did not benefit from rice price hike suffered from capital problem and preferred projects that could help relax financial constraints. Second, compared to the null effects on public goods, the significant results on the intensive margin analysis, especially that of capital assistance, are not surprising. This can probably be explained by the difference in the degree of influence villages have on public goods and projects provision. While village communities can put pressure on district governments for public goods, districts hold the final decision. On the other hand, communities traditionally hold more power in projects implementation. Majority of village communities in Indonesia engage in some forms of democracy in deciding a policy.[46] They identify what they need and decide which projects to launch. This practice can potentially result in more projects to be implemented. My hypothesis is supported by Olken (2010) who finds that Indonesian communities randomly assigned to a more democratic system, i.e., plebiscites, to decide development projects reportedly had higher satisfaction, more knowledge about the projects, better perception of the benefits, and higher willingness to contribute compared to communities whose projects were decided through representative-based meetings.

5.3 Robustness

Sample Selection Bias In the main sample, I exclude provinces with special autonomy status, such as Nanggroe Aceh Darussalam, Special Capital Region of Jakarta (*Daerah Khusus Ibukota Jakarta or DKI Jakarta*), and the Special Region of Yogyakarta (*Daerah Istimewa Yogyakarta or DIY*), because these provinces have special arrangement different from other provinces. One

[46] Based on the 1997 Indonesia Family Life Survey (IFLS), a nationally representative dataset for more than 80 % of Indonesia population, more than 70 % of villages engage in either voting or "consensus building" (*musyawarah*), by which villagers are involved in group deliberation leading to consensus. In remaining villages, a policy is decided by elites or village head (27 %). Note that the 1997 IFLS was conducted before the fall of Soeharto, which means that more villages are more likely to engage in democracy after implementation of decentralization reform. Unfortunately, the subsequent wave of IFLS conducted after 1997 does not have information on communities policy decision making process.

may have concerns of sample selection bias affecting the main results. Thus, to address these concerns, I include those special-status provinces. The results are presented in Tables B.1 and B.2

Alternative Specifications For the next robustness test, I examine whether my main results change with alternative specifications. Specifically, I make two changes. First, I substitute district-specific trends in the main estimating Equation 2 with village-specific trends to address concerns of omitted variable bias at the village level may drive upward trends on the main outcomes. Results are presented in Tables B.3 and B.4. Second, in a separate regression, to address concerns on the sensitivity of results to price change definition, I construct an alternative definition, where the price change is defined as the difference between log price in $t+1$ and t. Results are presented in Tables B.5 and B.6.

Transitory Shocks Short-term transitory shocks can have short-term effects on village income which might affect the main results. To address this concern, I adjust the main estimation with rainfall shock. Following Levine and Yang (2014), I define rainfall shock as the deviation from its long-term mean, which is calculated from 1953-2014 but excludes rainfall in the given year. I focus on rainfall during wet season, which varies across provinces. The main precipitation information is obtained from Global Land Precipitation and Temperature, University of Delaware. The dataset covers monthly global temperature at 0.5 x 0.5 degree resolution or 55 km around the equator (Matsuura and Willmott, 2015). I use Version 4, which is available for 1900-2014. Results are presented in Tables B.7 and B.8.

Differential Preexisting Trend in Local Income The effects of rice price shocks on health facilities and development projects may occur due to differential preexisting trend in local income. For example, the main results in health public goods distribution could reflect the targeting policy by district governments to low-income villages regardless of rice price shocks. To test this hypothesis, I include interaction term between baseline nighttime lights measures (coverage and intensity) and year fixed effects.[47] Results for including interaction term of lights intensity and year fixed effects are presented in Tables B.9 and B.10. Results for including interaction term of lights coverage and year fixed effects are presented in Tables B.11 and B.12.

Price Shocks and Local Income Rice price hike may affect results through channels other than increased income related to rice-growing capacity. For example, rice price hike can affect variables that can serve as proxies for preexisting state of the local economy, such as local investment. To address this concern, I adjust main estimation by including interaction term between baseline nighttime lights intensity and year fixed effects. Tables B.13 and B.14 report the results for health

[47]Baseline here is the year 2000. This choice is reasonable because Indonesia experienced regime change and major economic crisis in 1998.

public goods and development projects, respectively.

Specific to Rice Growing Areas Lastly, I include rice suitability specific time-trend to rule out alternative explanation that my main results are driven by trends specific to rice-growing villages. Results for health public goods and development projects are shown in Tables B.15 and B.16, respectively.

Overall, the results from these robustness tests show that my main results and conclusion remain unchanged. This suggests that rice price shocks indeed have significant impacts on policy responses across villages.

6 Mechanisms

6.1 Aggregate Income

Examining the effects of rice price change on aggregate income in small areas without reliable income data is challenging. I follow the standard in the literature by examining two measures of nighttime lights: yearly growth in *coverage* and *intensity*. Bazzi et al. (2016) document that nighttime lights is a reliable proxy variable for income across Indonesian villages. In addition, I also examine the number of health insurance cards issued for the poor which can provide a rough indicator for poverty incidence at the village level. Higher number of health cards implies higher number of people eligible to receive social protection programs for the poor indicating higher poverty incidence.[48]

Table 4 presents the results. Across columns, I find positive impacts of rice price change on villages more suitable for rice production. As can be seen, the interaction coefficient on $Price \times Suitability$ is statistically significant and positive in the first two columns. The effects of rice price hike go beyond the extensive margin (column 1). It also leads to growth in the intensive margin (column 2). The coefficients of 0.476 and 0.249 in columns 1 and 2 imply that the rice price hike led to an increase of 14.8 % and 3.9 % in the coverage and intensity of nighttime lights relative to the mean. These estimates can be interpreted as the effects on local economic growth in high relative to low suitability villages.[49]

The coefficient is negative on the number of health cards issued for the poor (column 3) indicating reduction in poverty even though it could also imply a decrease in demand for the programs as local economy improves. Taken together, these findings suggest that rice import restriction

[48] This measure is by no means perfect. *Leakage* (inclusion error) and *undercoverage* (exclusion error) are common problems that affect targeting performance of social protection programs in developing countries, including health card program in Indonesia (Sparrow, 2008).

[49] The numbers are obtained by the following calculation: $0.148 = (0.1 \times 0.207 \times 0.476)/0.663$; $0.039 = (0.1 \times 0.207 \times 0.249)/1.329$.

via rice price hike increased local aggregate income for villages more suitable for rice production. The effects are monotonically increasing with rice suitability, as illustrated in Figure 5.

The resulting increase in local income can probably be explained by wage growth, especially in the agricultural sector. Bazzi (2017) finds that increased domestic rice price attributed to rice import restriction in Indonesia can explain positive wage growth in agricultural sector. Another study that examines the effect of major disruption in rice supply and price in a part of Java, Indonesia, also finds a faster wage growth for individuals working in the agricultural sector (Kirchberger, 2017). Even though the effects on both studies operate through different channel, their findings can provide a possible explanation to why rice price increases local income in more suitable villages.[50]

6.2 Nutrition

I have shown that rice import restriction through rice price hike has significant effects on aggregate income across villages of varying rice suitability. This may explain why villages that experienced income decline launched more capital assistance projects (extensive and intensive margins). However, it is not clear why those villages were more likely to have health facilities. To provide a better explanation, I examine the effects on nutrition, a primary input of health, because health itself can be affected by the presence of public health facilities.[51]

I merge the main village-level dataset with the nationally representative household-level data, National Socioeconomic Survey (*Susenas*). I leverage detailed information on calorie and protein of more than 200 foods based on the seven-day recall period from the consumption module of *Susenas*.[52] I use all available modules in the year that closely corresponds to the *Podes* waves: 2002, 2005, 2008, and 2011.[53,54,55]

Because *Susenas* is a cross-sectional household survey, it does not cover all villages over time preventing me to conduct within-village analysis as in the main specification. I slightly modify Equation 2.

$$Y_{hvpt} = \beta_0 + \beta_1 Price_{pt} + \beta_2 Price_{pt} \times RiceSuit_{vp} + \theta X_{vpt} + \theta Z_{hvpt} + \gamma_d + \delta_t + \sigma_d t + \epsilon_{vpt} \tag{3}$$

The household outcome variables Y_{hvpt} include the total amount of daily calories and protein

[50] The findings of both studies are not representative at the village level. There is no nationally representative data that provides information on wages at the village level.

[51] I cannot disentangle whether change in the nutritional content of food consumption is directly driven by the changes in rice price or income.

[52] Until 2008, the consumption module was collected every three years, but it has since been collected annually.

[53] I am unable to use the 2014 *Susenas* because it does not include village identifier.

[54] The final sample includes more than 300,000 households out of 25,000 unique villages.

[55] I use variables from the 2000 *Podes* to correspond with the 2002 *Susenas*.

consumption per capita (log) and share of food expenditure per capita (log).[56,57] In addition to village covariates X_{vpt} as in Equation 2, I also add a vector of household covariates Z_{hvpt} that control for factors affecting the amount and quality of household food consumption: an indicator for wife's education attainment (primary, junior and senior high school, university, and post-graduate education), wife's age and age squared, an indicator for marital status of the household head (not married, married, divorced, widowed), and indicators for the number of household members aged 0-4, 5-9, 10-14, 15-55, and above 55. I include district fixed effects γ_d instead of village fixed effects. I also control for district-specific trends $\sigma_d t$. Standard errors are clustered at the district level.

Table 5 reports the results. In line with existing evidence (e.g., Stillman and Thomas, 2008), I find that households in villages that benefited from rice price hike enjoyed better nutrition both in terms of calories and protein (columns 1 and 2).[58] Food expenses are higher than those who live in adversely affected villages but the difference is not statistically different from zero (column 3). Because health status increases in its input, i.e., nutrition (e.g., Grossman, 1972; Strauss and Thomas, 1998), this analysis lends further support for the demand-side channel for health facilities.

6.3 Heterogeneity Treatment Effects

6.3.1 Wealth Inequality

Studies have shown that landholding inequality is an important determinant for provision of public goods and local projects, but the evidence is mixed. High inequality is positively correlated with resources or public goods received from higher-tier governments due to the political connection and lobbies from large landowners (Banerjee and Somanathan, 2007; Dell, 2010). On the other hand, high inequality may contribute to reduction in collective action that could lead to lower provision of public goods and local projects (e.g., Alesina and La Ferrara, 2000).[59] Those studies take land or wealth inequality as relatively constant due to absence of exogenous shocks. In this paper, the values of land change due to increased rice price, which can amplify the influence of inequality in public goods and development projects.

Motivated by the existing evidence, I complement the mechanisms analysis by examining

[56]To obtain per capita measure, I adjust household size with equivalent scales as suggested by Deaton (1997). Equivalent scales dictates that household member aged 0-4 years old is equivalent to 0.4 adult, 0.5 for 5-14 years old, and 1 for above 15.

[57]Nutrition measures are constructed from the following food groups: cereals (e.g., rice), roots and tubers, fish and seafood, meat, eggs and milk, vegetables, pulses, legumes and nuts, fruits, oil/fats, sugar/honey, and others (e.g., bread).

[58]I find little evidence that the effects on nutrition differ by whether foods are bought, as shown in Table A.1.

[59]Many studies have argued the role of inequality on public goods provision or local projects in various contexts (Galasso and Ravallion, 2005; Banerjee et al., 2007; Araujo et al., 2008)

treatment effect heterogeneity by wealth inequality, measured by landholding inequality, at the village level. Additionally, while results presented thus far help understand the demand-side story of the main results, it is incomplete given the variation of wealth across Indonesian villages. Using complete records of the 2003 Agricultural Census, I construct Gini coefficient of landholding to measure existing wealth inequality at the village level. The land inequality is high, 0.54, as shown in Table 1. For easier interpretation, Gini coefficient is transformed to a binary variable taking the value of one if the value is above the median.

Public Goods Figure 9 plots coefficients from subsample regressions for health public goods. The corresponding regression results are presented in Table 6. I find significant effects among villages with high inequality. Column 3 shows that the coefficient on of the effects are higher than that of the main result, -0.123 vs -0.085 (Column 3 of Table 2), but the difference is not significant. On the other hand, there is no evidence that price shock has any effects on the presence of health facilities among low-inequality villages (Columns 1 to 4). Interestingly, Column 6 shows positive significant effect on the main health facility indicating that adversely affected villages with low inequality received less facilities. Together, all these results are consistent with the existing evidence suggesting that large landowners which are more common in more unequal communities have relatively more power to lobby for public goods. This is even more relevant in the context of decentralization era when villages can have more influences over districts decision than in the New Order era when decisions were highly centralized.

Development Projects Figure 10 plots coefficients from subsample regressions for development projects. The corresponding regression results are presented in Table 7. Different from public goods results, I find significant negative relationship among villages with *low* inequality. Adversely affected villages in low inequality environment were more likely to launch capital assistance projects. The result also extends to intensive margin result, as illustrated in Panel B of Figure 10. The difference with public goods result is interesting. It is in line with the mixed evidence in the literature. High inequality helps in lobbying for public goods from higher tier-governments but low inequality helps reach decision in launching and choosing development projects. One potential explanation for this contrasting result is that low inequality is correlated with high collective action that can have positive influence over provision of local projects (e.g., Bardhan, 2000; Dayton-Johnson, 2000; Khwaja, 2004). Collective action is more likely to have more influence in the context when it is more relevant, which is the case for development projects. Villages have relatively more control over types and number of projects to launch than that of public goods, where district governments hold the final decision. To formally test this conjecture, I examine relationship between inequality and social capital, a variety of collective action measure, in the next section.

6.3.2 Price Shock Magnitude and Ethnic Diversity

In addition to the heterogeneity in wealth inequality, I also examine heterogeneity treatment effects in price shock magnitude and ethnic diversity for two reasons. First, district governments may react differently to severity of price shock by distributing disproportionately more resources to low suitability villages. Second, it is natural to examine the influence of ethnic diversity given the diversity of ethnicity in Indonesia and numerous studies having documented ethnic diversity as a determinant of public good provision (e.g., Alesina et al., 1999; Miguel and Gugerty, 2005; Habyarimana et al., 2007), including in Indonesia (e.g., Bandiera and Levy, 2010; Tajima et al., 2018).

The magnitude of price shock refers to the interaction term between rice price and rice suitability, $Price \times RiceSuit$. Ethnic diversity is measured by ethnolinguistic fractionalization (ELF). Information on self-reported ethnicity is obtained from complete record of the 2000 Population Census.[60] ELF reflects the probability that two randomly selected individuals from a population belong to different groups (Alesina et al., 2003). Higher value implies higher diversity.[61]

Figures A.6 and A.7 plot coefficients from subsample regressions for health public goods and development projects. The corresponding regression results are presented in Tables A.2 and A.3. There are two points to highlight. First, in general, I do not find significant effects in villages that experienced small or large shocks. This implies that the district governments did not seem to consider severity of shock as a top criterion for public goods provision, which could mean two things. First, district governments opted for more even distribution of resources. Second, there are other unobserved factors that affected the allocation decision, such as influence from large landowners, as I show in the previous subsection. Second, I find significant effects among villages with low ethnic diversity, especially in the launching of capital assistance projects. This finding can probably explained by a theory proposed in Bandiera and Levy (2010).[62] Income decline and low diversity may give rise to the general projects because low diversity among the poor give less weight to the preferences of the local elites making it hard to form a stable coalition that could give rise to the elite-specific projects. The main assumption is that rice price hike hits the poor more heavily in the less suitable villages such that they needed capital assistance more than the elites.

[60] In total, there are more than 1,000 self-reported ethnicities recorded in the 2000 Census.

[61] ELF is calculated as follows

$$\text{ELF}_j = 1 - \sum_{i=1}^{N} s_{ij}^2$$

where s_{ij} is the share of ethnic i(i=1 …N) in village j.

[62] Bandiera and Levy (2010) find that in the democratic Indonesian villages, the level of ethnic diversity is positively correlated with the provision of public goods closer to the preference of the wealthy elites.

6.4 Social Capital

Another plausible channel through which price shocks can lead to changes in the allocation of public goods or development projects is social capital, broadly defined as information, trust, and norms of reciprocity in one's social networks that enabled people to act collectively (Woolcock, 1998; Woolcock and Narayan, 2000).[63] A higher level of social capital has been documented to strengthen social cohesion and cooperation which could increase governments responsiveness potentially resulting in increases in projects or public goods (Tavits, 2006; Khwaja, 2009; Casey et al., 2012; Cameron et al., 2019) .

