Thailand Vietnam Socio Economic Panel

Decoupled but not neutral: The effects of stochastic transfers on investment and incomes in rural Thailand

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Decoupled but not neutral: The effects of stochastic transfers on investment and incomes in rural Thailand

Andreas Wagener [(1)] and Juliane Zenker [(2)]

Abstract

In 2009, the Thai government implemented a price insurance scheme for rice farmers. The program, which was abandoned after only one year, added to the incomes of registered farmers a non-negative but stochastic amount that was decoupled from farmers' agricultural activities. A rich panel data set spanning from 2008 to 2013 enables us to control for self-selection into the program and to study its impact on small-scale rice farmers in relatively poor Northeastern Thailand. Program participation increases rice production but also leads to shifts in the composition of income generating activities away from agriculture, which may be beneficial for rural development. Decreasing risk-aversion and relieved credit constraints may be possible channels for these effects.

Keywords: Cash transfers, Agricultural subsidies, Farm households, Thailand, Propensity score matching

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1 Introduction

Governments implement and finance agricultural support programs for a variety of reasons: to shield farmers against the exposure to market fluctuations, as hedges against agricultural risks, as political devices to garner popularity with a rural electorate, as tools of social assistance or rural development or to avoid the discipline of global trade rules by the World Trade Organization (Mahul and Stutley, 2010). Depending on their purpose, agricultural support programs come in various shapes. One design feature that has gained substantial practical relevance and scientific attention over the last two decades is so-called "decoupling", where the support payments to farmers are deliberately unrelated to the type or volume of their actual production.[1] Originally, the rationale of decoupling was to provide support for farmers and to smooth their disposable incomes across contingencies in a way that would minimize distortions in competitive markets (Russo et al., 2011) and eliminate moral hazard (Smith and Glauber, 2012). Subsequent empirical studies and theoretical analyses have found that decoupled payments may not be as neutral as initially expected; decoupling in the real world hardly ever achieves the ideal non-conditionality of textbook lump-sum transfers.[2]

The magnitudes and even the directions of the effects of decoupled support schemes often remain theoretically disputed, empirically non-identified and economically rather small. Still, various channels why decoupled support schemes are non-neutral have been conceived (also see Section 2). For example, by altering the composition and the stochastic distribution of farmers' incomes, decoupled payments impact on farmers' time and labor allocation and on their risk-management via income, portfolio and insurance effects (Hennessy, 1998, Wright and Hewitt, 1994). Moreover, they potentially affect investment decisions, risk attitudes or consumption choices and,

[1]Nomenclature is quite diverse here. Sometimes, decoupled programs are called "direct", "counter-cyclical" or "unconditional". In WTO jargon, decoupled payments are classified as Green Box transfers. In practice, decoupled programs often carry fanciful names.

[2]In an ideal decoupled program, there would be no difference in the responses of decision makers and markets to any other exogenous shock arising on the demand or the supply side. Hence, demand and supply functions as well as market equilibria would remain unchanged.

thus, may have longer-lasting impact on farmers' wealth and well-being (Alderman and Yemtsov, 2014).

Distortionary production and side effects may be unwarranted in competitive markets and high-income developed economies. In developing economies where low incomes, lack of assets, credit constraints and high risk aversion are major obstacles to investments and the eventual prosperity of poor farm households (Rosenzweig and Binswanger, 1993, Karlan et al., 2014, Hill and Viceisza, 2012, Cole et al., 2013, Cai et al., 2015) such effects – if positive – may be quite beneficial. If decoupled payments stimulate farmers' investments, help to diversify their portfolio of income-generating activities or decrease their risk aversion they could help to kick-start economic development in poor rural areas or help to secure a stable food supply.

Against this backdrop, the present article analyzes a so-called "price insurance scheme (PIS)", an agricultural support program that was in effect (only) for one year from 2009 to 2010 in Thailand. The PIS granted payments to Thai rice, maize and tapioca farmers that moved (weakly) counter-cyclically with the respective crop price, depended on the base acreage that farmers registered for each crop but were otherwise unlinked to farmers' actual production activities or output (see Section 3 for a detailed description).