For my empirical analysis, I merge village-level data with *Susenas* to estimate the effects of village price shocks on social capital at the individual level.[64] To obtain broader measures of social capital, I construct eight variables that appear in both the 2009 and 2012 sociocultural module of National Socioeconomic Survey (*Susenas*).[65] Particularly, I construct the following variables: trust towards local village governments, trust the neighbors to watch one's house when all household members are away, trust the neighbors to care for one's children (aged 0-12) when adults are not home, willingness to help neighbors in need, frequency of participation in community activities (e.g., religious, sports, ROSCA, etc.), and feelings towards activities of people from different ethnicities. Some variables are measured in 1-4 scale, while others in 1-5 scale. Higher value reflects stronger support for each variable. For easier interpretation, I standardize all variables. Then I construct a mean index by taking the average out of all variables as the main measure of social capital.[66]

Table 8 presents the results. The top row reports the baseline effects of price shock (all sample). Individuals in villages less suited for growing rice had higher overall social capital level (column 1) that appears to be driven by trust (columns 2 and 3) and tolerance toward different ethnicity (column 8). Similar pattern has also been documented in developing and developed countries settings where individuals experience major income shocks. Cassar et al. (2017) find higher level of trust after the massive tsunami in Aceh, Indonesia, partly because people received help from others in difficult situations. Whitt and Wilson (2007) find increased group cooperation among Hurricane Katrina refugees.

In addition to baseline specification, I also examine whether the effect differs by land inequal-

[63] A large literature in social science has attempted to define social capital, but the exact definition of social capital is not entirely clear and elusive (Durlauf and Fafchamps, 2005).

[64] I am unable to conduct heterogeneity analysis as in the previous section because *Susenas* is not representative at the village level. Thus, the analysis in this section can only provide suggestive evidence on the role of social capital in contributing to the main results.

[65] The sociocultural module is included in *Susenas* every three years. The module was introduced in 2006, but it does not include village identifier preventing me to use it in the analysis. After merging with *Podes* and excluding special status provinces, the final sample includes more than 200,000 households out of 15,000 unique villages.

[66] I estimate equation 3, but instead of household covariates I include individual covariates, such as sex indicator, age, and age square.

ity. I find significant negative relationship among villages with low inequality, but not among highly unequal villages, as illustrated in Figure 11. This finding can help explain why adversely affected villages with low inequality were more likely to launch development projects, especially capital assistance.

Taken together, all these results suggest that social capital, broadly defined, plays an important role in increased development projects in villages hurt by rice price shock. This finding is in line with a recent paper studying provision of sanitation facilities in Indonesian communities. Using a randomized experiment on community-led program intended to create demand for sanitation, Cameron et al. (2019) show that villages with higher initial social capital were more responsive to health information by building public toilets.

7 Did Public Health Facilities Mitigate Effects on Mortality?

Evidence presented thus far have shown strong negative relationship between price shocks and public health facilities in less suitable villages. One natural question that may arise is whether these facilities help communities by alleviating some effects of negative income shock. To address this question I examine the effects of health facilities on infant (IMR) and maternal mortality rate (MMR) at the village level.

I combine the main data with complete records of the 2010 Population Census. The Census records information on deaths in the past year (2009 and 2010). Importantly, it also provides information on details on pregnancy-related deaths which allows me to construct maternal mortality rate (MMR).[67] Following the standard in the literature, I restrict the sample for women aged 15 to 49 years old who died while pregnant, during delivery or the 2 months after birth. There were more than 8,000 pregnancy-related deaths and more than 5.8 million surviving pregnancy and delivery.[68]

Figure 12 plots coefficients of effects on extensive (Panel A) and intensive margin (Panel B), while regression results are presented in Table 9.[69] In line with the existing evidence in developing countries (e.g., Baird et al., 2011), I find that price shock increased the presence of IMR and MMR in less suitable villages by 5.2 % and 15.5 %, respectively, as shown by the coefficient from baseline specification of Table 9.[70] This result is consistent with the finding that households in low suitability villages experienced lower nutrient intake, as shown in Table 5. This pattern,

[67] The Census asks the following question: Has there been a death in this household since January 1st, 2009? If yes, and the person who died was female and over 10 years old: Did [name] die while pregnant, during delivery or the 2 months after birth?

[68] Both IMR and MMR are calculated per 1,000 live births.

[69] The price change variable in the estimation is measured between 2006 to 2009 to correspond with the first recorded birth and death in January 2009. Measures on the support and total public health centers are based on the 2008 *Podes*.

[70] Price increased on average by 0.084 log points between 2006-2009.

however, does not apply to the intensive margin result, as shown in Panel B of Figure 12. In absence of public health facility, the effect of income shock on the prevalence of IMR is negative and significant suggesting that IMR increased in the adversely affected villages. However, the effect becomes null when there is at least one public health facility in a village suggesting that access to health facility helps mitigate some of the adverse effects. This pattern, however, does not apply to MMR. In conclusion, villages that experienced income decline were more likely to have a case of IMR and MMR, but the presence of public health facilities help mitigate it.

8 Conclusion

Existing evidence shows the importance of investment in social infrastructure and provision of public goods to communities adversely affected by trade policies, but schemes to help them are relatively unknown. One main problem is because the trade-induced income shock affects local tax revenues which limit government's financial ability to fund and implement necessary schemes. When governments rely heavily on local tax revenues, the adverse effects on communities are amplified because public goods are negatively affected (Feler and Senses, 2017).

This paper provides evidence that when local governments do not depend heavily on local tax revenues, they distribute more resources to adversely affected communities. In the context of rice import restriction in Indonesia that imposed sharp increase in domestic rice price, villages less suited to grow rice received more public health facilities than the more suited ones, but only if they did not previously have one facility. Using grants from the higher-tier governments and other sources, the less suited villages launched more development projects to empower themselves, especially through capital assistance projects. Demand-side mechanism, land inequality, and social capital explain the main results. I also find suggestive evidence that the presence of public health facilities mitigates some of adverse effects on infant mortality. Unfortunately, my dataset prevents me to further explore whether the health facility distribution was politically motivated, which is common in developing countries.

Taken together, all these results have two policy implications. First, price and income shocks help district governments allocate public goods provision to adversely affected communities when district governments have legitimate authorities. This implies that decentralization reform is crucial. It may not be possible during the New Order era when virtually every decision concerning villages required approval from the central government. Second, my findings highlight the roles of social capital and wealth inequality in helping communities empower themselves in the presence of economic adversity. This suggests that the design of social protection programs or other government programs should aim for enhanced integration and inequality reduction within communities.

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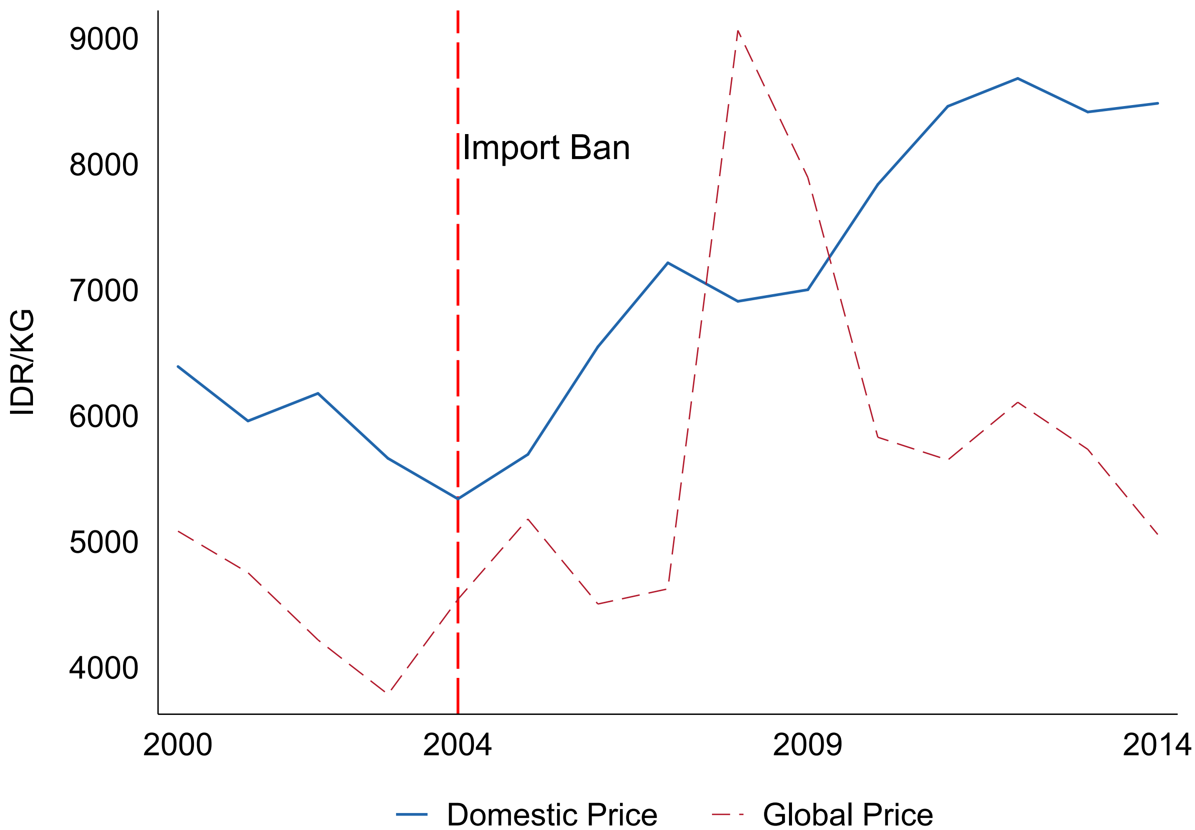
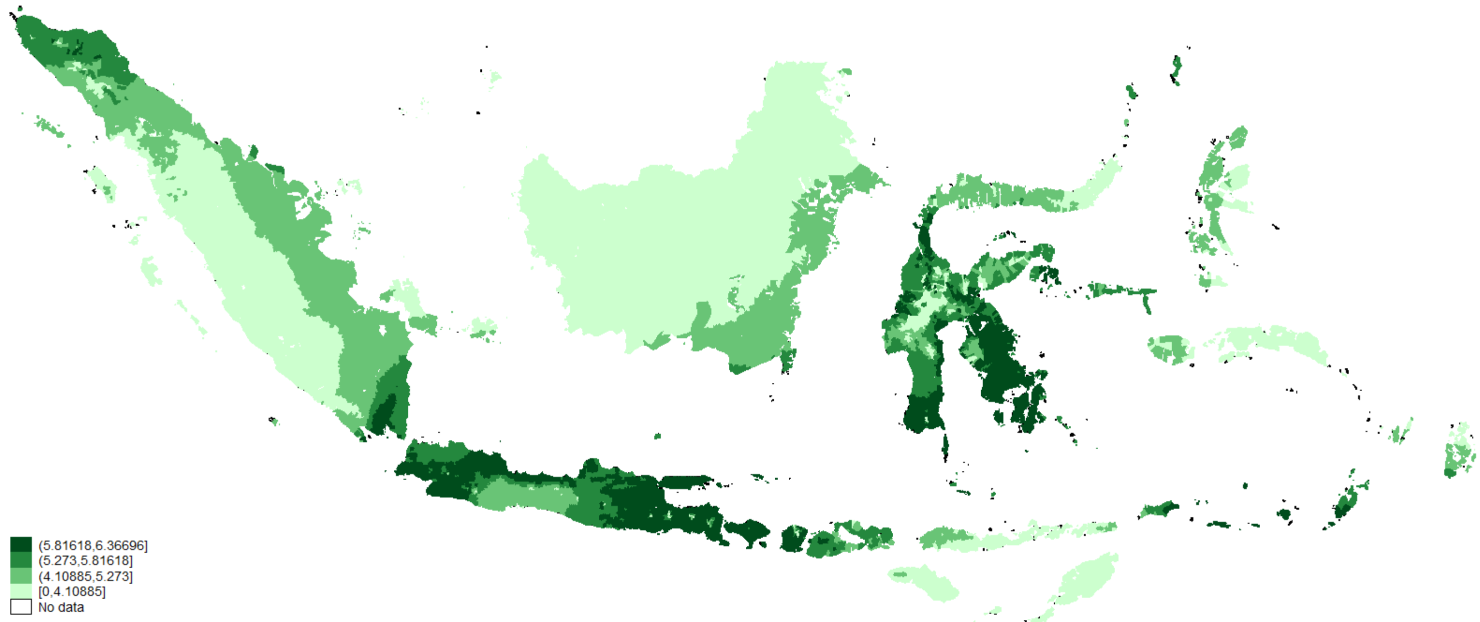
Figures

Figure 1: Domestic and Global Prices of Rice, 2000-2014



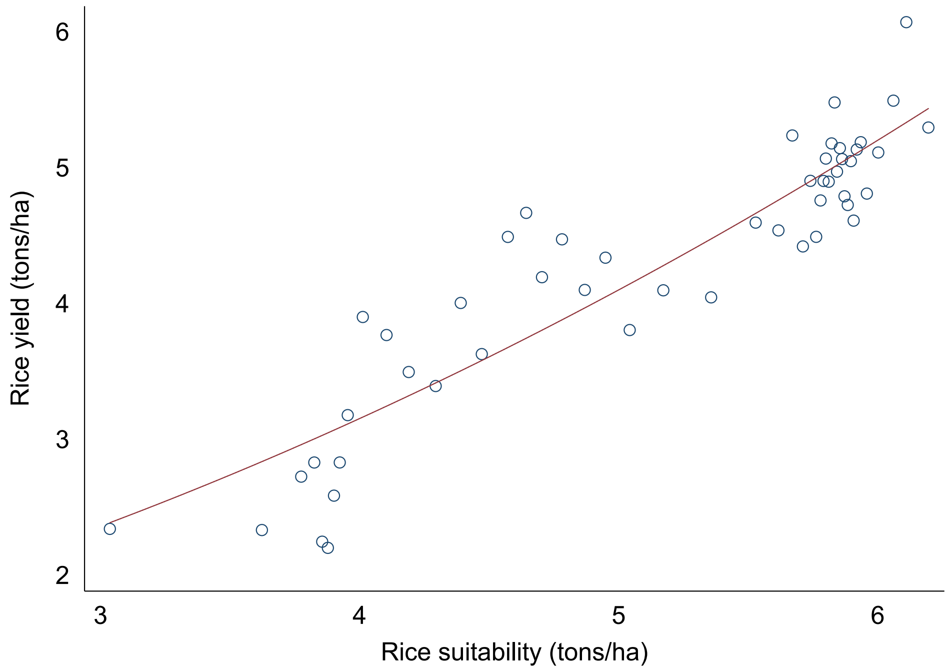
Note: This figure shows the movement of domestic and global rice price from 2000 to 2014. Nominal rice prices are deflated by the national CPI. Global price and domestic rice price are in IDR/Kilogram. Global price refers to price of Thailand milled rice in US $ converted to IDR in current prices using market exchange rate and converted to retail price by adding $20/ton for shipping and a 10 % of mark-up from wholesale to retail (Dawe, 2008). Domestic price is the average of retail prices collected from major markets. Source: Central Bureau of Statistics (BPS) obtained via CEIC database for domestic price and IMF Statistics for global price and market exchange rate (IDR/USD).

Figure 2: Rice Suitability Distribution.



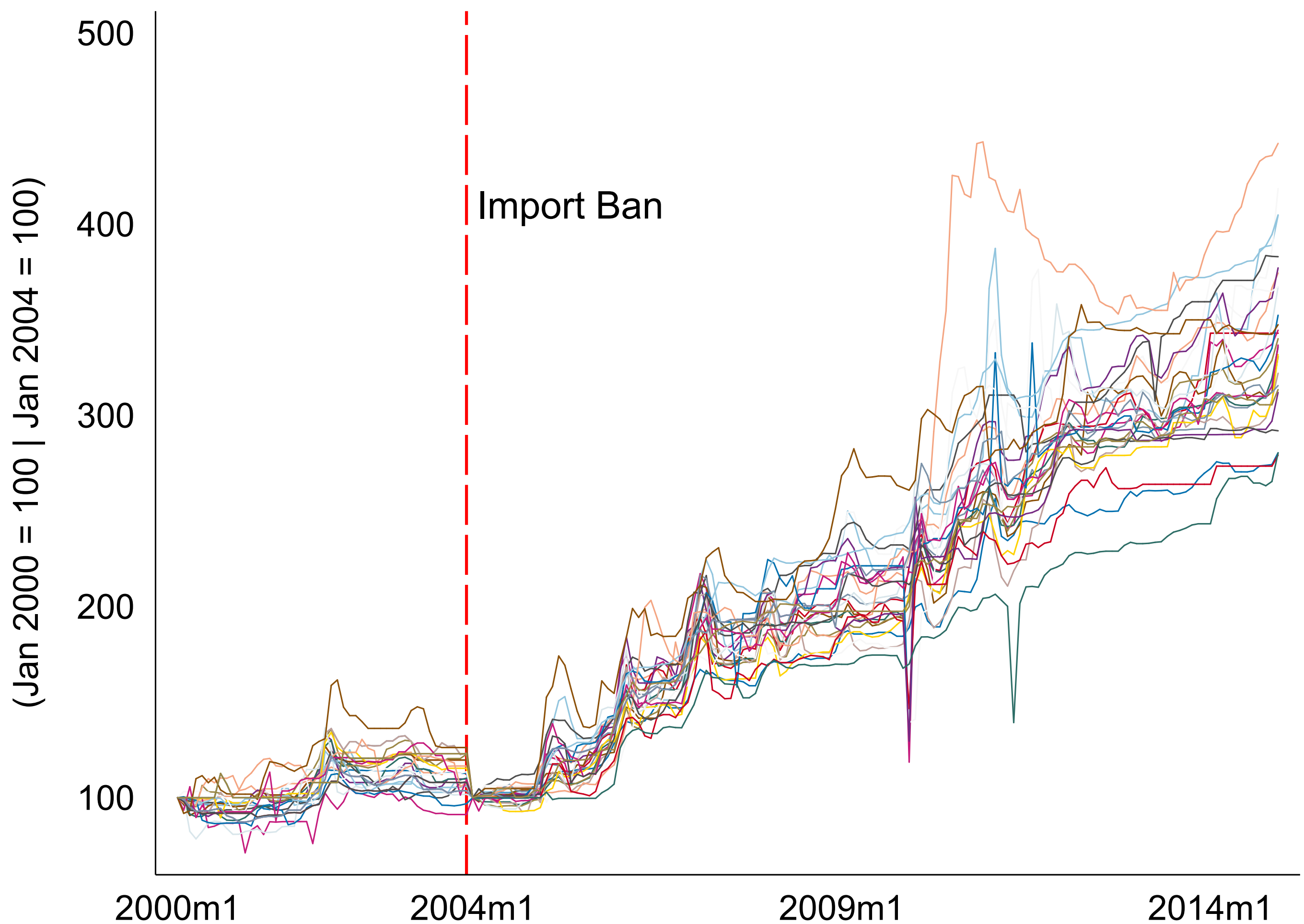
Note: This figure shows distribution of rice suitability in Indonesian villages in 2000, excluding Papua island. Rice suitability measures potential or maximum attainable yields in tons per hectare. Darker shade implies higher suitability than that of lighter shade. Source: FAO-GAEZ.

Figure 3: Rice Productivity and Rice Suitability



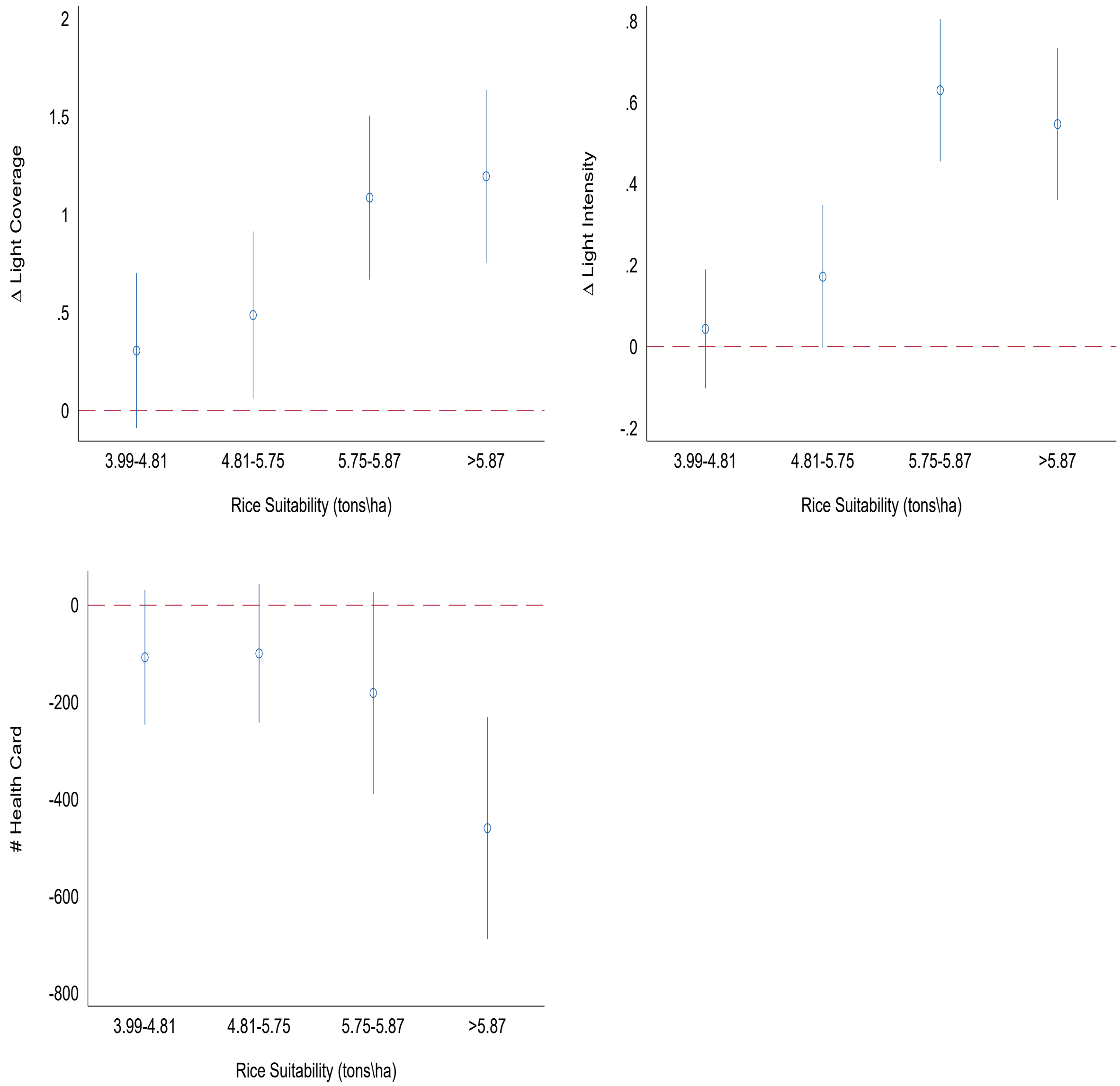
Note: This figure summarizes relationship between rice suitability and productivity, as measured by rice yields. Both variables are measured in tons per hectare. Source: rice suitabiltiy (FAO-GAEZ) and rice yields (the 2003 PODES).

Figure 4: Domestic Annual Rice Price Change: 2000-2014



Note: This figure shows monthly price of rice in Indonesia across cities in Indonesia, 2000-2014. Prices are normalized to 100 in January 2000 and again in January 2004 to emphasize the evolution of price before and after the import ban. Source: Central Bureau of Statistics (BPS) obtained via CEIC database.

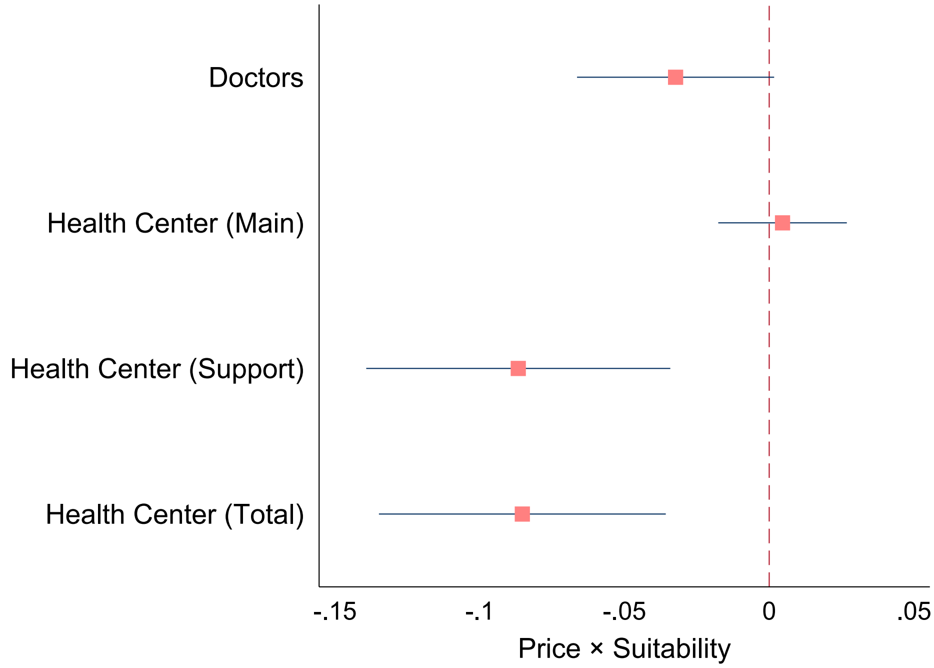
Figure 5: Rice Suitability and Aggregate Income Indicators



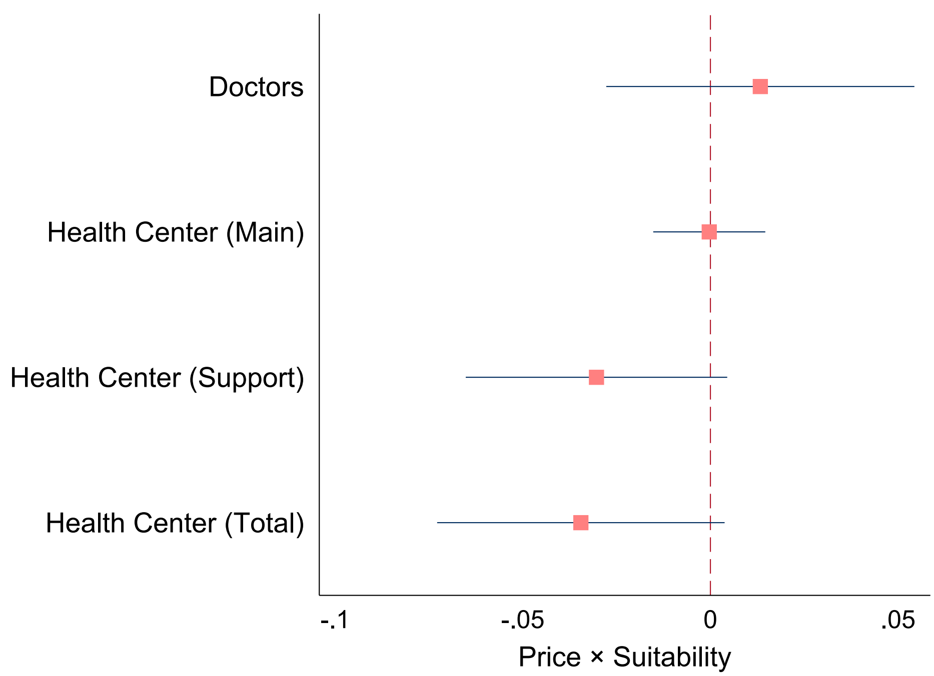
Note: These graphs figure show regression coefficients of estimating Equation 2 by quantiles of rice suitability (tons/ha). Standard errors are clustered at the district level with 90% confidence interval.

Figure 6: Effects on Public Health Facilities and Personnel

(a) Changes in Extensive Margin

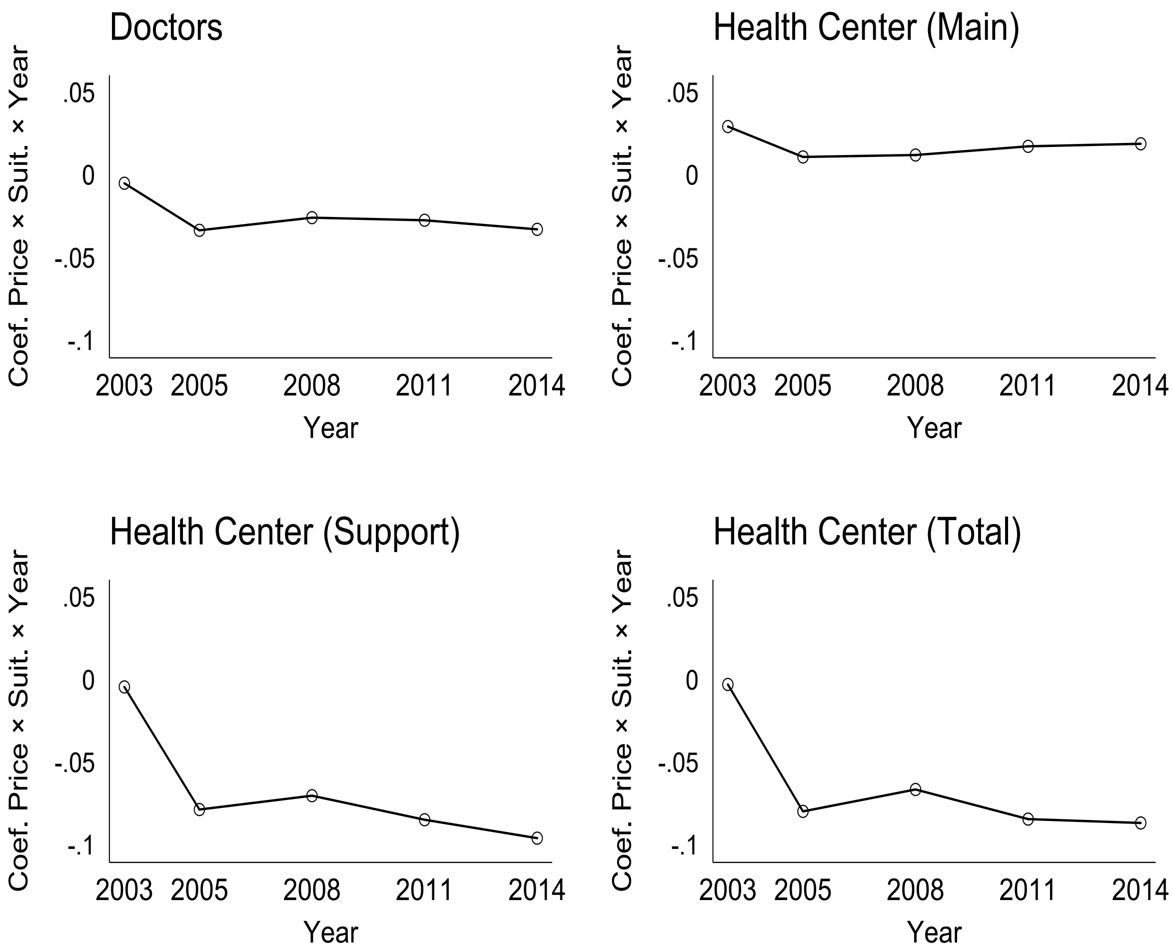


(b) Changes in Intensive Margin



Note: This figure plots regression coefficients of estimating Equation 2. Each coefficient comes from each regression conducted separately. Panel (a) and Panel (b) plot effects on changes in the presence and number of public health facilities and personnel, respectively. Standard errors are clustered at the district level with 90% confidence interval.