We study this decoupled and voluntary support program and its effects on participants (versus non-participants). Specifically, we show how participation in the Thai PIS causally affected rice farmers' choices on rice cultivation, other income generating activities, asset holdings and risk attitudes. Our analysis uses data from three Thai waves of the Thailand Vietnam Socio-Economic Panel (TVSEP), a rich and large panel of rural and mainly rice-farming households from Northeastern Thailand (see Section 5). We take advantage of the ad-hoc implementation and short-livedness of the Thai PIS. In between "coupled" rice pledging schemes, the PIS was flaring up only for one year (2009/2010), after political turmoil. Due to the one-time character of the program, its advantages and procedures were not fully absorbed by the targeted clientele, who had to select into the scheme by registration with a local authority. To eliminate the effects from self-selection with respect to registration to the program in our empirical analysis we conduct a propensity score matching augmented with farm household-fixed effects (see Section 6). We use panel waves that span around the one-year program phase over the period from 2008 to 2013. We can, thus, observe the (positive) effects of PIS on its participants also three years after the program was dismantled, evidencing the medium-run potential of such programs.

The Thai PIS is of particular interest for at least three reasons. First, for developing economies, where indemnifiable losses in agricultural insurance programs are commonly still endogenous to the actions taken by the insured farmer, the PIS is a rare and unprecedented example of a decoupled program. Its payouts are independent of the participants' activities, except for registration. Most case studies on decoupling come from developed economies, often from the 1992 Federal Agriculture Improvement and Reform (FAIR) and the 2002 Food Security and Rural Improvement Act (FSRIA) in the U.S. or for the Luxembourg Agreement on the reform of the Common Agricultural Policy (CAP) in the European Union. Evidence on decoupling from developing countries is (to our knowledge) non-existent, due both to the very small number of such programs and to the general lack of informative micro-data. The short-lived PIS, thus, provides a rare opportunity to study decoupling in an emerging economy – and the TVSEP project provides uniquely rich panel data for such an endeavor.

Second, traditional farm support programs in developing economies require that participants pledge and eventually sell their produce. This often excludes – or at least disadvantages – subsistence and poor smallholder farmers who, to a large degree, produce for their own consumption. Subsistence farming is highly prevalent in many developing economies and, notably, in poor Northeastern Thailand, our study area. Analyzing the PIS, where payments are based on registered land size instead of actual crop sales, provides information on the impact of agricultural support programs on poor farmers – a clientele that is often ignored in studies for developed countries (Goodwin and Mishra, 2005).

Third, the theoretical literature on decision making under uncertainty is concerned with changes in behavior when the underlying random variables undergo stochastic or deterministic transformations (for survey, see Eeckhoudt and Gollier, 2000). First-order stochastic dominance shift in random variables are an elementary concept in that literature – but such changes rarely occur in reality. The PIS is a case in point: it adds stochastic, exogenous but non-negative payments to farmers' disposable incomes. Our study of the behavioral effects of the PIS, thus, puts conceptual theoretical considerations of choice under risk to an empirical test (which they, by and large, pass).

In line with hypotheses derived from a theoretical model (see Section 4), our empirical findings (reported in Section 7) show that, compared to farmers who did not register for the program, rice farmers in the Thai PIS...

- increased their rice investment: farmers under the PIS increased the size of land used for rice cultivation, spent more on agriculture expenditures, and took up higher loans related to agricultural investments or expenses;
- hold, in the medium run, larger assets for rice-farming;
- changed the portfolio composition of their income-generating activities in favor of off-farm employment and away from self-employment.[3]

In short, our analysis suggests that the decoupling inherent in the PIS is *not* neutral: registered farmers do invest, produce, and sell more rice compared to their non-registered counterparts. Yet, farmers also seem to have utilized their participation in the PIS to change their income portfolio – in a direction that is generally held to be conducive to rural development and poverty alleviation.