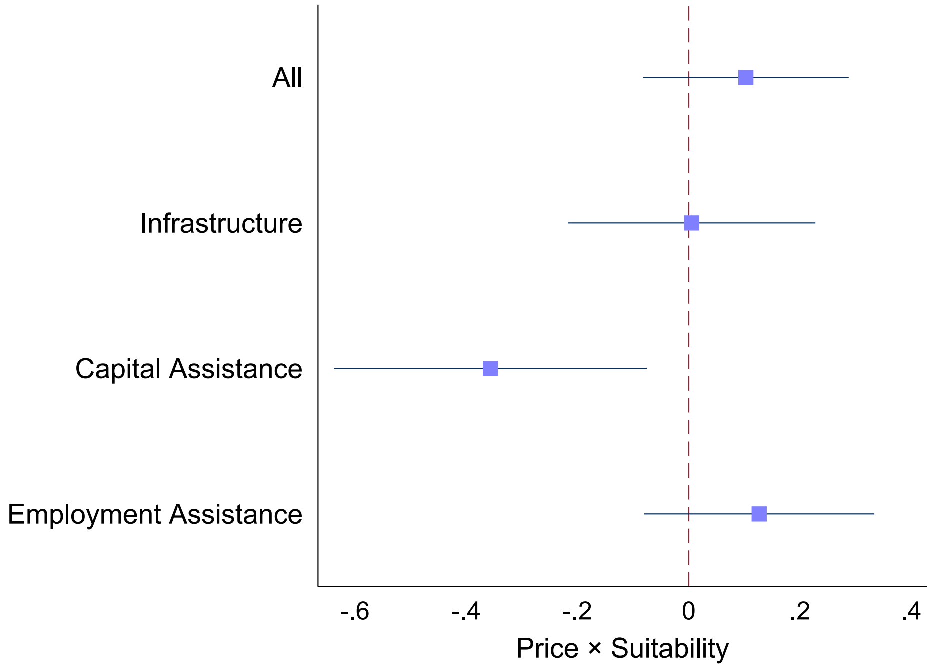
Figure 7: Effects on Public Health Facilities and Personnel by Year – Extensive Margin



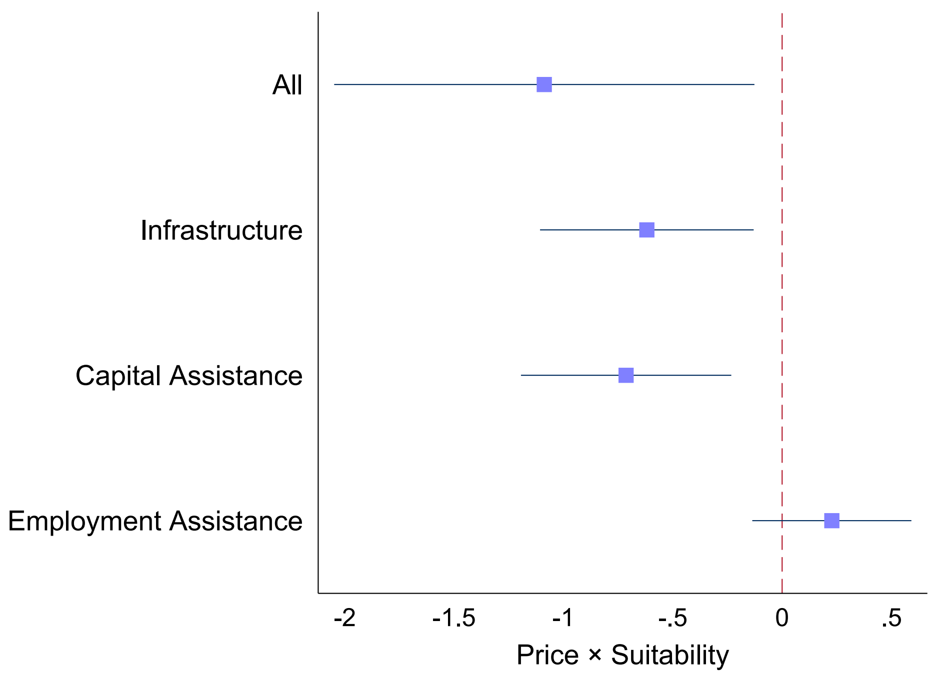
Note: These graphs figure plot regression coefficients of estimating a slightly modified version of Equation 2, where $Price \times Suitability$ is interacted by year. Standard errors are clustered at the district level with 90% confidence interval.

Figure 8: Effects on Development Projects

(a) Extensive Margin



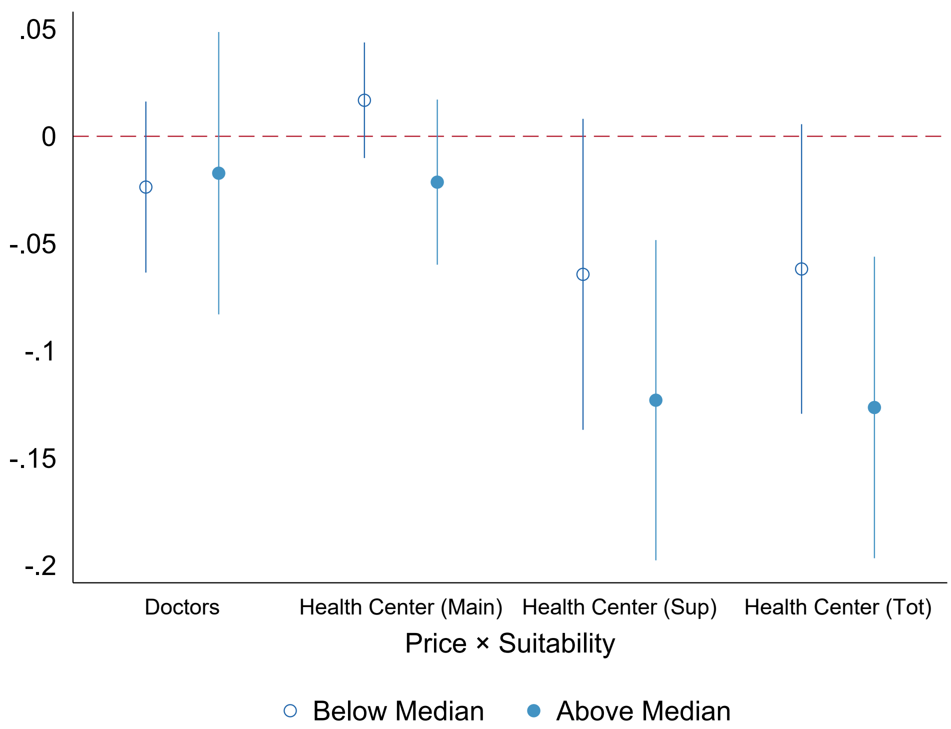
(b) Intensive Margin



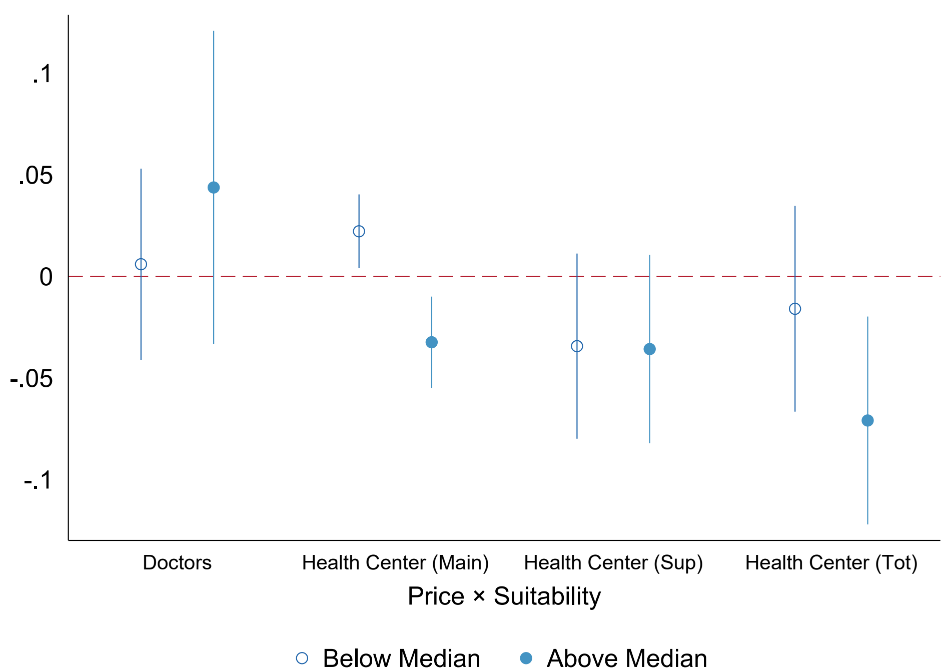
Note: This figure plots regression coefficients of estimating Equation 2. Each coefficient comes from each regression conducted separately. Panel (a) and Panel (b) plot effects on changes in the presence and number of development project, respectively. Standard errors are clustered at the district level with 90% confidence interval.

Figure 9: Effects on Public Health Facilities and Personnel by Land Inequality

(a) Changes in Extensive Margin



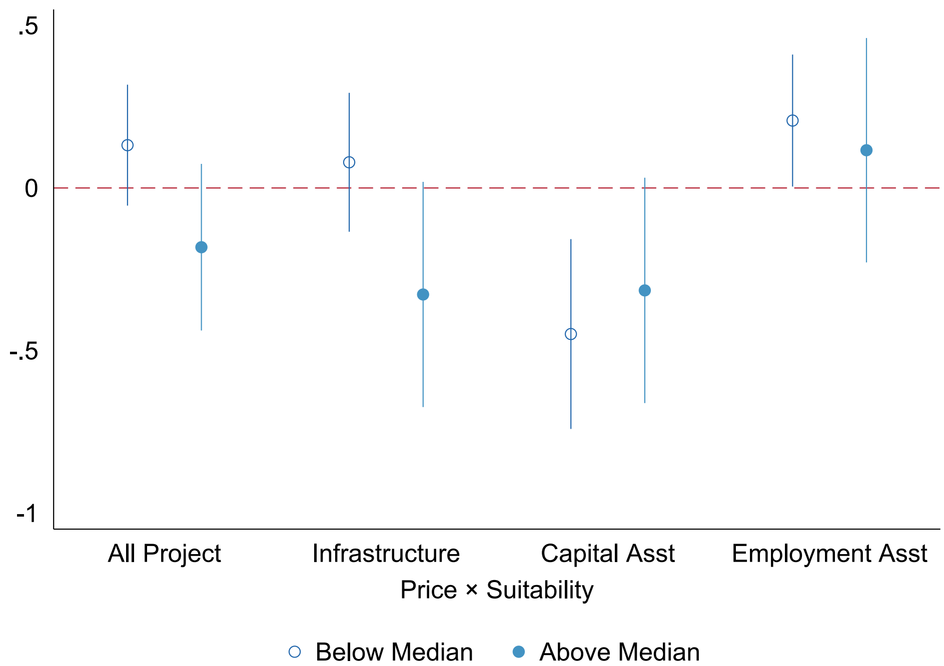
(b) Changes in Intensive Margin



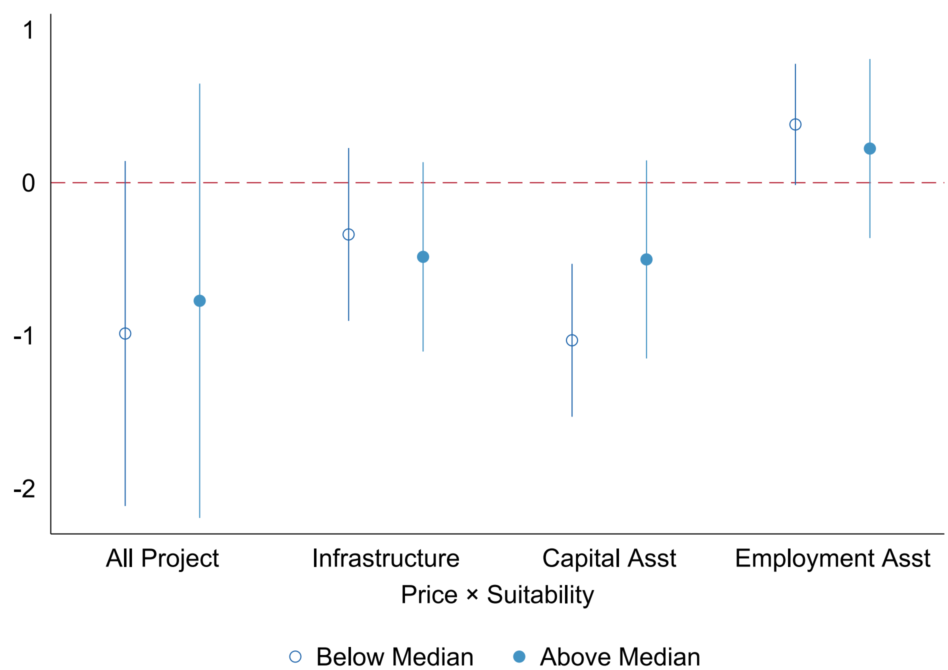
Note: This figure plots regression coefficients of estimating Equation 2. Each coefficient comes from each regression conducted separately. Panel (a) and Panel (b) plot effects on changes in the presence and number of public health facilities and personnel, respectively. Standard errors are clustered at the district level with 90% confidence interval.

Figure 10: Effects on Development Projects by Land Inequality

(a) Changes in Extensive Margin

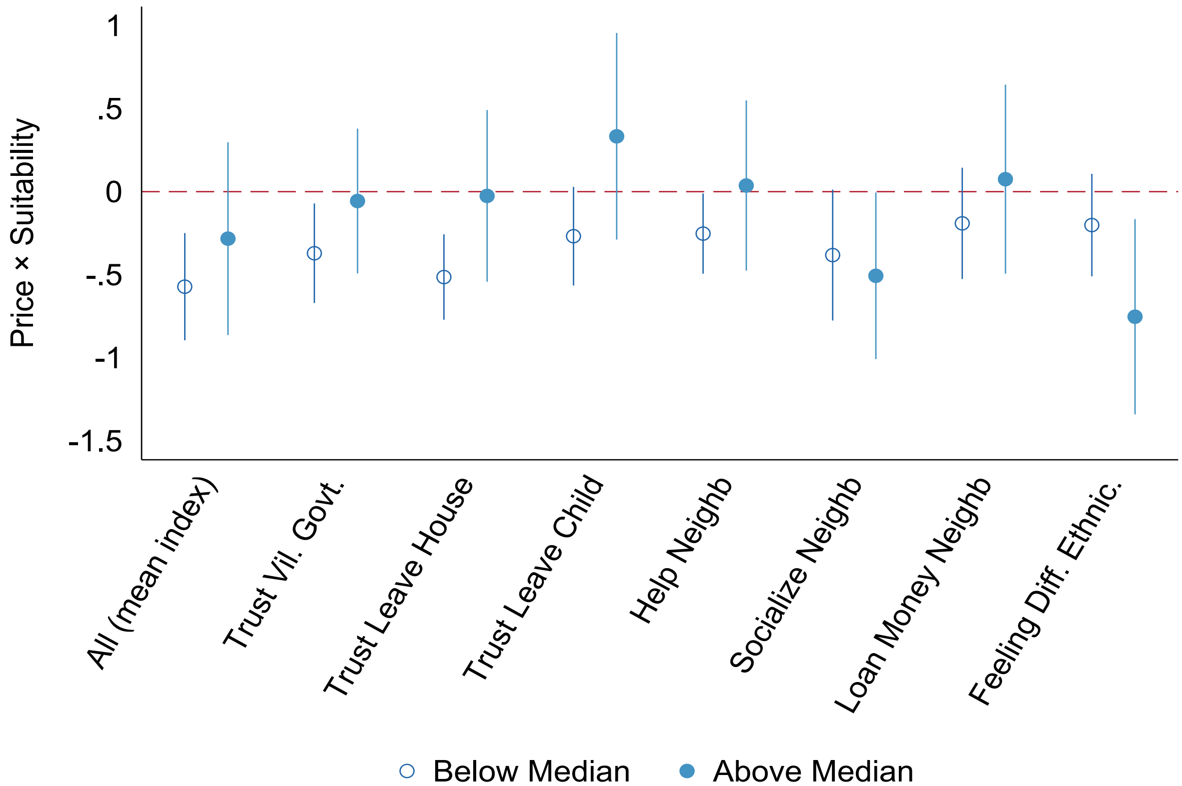


(b) Changes in Intensive Margin



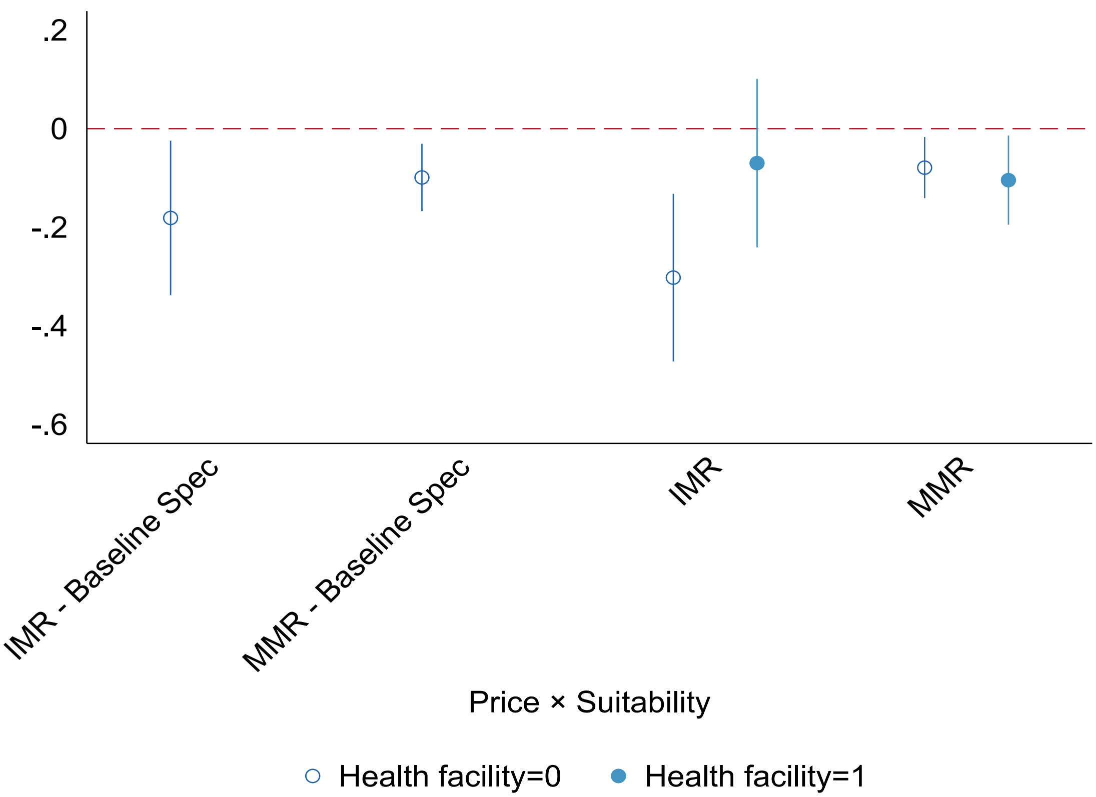
Note: This figure plots regression coefficients of estimating Equation 2. Each coefficient comes from each regression conducted separately. Panel (a) and Panel (b) plot effects on the presence and number of development projects, respectively. Standard errors are clustered at the district level with 90% confidence interval.