[3]Throughout our specifications, we also find positive, yet not always significant, coefficients that suggest a raise in total income for registered farmers in the medium run. These effects may be interpreted as suggestive evidence that programs like PIS could potentially create positive effects on total income for farmers who signed up. Yet, our results are not sufficiently robust to allow for final conclusive statements.

2 Related literature

While playing a prominent role in agricultural policies in North America and Europe, decoupled support programs for farmers are virtually unheard of in developing countries (see, e.g., Anderson, 2016, Chapter 5).[4] This makes the Thai PIS a rare (and already extinct) animal. Below we summarize the existing literature that mainly originates from developed-country contexts, focusing on evidence related to production and labor supply choices, as well as relevant possible effect channels.

2.1 Effects on production

In a development context, decoupled farm support is primarily discussed in view of the impact of decoupled programs in the EU or the U.S. on developing countries and on international trade (Boysen et al., 2016, Urban et al., 2016, Anderson, 2016). Within developed economies, the debate on decoupling has centered around the question of their neutrality, in particular with respect to production decisions. Reviewing the literature, Bhaskar and Beghin (2009) identify five channels how decoupled payments violate neutrality and affect farmers' current production decisions: by changing the risk distribution, by easing credit constraints, by influencing labor participation and allocation, by changing incentives to keep land in agricultural use due to increased land values and rents, and by changing expectations about future incomes and decoupled payments. These channels have been studied in theoretical models, simulation studies and empirical analyses; with McIntosh et al. (2007) even an experimental study exists.

[4] Anderson et al. (2013, Section 3.4) discuss the movement in agricultural policies of high-income countries away from traditional price support and toward decoupled measures. They argue that decoupling is more easily viable the better is a country's administrative capacity to tax and subsidize incomes, the more competition prevails in the political marketplace, the more open is the economy and the greater importance is placed on political transparency. These factors may explain why decoupling has not yet been feasible in developing countries.

Theoretical research. Formal models on the effects of lump-sum subsidies on farmers' choices and well-being typically consider a farmer with a solely-owned operation who generates (stochastic) market income via agricultural production plus, in more recent studies, via off-farm investment opportunities and/or participation in an off-farm labor market. In a pioneering study, Hennessy (1998) showed that decoupled payments could in fact stimulate (risky) production by reducing farmers' level of absolute risk aversion via a wealth effect and, if payments are linked to, say, price floors, by decreasing the volatility of farm incomes (insurance effect). Chambers and Voica (2016) argue that such non-neutrality of lump-sum subsidies is due to the partial nature of the underlying model. Based on separation results as in Chambers and Quiggin (2005), they show that in a general-equilibrium framework production decisions of rational farmers are, at the margin, only driven by the (stochastic) prices they face exogenously, and neither by initial wealth levels nor by deterministic or stochastic lump-sum subsidies. Thus, the neutrality of decoupling is restored.

Simulation exercises. By and large, simulation studies corroborate the inconclusiveness of theoretic studies. Here, decoupled transfers to farmers are typically built into North-American or European model countries and dynamically calibrated. For example, Chau and de Gorter (2005) predict that, by implicitly discouraging the market exit of not-so-profitable farms, the decoupling of transfer payments in the U.S. has a positive but small effect on aggregate production. In a dynamic optimization framework, Bhaskar and Beghin (2010) show that the expectation that future parameters of decoupled support programs may be anchored in today's production choices generates positive output effects already now. Effects on risk behavior are simulated, e.g., in Serra (2006). Further, Just (2011) demonstrates that the unconditional wealth transfers in decoupled support programs do not change recipients' risk attitudes by much, suggesting that constant absolute risk aversion (rather than DARA) approximates farmers' risk behavior quite well.