Figure 11: Effects on Social Capital by Land Inequality



Note: This figure shows regression coefficients obtained from estimating effects on social capital by land inequality. Each coefficient comes from each regression conducted separately. Standard errors are clustered at the district level with 90% confidence interval.

Figure 12: Effects on Prevalence of Infant and Maternal Mortality by Public Health Facilities



Note: This figure shows regression coefficients obtained from estimating effects on prevalence of infant and maternal mortality by presence of public health facilities. Each coefficient comes from each regression conducted separately. Standard errors are clustered at the district level with 90% confidence interval.

Tables

Table 1: Summary Statistics

	Mean	SD	Obs.
Panel A: Demographic and administrative characteristics			
Number of population (thousands)	3.59	4.21	318912
Number of villages (hundreds)	2.71	1.31	318912
Ethnic fractionalization	0.18	0.24	317418
Proportion of high education (> primary school)	0.23	0.15	317418
Proportion of Muslim	0.84	0.33	317418
Urban village	0.17	0.38	318899
Distance to district capital (km)	41.31	45.84	318629
Distance to subdistrict capital (km)	8.66	11.91	318580
Panel B: Agricultural characteristics			
Price change (annual growth), 2000-2014	0.10	0.06	265285
Potential rice yields (suitability) (tons/ha)	5.06	0.89	309786
Paddy production (tons/ha)	4.26	3.98	252801
Paddy harvested area (thousands ha)	0.57	0.58	316896
Gini coefficient of land ownership	0.54	0.18	301128
Share of HH plant sawah (wetland) >0	0.37	0.31	301533
Share of HH plant palawija >0	0.29	0.31	301533
Share farmers sell and consume ag prod.	0.78	0.41	264928
Panel C: Public goods and development projects			
Presence of...			
Doctors	0.20	0.40	318912
Health center (Main)	0.13	0.33	318912
Health center (Support)	0.33	0.47	318912
Health center (Total)	0.44	0.50	318912
Development project (Total)	0.84	0.37	159456
Infrastructure project	0.71	0.46	159456
Capital asst. project	0.64	0.48	159456
Employment asst. project	0.27	0.45	159456
Number of...			
Doctors	0.54	1.53	265760
Health center (Main)	0.13	0.33	265760
Health center (Support)	0.35	0.50	265760
Health center (Total)	0.47	0.56	265760
Development project (Total)	3.14	2.61	159456
Infrastructure project	1.68	1.56	159456
Capital asst. project	1.04	1.04	159456
Employment asst. project	0.40	0.76	159456

Note: Number of observations varies due to variation in availability of some variables in village census (*Podes*) waves

Table 2: Public Health Facilities and Personnel

	Δ Presence				Δ Number			
	Doctors	Health Center (Main)	Health Center (Support)	Health Center (Total)	Doctors	Health Center (Main)	Health Center (Support)	Health Center (Total)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price	0.167*	-0.044	0.461***	0.417***	-0.098	-0.005	0.169*	0.181*
	(0.094)	(0.067)	(0.153)	(0.149)	(0.126)	(0.043)	(0.098)	(0.109)
Price × Suitability	-0.032	0.005	-0.087***	-0.085***	0.013	-0.000	-0.030	-0.035
	(0.021)	(0.013)	(0.032)	(0.030)	(0.025)	(0.009)	(0.021)	(0.023)
Village FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	237063	237063	237063	237063	190383	188955	188955	188955
R-Squared	0.080	0.096	0.075	0.073	0.131	0.155	0.130	0.136
Mean of Dep. Var.	0.199	0.129	0.335	0.442	0.639	0.131	0.350	0.482

Note: This table presents the effects on changes in public good provision in health facilities and personnels. Columns 1 to 4 present estimation results of changes in extensive margins. Columns 5 to 8 present estimation results of changes in intensive margins. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects. Dependent variables in columns 5 to 8 of Panel B are not available in PODES 2008. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level. $* \ p < 0.10$, $** \ p < 0.05$, $*** \ p < 0.01$

Table 3: Development Projects

	Presence				Number			
	All project	Infrastructure	Capital Asst	Employment Asst	All project	Infrastructure	Capital Asst	Employment Asst
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price	-0.063	0.124	1.691**	-0.593	4.037	1.850	3.292**	-1.072
	(0.509)	(0.634)	(0.780)	(0.599)	(2.673)	(1.352)	(1.327)	(1.052)
Price × Suitability	0.103	0.005	-0.357**	0.127	-1.088*	-0.619**	-0.714**	0.227
	(0.112)	(0.135)	(0.171)	(0.125)	(0.582)	(0.296)	(0.291)	(0.221)
Village FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	145654	145654	145654	145654	145654	145654	145654	145654
R-Squared	0.563	0.766	0.506	0.455	0.693	0.736	0.560	0.468
Mean of Dep. Var.	0.840	0.705	0.636	0.274	3.144	1.680	1.044	0.403

Note: The sample for all regressions only include PODES 2008 onwards because information on development projects only available starting in 2008. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects. All regressions include village and year fixed-effects as well as district-specific trends. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level.. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Night Light Intensity and Health Insurance Enrollment for the Poor

	Δ Lights Coverage (1)	Δ Lights Intensity (2)	Δ Health Card (3)
Price	-2.342***	-1.143***	506.316**
	(0.429)	(0.176)	(198.090)
Price × Suitability	0.476***	0.249***	-116.880***
	(0.081)	(0.035)	(41.340)
Village FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes
N	188076	188076	237063
R-Squared	0.143	0.299	0.295
Mean of Dep. Var.	0.663	1.329	435.137

Note: This table presents the results of changes in the presence and intensity of night-time lights as well as the number of membership of health insurance for the poor. The sample for dependent variables in columns 1 and 2 are only up to 2011. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Nutrient Intake and Share of Food Expenditure per Capita

	Calorie	Protein	Share of Food Exp per capita.
	(1)	(2)	(3)
Price	-0.072	-0.215	-0.014
	(0.167)	(0.198)	(0.053)
Price × Suitability	0.034*	0.050**	0.008
	(0.019)	(0.022)	(0.006)
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes
N	305460	305460	305460
R-Squared	0.177	0.170	0.253

Note: This table presents the effects on nutritional status and the share of food expenditure. Nutrition status is measured by per capita calorie (log) and protein (log) intake in the last seven days at the household level using data from the consumption module of the 2002, 2005, 2008, and 2011 National Socioeconomic Survey (Susenas). The sample covers 25,821 unique villages. To obtain per capita measures, household size is adjusted by equivalent scales. Calorie and protein intakes are converted from various food groups. In addition to the village-level covariates in the main specification, the regression specification also includes household covariates: indicator for wife's education attainment, wife's age and age squared, indicator for marital status of head of household (not married, married, divorced, widowed), and indicators for the number of household members aged 0-4, 5-9, 10-14, 15-55, and above 55. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at the district level.. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Effects on Public Health Facilities and Personnel by Land Inequality

	Δ Presence				Δ Number			
	Doctors	Health Center (Main)	Health Center (Small)	Health Center (Total)	Doctors	Health Center (Main)	Health Center (Small)	Health Center (Total)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Land Inequality: Above Median								
Price × Suitability	-0.017	-0.021	-0.123***	-0.126***	0.044	-0.032**	-0.036	-0.071**
	(0.040)	(0.023)	(0.045)	(0.043)	(0.047)	(0.014)	(0.028)	(0.031)
N	110679	110679	110679	110679	89028	88000	88000	88000
R-Squared	0.081	0.097	0.076	0.074	0.133	0.161	0.132	0.143
Land Inequality: Below Median								
Price × Suitability	-0.024	0.017	-0.064	-0.062	0.006	0.022**	-0.034	-0.016
	(0.024)	(0.016)	(0.044)	(0.041)	(0.028)	(0.011)	(0.028)	(0.031)
N	114400	114400	114400	114400	91709	91415	91415	91415
R-Squared	0.080	0.097	0.077	0.074	0.136	0.152	0.130	0.134

Note: This table presents effects on changes in health facilities and personnels by land inequality. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects, village and year fixed-effects as well as district-specific trends. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Effects on Development Projects by Land Inequality

	Presence				Number			
	All project	Infrastructure	Capital Asst	Employment Asst	All project	Infrastructure	Capital Asst	Employment Asst
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Land Inequality: Above Median								
Price × Suitability	-0.182	-0.327	-0.315	0.116	-0.772	-0.485	-0.502	0.223
	(0.155)	(0.210)	(0.210)	(0.209)	(0.861)	(0.375)	(0.392)	(0.355)
N	68705	68705	68705	68705	68705	68705	68705	68705
R-Squared	0.544	0.752	0.493	0.438	0.681	0.746	0.542	0.455
Land Inequality: Below Median								
Price × Suitability	0.132	0.079	-0.449**	0.207*	-0.986	-0.338	-1.031***	0.381
	(0.113)	(0.129)	(0.177)	(0.123)	(0.684)	(0.343)	(0.303)	(0.240)
N	69500	69500	69500	69500	69500	69500	69500	69500
R-Squared	0.576	0.784	0.507	0.458	0.694	0.727	0.564	0.468

Note: This table presents effects on development projects by land inequality. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects, village and year fixed-effects as well as district-specific trends. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Effects on Social Capital by Land Inequality

	All (Mean) (1)	Trust Vil. Govt. (2)	Trust Leave House (3)	Trust Leave Child (4)	Help Neighbor (5)	Socialize Neighbor (6)	Loan Money Neighbor (7)	Feeling Diff. Ethnic (8)
Baseline Specification (all sample)								
Price × Suitability	-0.523***	-0.290*	-0.412***	-0.119	-0.182	-0.361	-0.172	-0.448***
	(0.181)	(0.159)	(0.135)	(0.163)	(0.139)	(0.230)	(0.191)	(0.168)
N	229905	220092	197147	219876	209373	228846	198156	220741
R-Squared	0.074	0.041	0.083	0.053	0.049	0.059	0.055	0.065
Land Inequality: Above Median								
Price × Suitability	-0.283	-0.056	-0.026	0.333	0.037	-0.507*	0.075	-0.753**
	(0.352)	(0.264)	(0.313)	(0.377)	(0.310)	(0.304)	(0.345)	(0.356)
N	106898	101727	90026	101866	96795	106391	89910	102392
R-Squared	0.080	0.050	0.084	0.056	0.055	0.069	0.067	0.081
Land Inequality: Below Median								
Price × Suitability	-0.572***	-0.371**	-0.514***	-0.268	-0.253*	-0.382	-0.191	-0.201
	(0.196)	(0.182)	(0.156)	(0.180)	(0.146)	(0.239)	(0.203)	(0.187)
N	109223	105225	95027	104790	99709	108725	96544	104908
R-Squared	0.087	0.051	0.096	0.069	0.068	0.071	0.072	0.075

Note: This table presents baseline and heterogeneity effects on social capital by land ineqaulity using sociocultural module of the 2009 and 2012 National Socioeconomic Survey (Susenas). The sample covers 15,088 unique villages. Column 1 measures mean index of all social capital variables (columns 2 to 8). Price is omitted due to collinearity with district-specific trends. The sample varies across outcomes due to non-responses. The regression specification adds an indicator variable for being male, age, and age squared. Additional village-level covariates include those in the main specification. For ease of interpretation, dependent variables are standardized. All regressions include village and year fixed effects as well as district-specific trends. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Effects on Infant and Maternal Mortality by Presence of Health Centers

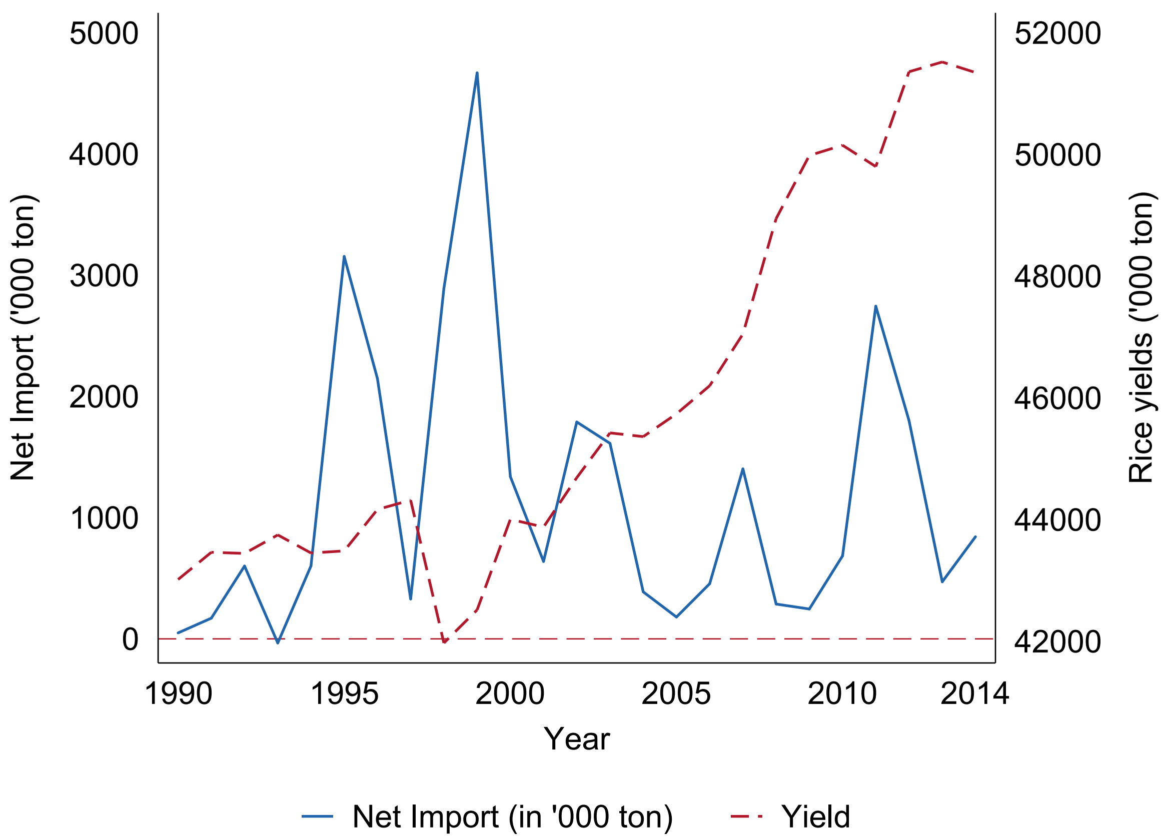
	Extensive Margins		Intensive Margins	
	Infant Mortality (1)	Maternal Mortality (2)	Infant Mortality (3)	Maternal Mortality (4)
Baseline Specification				
Price × Suitability	-0.181*	-0.099**	-4.786	-1.077
	(0.095)	(0.041)	(10.259)	(1.149)
N	52285	52285	52233	52267
R-Squared	0.127	0.037	0.029	0.007
Mean of Dep. Var	0.607	0.111	30.644	1.957
Health Centers (All): Present				
Price × Suitability	-0.070	-0.104*	3.011	-1.628
	(0.104)	(0.055)	(11.596)	(1.312)
N	25004	25004	24990	25002
R-Squared	0.122	0.039	0.031	0.009
Health Centers (All): Not Present				
Price × Suitability	-0.302***	-0.079**	-11.471	-0.212
	(0.103)	(0.038)	(10.199)	(1.420)
N	27281	27281	27243	27265
R-Squared	0.119	0.029	0.030	0.007

This table presents baseline (uninteracted) and heterogeneity treatment effects on infant and maternal mortality by the presence of public health centers. Information on public health centers are taken from the 2008 *Podes.* In addition to the village-level covariates in the main specification, all regressions include indicator for urban village, proportion of employment in agricultural sector, proportion of high educated people (higher than primary school). *Price*, which measures log annualized price change from 2006 to 2009, is included but not shown. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A Appendix

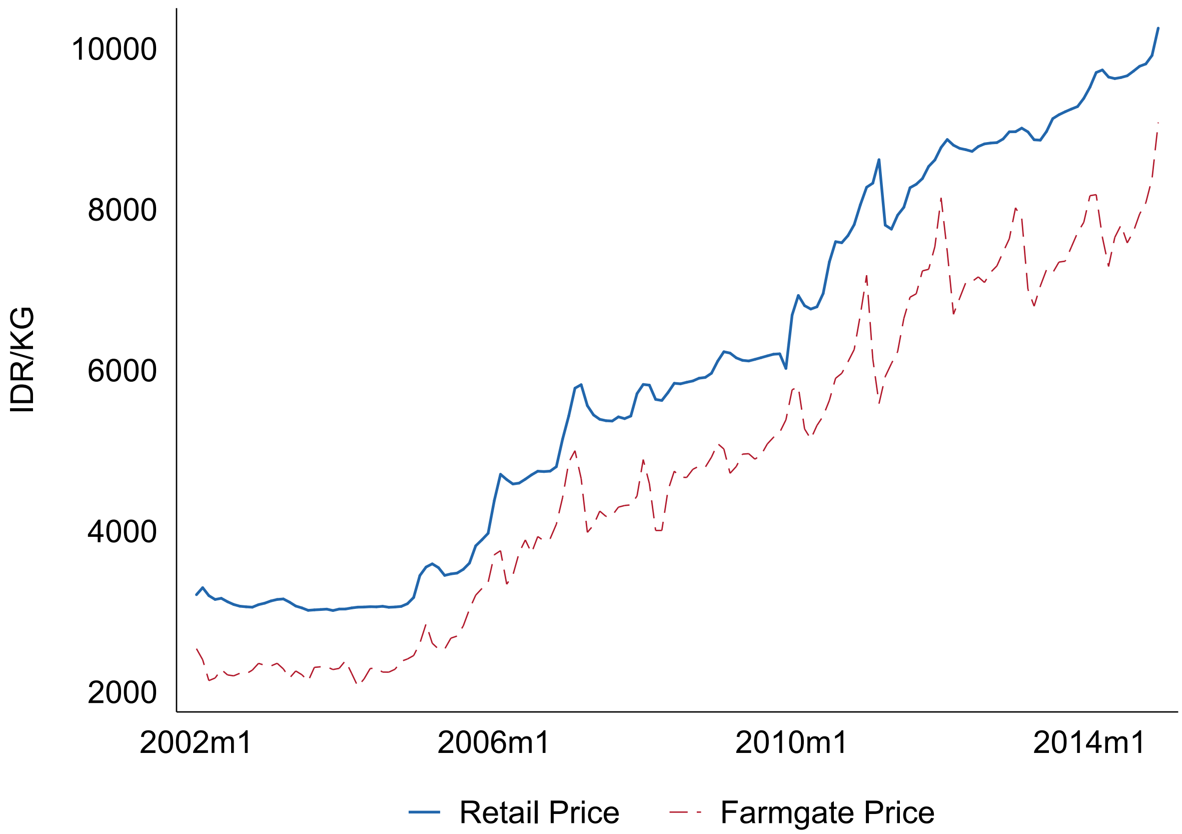
A.1 Figures

Figure A.1: Net Rice Imports and Rice Yields, 1990-2014.



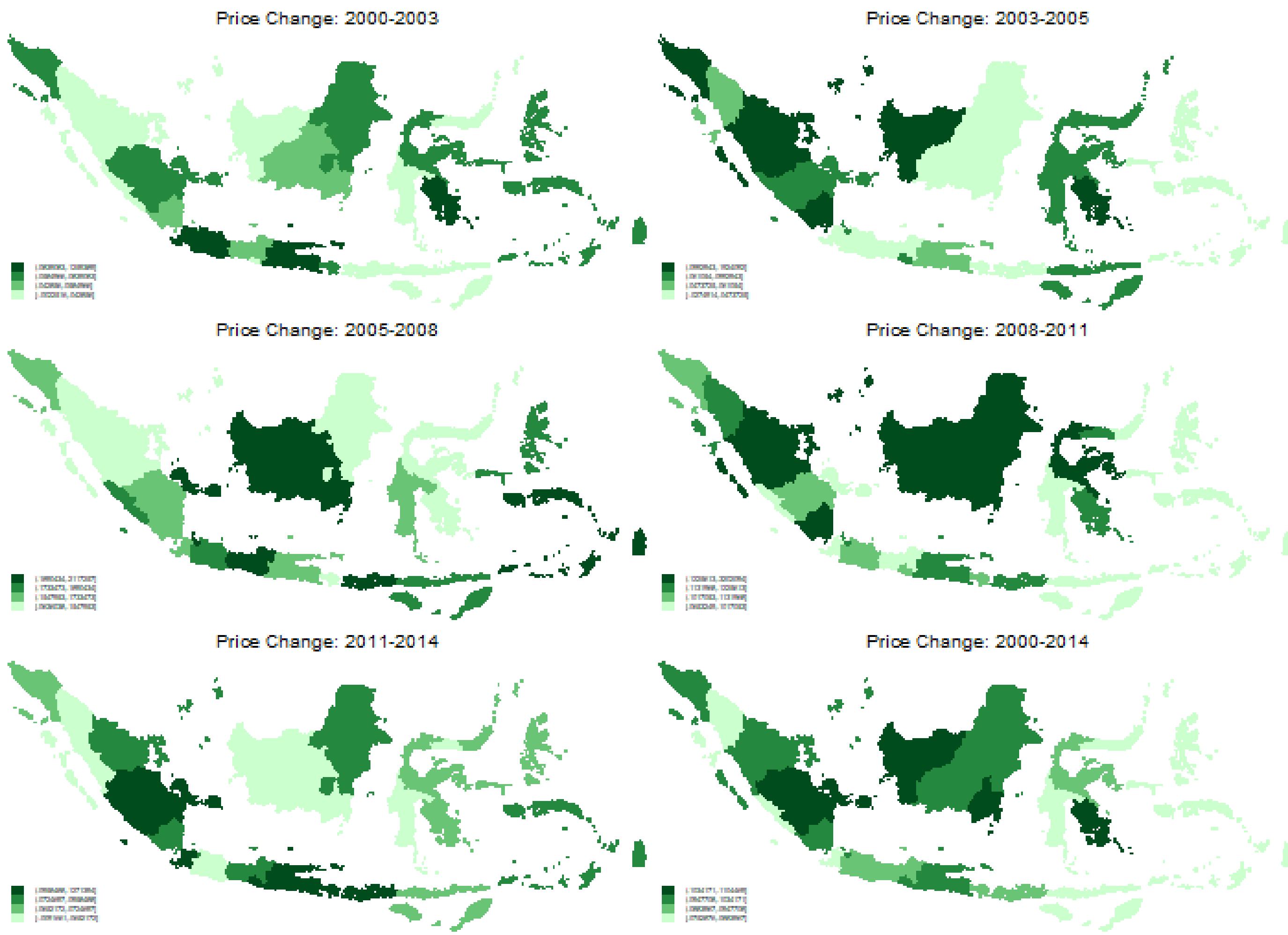
Note: This figure shows Indonesia's net import of rice and rice yields from 1990 to 2014. The rice yields reflect the amount of rice after going through a drying and milling process that converts 100 kilograms of wet paddy to roughly 55 kilograms of rice. Source: FAOSTAT.

Figure A.2: Domestic Retail and Farmgate Price: 2002-2014



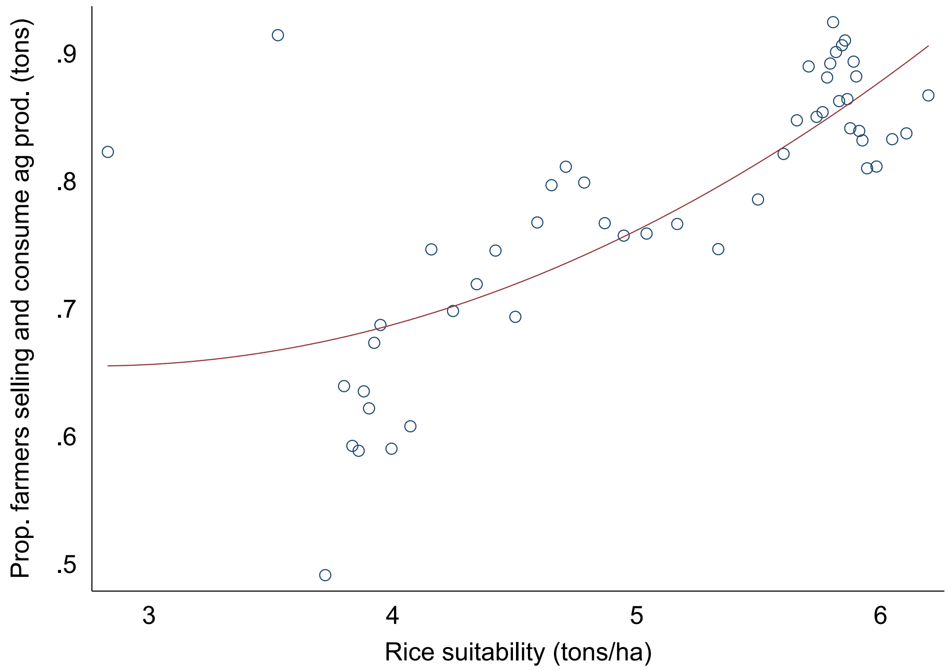
Note: This figure shows the close relatonship between national farmgate and retail rice prices from 2002 to 2014. Farmgate prices are quoted in wet paddy. Drying and milling process converts 100 kilograms of wet paddy to roughly 55 kilograms. Source: Central Bureau of Statistics (BPS) and CEIC database.

Figure A.3: Domestic Annual Rice Price Change Distribution: 2000-2014



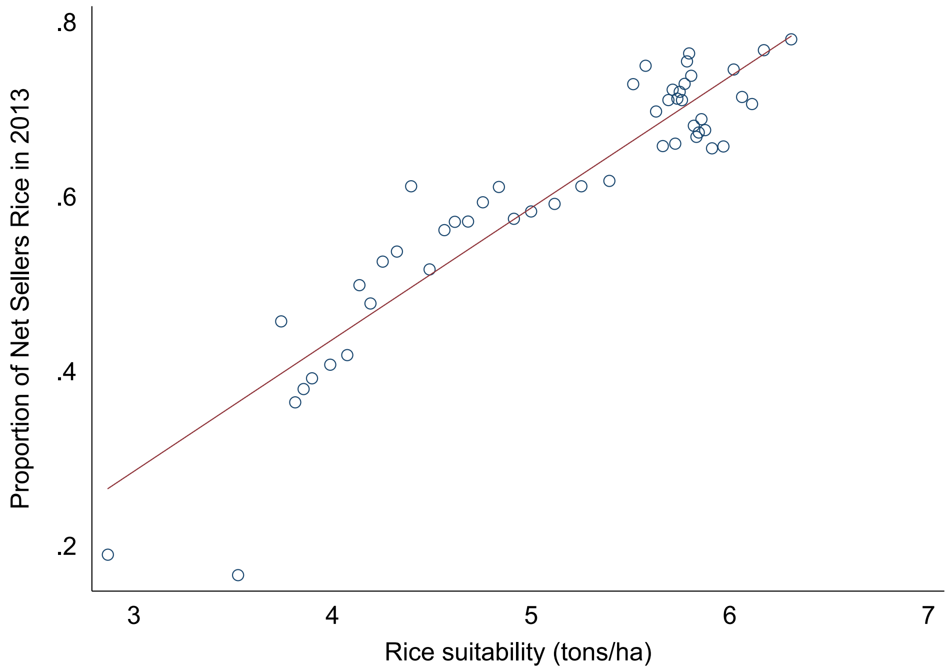
Note: his figure shows log annualized price change (log points) between 2000 to 2014 across provinces in Indonesia, excluding Papua island. Darker shade implies higher price change than that of lighter shade. Source: Central Bureau of Statistics (BPS) obtained via CEIC database.

Figure A.4: Proportion of Producer and Consumer Farmers and Rice Suitability.



Note: This figure summarizes relationship between rice suitability and proportion of farmers selling and consuming their agriculture products conditional on majority of villagers working in agricultural sector. Source: FAO-GAEZ (rice suitability) and PODES 2005 (proportion of farmers sellers).

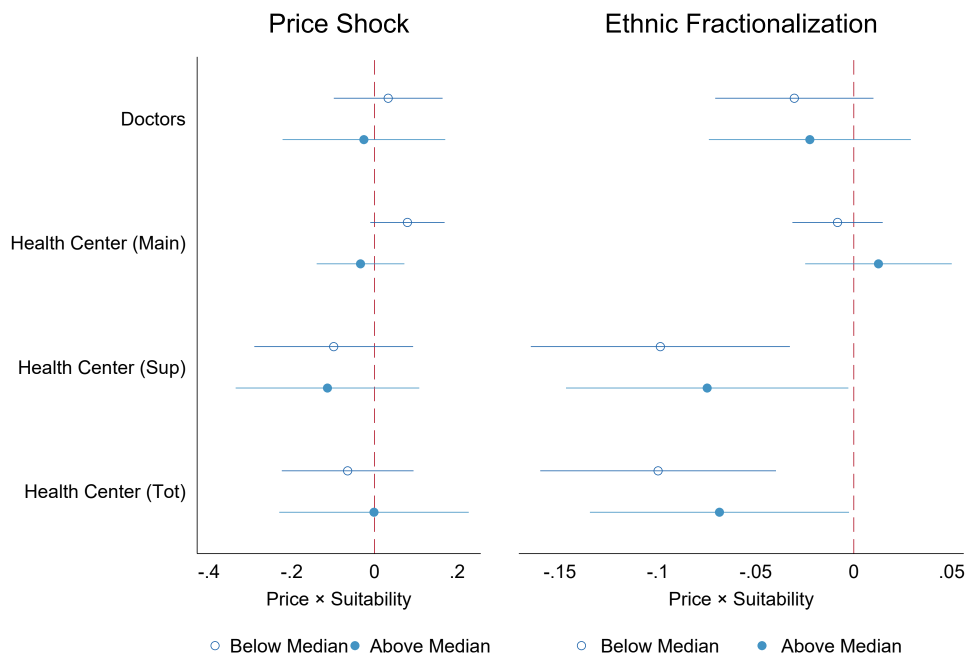
Figure A.5: Proportion of Net Seller Rice Farmers and Rice Suitability in 2013.



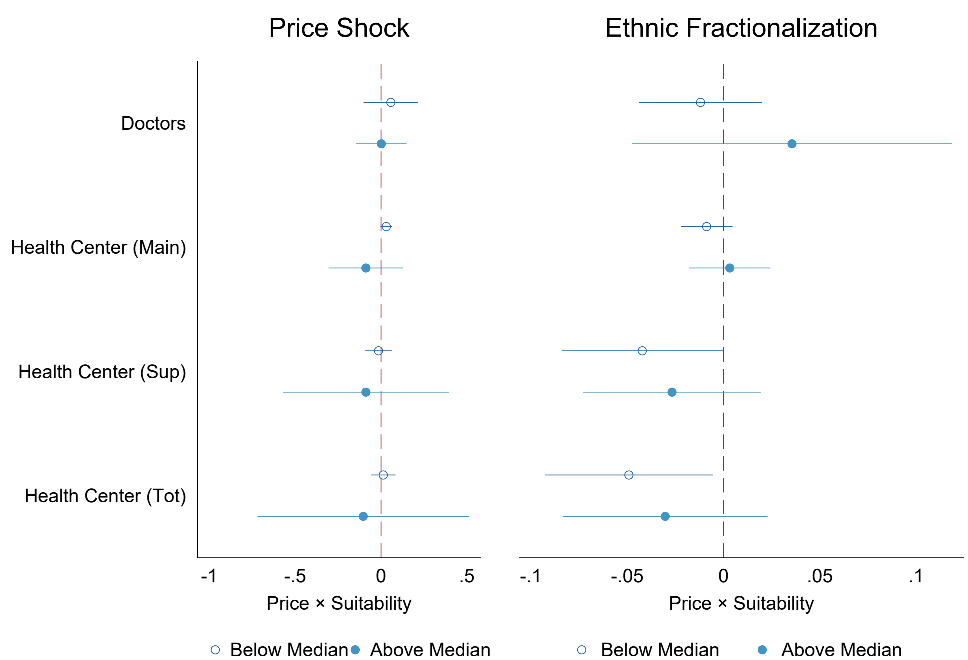
Note: This figure summarizes relationship between rice suitability and proportion of net seller rice farmers. Net seller is an indicator for whether a household sells some or all of their harvested rice. Source: FAO-GAEZ (rice suitability) and Agricultural Census 2013 (proportion of net sellers).

Figure A.6: Effects on Health Public Goods by Price Shock Magnitude and Ethnic Diversity

(a) Changes in Extensive Margin



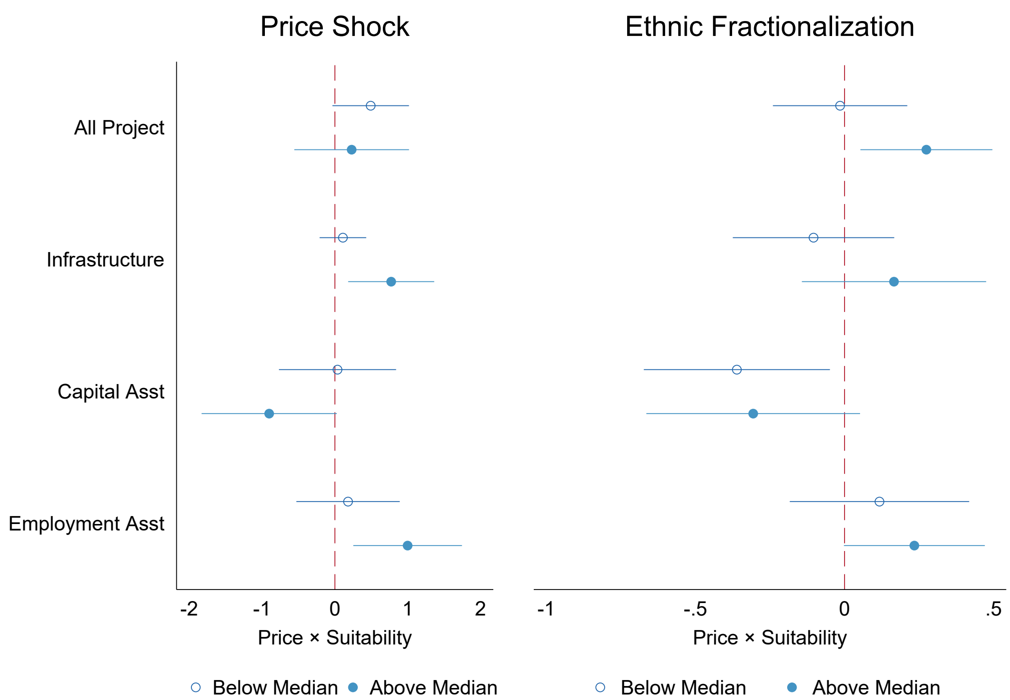
(b) Changes in Intensive Margin



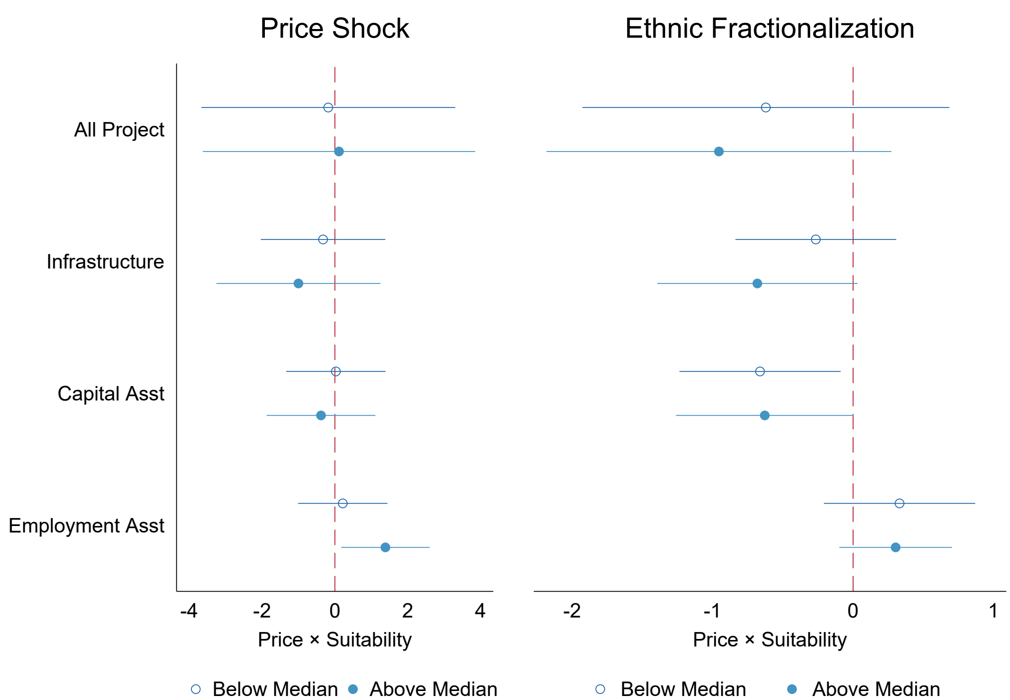
Note: This figure plots regression coefficients of estimating Equation 2. Each coefficient comes from each regression conducted separately. Panel (a) and Panel (b) plot effects on changes in the presence and number of public health facilities and personnel, respectively. Standard errors are clustered at the district level with 90% confidence interval.

Figure A.7: Effects on Development Projects by Price Shock Magnitude and Ethnic Diversity

(a) Changes in Extensive Margin



(b) Changes in Intensive Margin



Note: This figure plots regression coefficients of estimating Equation 2. Each coefficient comes from each regression conducted separately. Panel (a) and Panel (b) plot effects on changes in the presence and number of public health facilities and personnel, respectively. Standard errors are clustered at the district level with 90% confidence interval.

A.2 Tables

Table A.1: Nutrient Intake: Bought and Own Food

	Calorie Bought (All) (1)	Calorie Own (All) (2)	Calorie Bought (Unprocessed) (3)	Calorie Own (Unprocessed) (4)	Protein Bought (All) (5)	Protein Own (All) (6)	Protein Bought (Unprocessed) (7)	Protein Own (Unprocessed) (8)
Price	-0.036	0.084	0.052	-0.144	-0.237	0.647	-0.319	0.284
	(0.232)	(0.810)	(0.412)	(0.888)	(0.267)	(0.730)	(0.307)	(0.800)
Price × Suitability	0.014	0.201**	-0.040	0.145	0.039	0.087	-0.015	0.069
	(0.024)	(0.079)	(0.041)	(0.096)	(0.027)	(0.087)	(0.032)	(0.101)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	305292	208476	304488	185987	305255	207581	304486	185977
R-Squared	0.190	0.200	0.135	0.206	0.211	0.189	0.149	0.207

Note: This table presents the effects on nutritional status in the forms of per capita calorie (log) and protein (log) intake in the last seven days at the household level using data from the consumption module of the 2002, 2005, 2008, and 2011 National Socioeconomic Survey (Susenas). The sample covers 25,821 unique villages. To obtain per capita measures, household size is adjusted by equivalent scales. Calorie and protein intakes are converted from all and unprocessed food groups. All-food group includes processed and unprocessed food. Both food groups are further divided into whether the food are bought or obtained from household own production. In addition to the village-level covariates in the main specification, the regression specification also includes household covariates: indicator for wife's education attainment, wife's age and age squared, indicator for marital status of head of household (not married, married, divorced, widowed), and indicators for the number of household members aged 0-4, 5-9, 10-14, 15-55, and above 55. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at the district level.. $* \; p < 0.10, ** \; p < 0.05, *** \; p < 0.01$

Table A.2: Effects on Public Health Facilities and Personnel by Price Shock Magnitude and Ethnic Diversity

	Δ Presence				Δ Number			
	Doctors	Health Center (Main)	Health Center (Small)	Health Center (Total)	Doctors	Health Center (Main)	Health Center (Small)	Health Center (Total)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price Shock: Above Median								
Price × Suitability	-0.026	-0.034	-0.114	-0.001	0.002	-0.088	-0.088	-0.104
	(0.119)	(0.064)	(0.134)	(0.139)	(0.089)	(0.132)	(0.293)	(0.373)
N	110728	110728	110728	110728	97680	59818	59818	59818
R-Squared	0.218	0.277	0.248	0.245	0.245	0.372	0.353	0.361
Price Shock: Below Median								
Price × Suitability	0.033	0.080	-0.099	-0.065	0.057	0.031	-0.015	0.013
	(0.080)	(0.054)	(0.116)	(0.096)	(0.096)	(0.020)	(0.047)	(0.043)
N	106375	106375	106375	106375	64752	103456	103456	103456
R-Squared	0.289	0.289	0.272	0.268	0.431	0.279	0.260	0.265
Ethnic Fractionalization: Above Median								
Price × Suitability	-0.022	0.013	-0.075*	-0.069*	0.036	0.003	-0.027	-0.030
	(0.031)	(0.023)	(0.044)	(0.040)	(0.050)	(0.013)	(0.028)	(0.032)
N	114400	114400	114400	114400	91990	91103	91103	91103
R-Squared	0.083	0.098	0.078	0.075	0.135	0.160	0.134	0.143
Ethnic Fractionalization: Below Median								
Price × Suitability	-0.030	-0.008	-0.099**	-0.100***	-0.012	-0.009	-0.042*	-0.049*
	(0.024)	(0.014)	(0.040)	(0.036)	(0.019)	(0.008)	(0.025)	(0.026)
N	122013	122013	122013	122013	97869	97335	97335	97335
R-Squared	0.079	0.095	0.073	0.072	0.126	0.148	0.126	0.130

Note: This table presents heterogenous treatment effects on changes in public good provision (extensive margins): health facilities and personnels as well as public schools. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects, village and year fixed-effects as well as district-specific trends. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$.

Table A.3: Effects on Development Projects by Price Shock Magnitude and Ethnic Diversity

	Presence				Number			
	All project	Infrastructure	Capital Asst	Employment Asst	All project	Infrastructure	Capital Asst	Employment Asst
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price Shock: Above Median								
Price × Suitability	0.230	0.773**	-0.903	0.998**	0.112	-1.002	-0.382	1.387*
	(0.477)	(0.358)	(0.562)	(0.452)	(2.265)	(1.363)	(0.904)	(0.735)
N	87071	87071	87071	87071	87071	87071	87071	87071
R-Squared	0.620	0.803	0.562	0.504	0.719	0.772	0.595	0.514
Price Shock: Below Median								
Price × Suitability	0.491	0.110	0.036	0.180	-0.183	-0.326	0.026	0.216
	(0.317)	(0.193)	(0.486)	(0.429)	(2.105)	(1.032)	(0.824)	(0.741)
N	26249	26249	26249	26249	26249	26249	26249	26249
R-Squared	0.657	0.724	0.662	0.629	0.774	0.754	0.710	0.630
Ethnic Fractionalization: Above Median								
Price × Suitability	0.275**	0.166	-0.306	0.234	-0.955	-0.682	-0.629	0.303
	(0.134)	(0.187)	(0.217)	(0.143)	(0.744)	(0.432)	(0.383)	(0.243)
N	70775	70775	70775	70775	70775	70775	70775	70775
R-Squared	0.562	0.753	0.504	0.458	0.683	0.717	0.563	0.478
Ethnic Fractionalization: Below Median								
Price × Suitability	-0.015	-0.104	-0.361*	0.117	-0.621	-0.265	-0.663*	0.331
	(0.137)	(0.164)	(0.189)	(0.182)	(0.792)	(0.347)	(0.348)	(0.326)
N	74483	74483	74483	74483	74483	74483	74483	74483
R-Squared	0.568	0.782	0.507	0.453	0.706	0.761	0.557	0.461

Note: This table presents effects on development projects by price shock magnitude and ethnic diversity. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects, village and year fixed-effects as well as district-specific trends. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Robustness Tests Results

Table B.1: Public Goods: Health Facilities and Personnel – All Provinces

	Δ Presence			
	Doctors	Health Center (Main)	Health Center (Support)	Health Center (Total)
	(1)	(2)	(3)	(4)
Panel A: Extensive Margins				
Price	0.162*	-0.057	0.438***	0.378**
	(0.091)	(0.067)	(0.150)	(0.146)
Price × Suitability	-0.032	0.007	-0.083***	-0.078***
	(0.020)	(0.013)	(0.031)	(0.030)
Village FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes
N	263364	263364	263364	263364
R-Squared	0.080	0.097	0.075	0.073
Mean of Dep. Var.	0.194	0.126	0.318	0.424
	Δ Number			
Panel B: Intensive Margins				
Price	-0.098	-0.023	0.144	0.138
	(0.128)	(0.043)	(0.095)	(0.108)
Price × Suitability	0.011	0.004	-0.025	-0.025
	(0.025)	(0.009)	(0.021)	(0.023)
Village FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes
N	211429	209966	209966	209966
R-Squared	0.131	0.155	0.130	0.136
Mean of Dep. Var.	0.669	0.130	0.333	0.463

Note: This table presents the effects on changes in public good provision in health facilities and personnels. Panel A presents estimation results of changes in extensive margins. Panel B presents results of changes in intensive margins. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects. Dependent variables in columns 1 to 4 of Panel B are not available in PODES 2008. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level. $* \ p < 0.10, ** \ p < 0.05, *** \ p < 0.01$.

Table B.2: Development Projects – All Provinces

	Presence				Number			
	All project	Infrastructure	Capital Asst	Employment Asst	All project	Infrastructure	Capital Asst	Employment Asst
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price	-0.340	0.254	1.556**	-0.475	5.329**	3.002**	3.214**	-0.808
	(0.496)	(0.658)	(0.749)	(0.586)	(2.685)	(1.451)	(1.287)	(1.027)
Price × Suitability	0.166	-0.026	-0.328**	0.097	-1.404**	-0.894***	-0.698**	0.160
	(0.109)	(0.140)	(0.163)	(0.123)	(0.589)	(0.320)	(0.282)	(0.216)
Village FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	161761	161761	161761	161761	161761	161761	161761	161761
R-Squared	0.563	0.756	0.503	0.462	0.697	0.734	0.568	0.475
Mean of Dep. Var.	0.837	0.700	0.639	0.264	3.074	1.627	1.042	0.389

Note: The sample for all regressions only include PODES 2008 onwards because information on development projects only available starting in 2008. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects. All regressions include village and year fixed-effects as well as district-specific trends. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level.. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3: Public Goods: Health Facilities and Personnel – Village-Specific Trend

	Δ Presence			
	Doctors	Health Center (Main)	Health Center (Support)	Health Center (Total)
	(1)	(2)	(3)	(4)
Panel A: Extensive Margins				
Price	0.164	-0.051	0.475***	0.429**
	(0.108)	(0.077)	(0.175)	(0.171)
Price × Suitability	-0.032	0.007	-0.090**	-0.087**
	(0.024)	(0.015)	(0.036)	(0.035)
Village FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Village-specific Trend	Yes	Yes	Yes	Yes
N	237063	237063	237063	237063
R-Squared	0.229	0.237	0.204	0.198
Mean of Dep. Var.	0.199	0.129	0.335	0.442
	Δ Number			
Panel B: Intensive Margins				
Price	-0.140	-0.018	0.184	0.180
	(0.141)	(0.051)	(0.119)	(0.134)
Price × Suitability	0.023	0.003	-0.033	-0.034
	(0.028)	(0.011)	(0.026)	(0.029)
Village FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Village-specific Trend	Yes	Yes	Yes	Yes
N	190383	188955	188955	188955
R-Squared	0.383	0.393	0.311	0.324
Mean of Dep. Var.	0.639	0.131	0.350	0.482

Note: This table presents the effects on changes in public good provision in health facilities and personnels and schools. Panel A presents estimation results of changes in extensive margins. Panel B presents results of changes in intensive margins. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects. Dependent variables in columns 1 to 4 of Panel B are not available in PODES 2008. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4: Development Projects – Village-Specific Trend

	Presence				Number			
	All project	Infrastructure	Capital Asst	Employment Asst	All project	Infrastructure	Capital Asst	Employment Asst
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price	0.399	0.712	3.104**	-0.478	6.982	2.564	4.978**	-0.441
	(0.828)	(1.087)	(1.344)	(1.029)	(4.289)	(2.254)	(2.240)	(1.675)
Price × Suitability	0.005	-0.119	-0.655**	0.104	-1.705*	-0.771	-1.067**	0.098
	(0.180)	(0.233)	(0.293)	(0.218)	(0.944)	(0.492)	(0.493)	(0.354)
Village FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village-specific Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	145654	145654	145654	145654	145654	145654	145654	145654
R-Squared	0.838	0.888	0.766	0.745	0.860	0.869	0.799	0.757
Mean of Dep. Var.	0.840	0.705	0.636	0.274	3.144	1.680	1.044	0.403

Note: The sample for all regressions only include PODES 2008 onwards because information on development projects only available starting in 2008. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects. All regressions include village and year fixed-effects as well as Village-specific trends. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level.. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.5: Public Goods: Health Facilities and Personnel – Alternative Price Change Definition

	Δ Presence			
	Doctors	Health Center (Main)	Health Center (Support)	Health Center (Total)
	(1)	(2)	(3)	(4)
Panel A: Extensive Margins				
Price	0.055	-0.016	0.142**	0.124**
	(0.035)	(0.024)	(0.057)	(0.056)
Price × Suitability	-0.010	0.002	-0.025**	-0.024**
	(0.008)	(0.005)	(0.012)	(0.011)
Village FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes
N	237063	237063	237063	237063
R-Squared	0.080	0.096	0.075	0.073
Mean of Dep. Var.	0.199	0.129	0.335	0.442
	Δ Number			
Panel B: Intensive Margins				
Price	-0.024	-0.002	0.020	0.026
	(0.042)	(0.016)	(0.035)	(0.040)
Price × Suitability	0.002	-0.000	-0.002	-0.003
	(0.008)	(0.003)	(0.008)	(0.009)
Village FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes
N	190383	188955	188955	188955
R-Squared	0.131	0.155	0.129	0.136
Mean of Dep. Var.	0.639	0.131	0.350	0.482

Note: This table presents the effects on changes in public good provision in health facilities and personnels. Panel A presents estimation results of changes in extensive margins. Panel B presents results of changes in intensive margins. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects. Dependent variables in columns 1 to 4 of Panel B are not available in PODES 2008. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.6: Development Projects – Alternative Price Change Definition

	Presence				Number			
	All project (1)	Infrastructure (2)	Capital Asst (3)	Employment Asst (4)	All project (5)	Infrastructure (6)	Capital Asst (7)	Employment Asst (8)
Price	-0.015	0.044	0.622**	-0.211	1.495	0.654	1.236**	-0.387
	(0.192)	(0.240)	(0.295)	(0.225)	(1.005)	(0.506)	(0.502)	(0.395)
Price × Suitability	0.037	0.002	-0.132**	0.045	-0.408*	-0.227**	-0.269**	0.082
	(0.042)	(0.051)	(0.064)	(0.047)	(0.218)	(0.110)	(0.110)	(0.083)
Village FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	145654	145654	145654	145654	145654	145654	145654	145654
R-Squared	0.563	0.766	0.506	0.455	0.693	0.736	0.560	0.468
Mean of Dep. Var.	0.840	0.705	0.636	0.274	3.144	1.680	1.044	0.403

Note: The sample for all regressions only include PODES 2008 onwards because information on development projects only available starting in 2008. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects. All regressions include village and year fixed-effects as well as district-specific trends. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level.. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.7: Public Goods: Health Facilities and Personnel – Control for Rainfall Shock

	Δ Presence			
	Doctors	Health Center (Main)	Health Center (Support)	Health Center (Total)
	(1)	(2)	(3)	(4)
Panel A: Extensive Margins				
Price	0.170*	-0.046	0.465***	0.420***
	(0.095)	(0.068)	(0.154)	(0.149)
Price × Suitability	-0.033	0.005	-0.088***	-0.086***
	(0.021)	(0.014)	(0.032)	(0.030)
Village FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes
N	237063	237063	237063	237063
R-Squared	0.080	0.096	0.075	0.073
Mean of Dep. Var.	0.199	0.129	0.335	0.442
	Δ Number			
Panel B: Intensive Margins				
Price	-0.089	-0.008	0.170*	0.180*
	(0.126)	(0.044)	(0.097)	(0.109)
Price × Suitability	0.009	0.001	-0.031	-0.034
	(0.025)	(0.009)	(0.021)	(0.023)
Village FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes
N	190383	188955	188955	188955
R-Squared	0.131	0.155	0.130	0.136
Mean of Dep. Var.	0.639	0.131	0.350	0.482

Note: This table presents the effects on changes in public good provision in health facilities and personnels. Panel A presents estimation results of changes in extensive margins. Panel B presents results of changes in intensive margins. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects, and rainfall shock. Dependent variables in columns 1 to 4 of Panel B are not available in PODES 2008. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.8: Development Projects – Control for Rainfall Shock

	Presence				Number			
	All project	Infrastructure	Capital Asst	Employment Asst	All project	Infrastructure	Capital Asst	Employment Asst
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price	-0.056	0.119	1.702**	-0.585	4.053	1.828	3.316**	-1.057
	(0.513)	(0.634)	(0.777)	(0.602)	(2.672)	(1.358)	(1.321)	(1.055)
Price × Suitability	0.103	0.005	-0.357**	0.127	-1.088*	-0.618**	-0.714**	0.227
	(0.112)	(0.135)	(0.170)	(0.126)	(0.582)	(0.297)	(0.290)	(0.221)
Village FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	145654	145654	145654	145654	145654	145654	145654	145654
R-Squared	0.563	0.766	0.506	0.455	0.693	0.736	0.560	0.468
Mean of Dep. Var.	0.840	0.705	0.636	0.274	3.144	1.680	1.044	0.403

Note: The sample for all regressions only include PODES 2008 onwards because information on development projects only available starting in 2008. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects, and rainfall shock. All regressions include village and year fixed-effects as well as district-specific trends. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level.. * p < 0.10, ** p < 0.05, *** p < 0.01

Table B.9: Public Goods: Health Facilities and Personnel – Controlling for Baseline Lights Coverage Interacted with Year Fixed Effects

	Δ Presence			
	Doctors	Health Center (Main)	Health Center (Small)	Health Center (Total)
	(1)	(2)	(3)	(4)
Price	0.046	-0.052	0.435***	0.374**
	(0.096)	(0.075)	(0.160)	(0.156)
Price × Suitability	-0.007	0.005	-0.081**	-0.077**
	(0.021)	(0.015)	(0.033)	(0.032)
Village FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes
N	237063	237063	237063	237063
R-Squared	0.080	0.096	0.075	0.073
Mean of Dep. Var.	0.199	0.129	0.335	0.442
Panel B: Intensive Margins				
Price	-0.244*	-0.017	0.184*	0.188*
	(0.134)	(0.044)	(0.100)	(0.111)
Price × Suitability	0.046*	0.001	-0.034	-0.037
	(0.027)	(0.009)	(0.022)	(0.024)
Village FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes
N	190383	188955	188955	188955
R-Squared	0.131	0.155	0.130	0.136
Mean of Dep. Var.	0.639	0.131	0.350	0.482

Note: This table presents the effects on changes in public good provision in health facilities and personnels. Panel A presents estimation results of changes in extensive margins. Panel B presents results of changes in intensive margins. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects, and baseline (in 2000) nighttime lights coverage interacted with year fixed effects. Dependent variables in columns 1 to 4 of Panel B are not available in PODES 2008. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.10: Development Projects – Controlling for Baseline Lights Coverage Interacted with Year Fixed Effects

	Presence				Number			
	All project	Infrastructure	Capital Asst	Employment Asst	All project	Infrastructure	Capital Asst	Employment Asst
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price	0.229	0.323	1.091	-0.337	2.907	0.512	2.857**	-0.576
	(0.505)	(0.654)	(0.711)	(0.616)	(2.762)	(1.389)	(1.290)	(1.096)
Price × Suitability	0.036	-0.040	-0.219	0.068	-0.828	-0.311	-0.613**	0.113
	(0.111)	(0.139)	(0.159)	(0.129)	(0.603)	(0.299)	(0.286)	(0.230)
Village FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	145654	145654	145654	145654	145654	145654	145654	145654
R-Squared	0.563	0.767	0.507	0.455	0.693	0.736	0.560	0.468
Mean of Dep. Var.	0.840	0.705	0.636	0.274	3.144	1.680	1.044	0.403

Note: The sample for all regressions only include PODES 2008 onwards because information on development projects only available starting in 2008. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects, and baseline (in 2000) nighttime lights coverage interacted with year fixed effects. All regressions include village and year fixed-effects as well as district-specific trends. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.11: Public Goods: Health Facilities and Personnel –Controlling for Baseline Lights Intensity Interacted with Year Fixed Effects

	Δ Presence			
	Doctors	Health Center (Main)	Health Center (Small)	Health Center (Total)
	(1)	(2)	(3)	(4)
Price	0.197	0.035	0.376**	0.369**
	(0.133)	(0.100)	(0.187)	(0.180)
Price × Suitability	-0.036	-0.021	-0.066*	-0.080**
	(0.029)	(0.020)	(0.039)	(0.037)
Village FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes
N	110127	110127	110127	110127
R-Squared	0.176	0.190	0.179	0.176
Mean of Dep. Var.	0.199	0.129	0.335	0.442
Panel B: Intensive Margins				
Price	-0.164	0.054	0.012	0.113
	(0.168)	(0.051)	(0.112)	(0.117)
Price × Suitability	0.032	-0.016	0.002	-0.024
	(0.035)	(0.011)	(0.024)	(0.025)
Village FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes
N	85019	84580	84580	84580
R-Squared	0.233	0.242	0.227	0.232
Mean of Dep. Var.	0.639	0.131	0.350	0.482

Note: This table presents the effects on changes in public good provision in health facilities and personnels. Panel A presents estimation results of changes in extensive margins. Panel B presents results of changes in intensive margins. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects, and baseline (in 2000) nighttime lights coverage interacted with year fixed effects. Dependent variables in columns 1 to 4 of Panel B are not available in PODES 2008. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.12: Development Projects Controlling for Baseline Lights Intensity Interacted with Year Fixed Effects

	Presence				Number			
	All project	Infrastructure	Capital Asst	Employment Asst	All project	Infrastructure	Capital Asst	Employment Asst
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price	0.044	0.170	1.818**	-0.873	4.690	1.848	4.166**	-1.291
	(0.575)	(0.657)	(0.914)	(0.690)	(2.932)	(1.623)	(1.655)	(1.091)
Price × Suitability	0.071	-0.011	-0.374*	0.160	-1.263**	-0.608*	-0.889**	0.220
	(0.124)	(0.137)	(0.199)	(0.143)	(0.637)	(0.357)	(0.358)	(0.230)
Village FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	60361	60361	60361	60361	60361	60361	60361	60361
R-Squared	0.611	0.791	0.556	0.509	0.726	0.768	0.606	0.522
Mean of Dep. Var.	0.840	0.705	0.636	0.274	3.144	1.680	1.044	0.403

Note: The sample for all regressions only include PODES 2008 onwards because information on development projects only available starting in 2008. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects, and baseline (in 2000) nighttime lights coverage interacted with time trend. All regressions include village and year fixed-effects as well as district-specific trends. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level.. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.13: Public Goods: Health Facilities and Personnel – Controlling for Price Change Interacted with Baseline Lights Coverage

	Δ Presence			
	Doctors	Health Center (Main)	Health Center (Small)	Health Center (Total)
	(1)	(2)	(3)	(4)
Price	0.110	-0.038	0.465***	0.418***
	(0.094)	(0.068)	(0.153)	(0.148)
Price × Suitability	-0.008	0.002	-0.089***	-0.086***
	(0.020)	(0.014)	(0.033)	(0.031)
Village FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes
N	237063	237063	237063	237063
R-Squared	0.080	0.096	0.075	0.073
Mean of Dep. Var.	0.199	0.129	0.335	0.442
Panel B: Intensive Margins				
Price	-0.162	-0.004	0.175*	0.190*
	(0.133)	(0.043)	(0.097)	(0.107)
Price × Suitability	0.043	-0.001	-0.034	-0.040*
	(0.027)	(0.009)	(0.021)	(0.023)
Village FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes
N	190383	188955	188955	188955
R-Squared	0.131	0.155	0.130	0.136
Mean of Dep. Var.	0.639	0.131	0.350	0.482

Note: This table presents the effects on changes in public good provision in health facilities and personnels. Panel A presents estimation results of changes in extensive margins. Panel B presents results of changes in intensive margins. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects, and price change interacted with baseline (in 2000) nighttime lights coverage. Dependent variables in columns 1 to 4 of Panel B are not available in PODES 2008. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.14: Development Projects – Controlling for Price Change Interacted with Baseline Lights Coverage

	Presence				Number			
	All project	Infrastructure	Capital Asst	Employment Asst	All project	Infrastructure	Capital Asst	Employment Asst
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price	-0.058	0.132	1.661**	-0.606	3.939	1.806	3.259**	-1.099
	(0.510)	(0.633)	(0.751)	(0.603)	(2.636)	(1.343)	(1.303)	(1.056)
Price × Suitability	0.092	-0.011	-0.300*	0.152	-0.901	-0.536*	-0.651**	0.278
	(0.114)	(0.137)	(0.163)	(0.128)	(0.587)	(0.297)	(0.291)	(0.226)
Village FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	145654	145654	145654	145654	145654	145654	145654	145654
R-Squared	0.563	0.767	0.507	0.455	0.693	0.736	0.560	0.468
Mean of Dep. Var.	0.840	0.705	0.636	0.274	3.144	1.680	1.044	0.403

Note: The sample for all regressions only include PODES 2008 onwards because information on development projects only available starting in 2008. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects, and price change interacted with baseline (in 2000) nighttime lights coverage. All regressions include village and year fixed-effects as well as district-specific trends. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level.. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.15: Public Goods: Health Facilities and Personnel – Controlling for Time Trends Interacted with Rice Suitability

	Δ Presence			
	Doctors	Health Center (Main)	Health Center (Small)	Health Center (Total)
	(1)	(2)	(3)	(4)
Price	0.157*	-0.047	0.463***	0.411***
	(0.095)	(0.068)	(0.154)	(0.149)
Price × Suitability	-0.030	0.005	-0.087***	-0.084***
	(0.021)	(0.014)	(0.032)	(0.030)
Village FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes
N	237063	237063	237063	237063
R-Squared	0.080	0.096	0.075	0.073
Mean of Dep. Var.	0.199	0.129	0.335	0.442
Panel B: Intensive Margins				
Price	-0.099	-0.008	0.174*	0.178
	(0.126)	(0.044)	(0.099)	(0.111)
Price × Suitability	0.013	0.000	-0.031	-0.034
	(0.025)	(0.009)	(0.022)	(0.024)
Village FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes
N	190383	188955	188955	188955
R-Squared	0.131	0.155	0.130	0.136
Mean of Dep. Var.	0.639	0.131	0.350	0.482

Note: This table presents the effects on changes in public good provision in health facilities and personnels. Panel A presents estimation results of changes in extensive margins. Panel B presents results of changes in intensive margins. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects, and rice suitability interacted with time-trend. Dependent variables in columns 1 to 4 of Panel B are not available in PODES 2008. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.16: Development Projects – Controlling for Time Trends Interacted with Rice Suitability

	Presence				Number			
	All project	Infrastructure	Capital Asst	Employment Asst	All project	Infrastructure	Capital Asst	Employment Asst
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Price	0.367	0.785	2.796***	-0.440	6.687**	2.530	4.771***	-0.529
	(0.656)	(0.859)	(1.055)	(0.801)	(3.351)	(1.803)	(1.749)	(1.302)
Price × Suitability	0.011	-0.135	-0.591**	0.094	-1.649**	-0.763*	-1.027***	0.112
	(0.144)	(0.184)	(0.231)	(0.169)	(0.738)	(0.394)	(0.385)	(0.275)
Village FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-specific Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	145654	145654	145654	145654	145654	145654	145654	145654
R-Squared	0.563	0.767	0.506	0.455	0.693	0.736	0.560	0.468
Mean of Dep. Var.	0.840	0.705	0.636	0.274	3.144	1.680	1.044	0.403

Note: The sample for all regressions only include PODES 2008 onwards because information on development projects only available starting in 2008. All regressions include population (log), distance to district capital (log), distance to sub district capital (log), village area (log) interacted with year fixed effects, harvested areas (log) allocated for planting rice interacted with year fixed effects, village area (log) interacted with year fixed effects, and rice suitability interacted with time-trend. All regressions include village and year fixed-effects as well as district-specific trends. Standard errors, reported in parentheses, are robust to heteroskedasticity and clustered at district level.. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$