Empirical analyses. Direct and causal evidence evaluating the impact of decoupled support policies on production decisisons is relatively scarce, mostly because counter-factual groups are lacking. While, earlier studies use reduced-form approaches that suffer from multi-collinearity problems and omitted variable bias (see, e.g., Goodwin and Mishra, 2005, 2006), a few more recent studies take on the identification challenge, often based on instrumental variable and differencing techniques. For example, Weber and Key (2012) argue that the inclusion of soybeans and other oil-seeds, which were historically ineligible for decoupled payments in the U.S., had only little effect on the aggregate production and value of these crops. Kazukauskas et al. (2013) show that the move towards decoupling in EU agricultural policies facilitated exit for farms engaged in livestock production and those that were already in the process of leaving the sector. Moreover, Kazukauskas et al. (2014) observe that the decoupling policy in the EU increased farm productivity and promoted farm specialization. O'Toole and Hennessy (2015) find that decoupled payments ease the credit constraints faced by farmers in imperfect credit markets. Finally, McIntosh et al. (2007) show with the help of a lab experiment on undergraduate economics students that payments may induce investments in program (base) crops despite being decoupled from current production decisions.

2.2 Effects on (off-farm) labor supply

In developing countries (including our sample area in Thailand), off-farm activities increasingly provide critical income sources to farm households, contributing significantly to rural development, food security, and poverty alleviation (see, e.g., Glauben et al., 2008, Babatunde and Qaim, 2010, Brünjes et al., 2013, Chawanote and Barrett, 2014). Theoretically, decoupled transfer payments cause a substitution effect (i.e., farmers replace farm work by more profitable off-farm work) and a wealth effect (i.e., farmers choose to increase leisure while cutting back on time devoted to work). The total effects on labor supply and composition, thus, remain theoretically unclear (Hennessy and Rehman, 2008). In an empirical study on the U.S., Ahearn et al. (2006) show that government payouts, whether coupled or decoupled, reduce the off-farm labor participation of farm operators; there is no special effect originating from decoupling. By contrast, Hennessy and Rehman (2008) observe that farmers in

Ireland increased their off-farm labor supply when receiving decoupled payments.

In summary, (empirical) studies on decoupling investigate US- or Europe-based assistance programs, which cover richer and less vulnerable farmers compared to poor small-scalers in Thailand or other developing economies. Since effects on production, investment and risk-taking may vary with initial wealth and volatility levels of income, extant findings cannot be simply transferred to developing economies. In addition, many previous findings are inconclusive and causal interpretation of estimated coefficients is limited.

3 The Thai Rice Price Insurance Scheme (PIS)

This section provides contextual information on the design of the Thai "Price Insurance Scheme" (PIS). Quick overviews of the program are provided in World Bank (2010), USDA (2009b,a, 2010). For a full survey (in Thai), see Isvilanonda (2010).

General features. The PIS was launched by the Thai Government in July 2009 and was effective (only) from 2009 till 2010.[5] It covered rice, maize, and tapioca farmers in similar ways; in view of our sample we restrict attention to the rice-related parts only. The program replaced – and was succeeded by – a traditional rice pledging (mortgage) scheme. Both the pledging scheme and the PIS aimed to protect farmers against crop price shocks. With the pledging scheme the government bought rice crops from farmers at previously fixed prices and re-sold the produce in the market.[6]

[5] Officially the program was active from mid-2009 to mid-2011. However, only the first year of the PIS was carried out as announced. During the following rice harvesting period, payments were no longer reliable and many delays and regional inconsistencies occurred. In the wake of a government change the program was finally replaced by a rice price-pledging scheme in 2011.

[6] The pledging scheme aimed to supply illiquid farmers with low-interest loans early in the harvesting season to enable them to delay sales of their produce until the rice price rose later. The government essentially lent money to farmers, taking their rice as a collateral. Farmers paid an annual net interest of three percent for their loan. If they did not redeem their pledge after five months, the rice would go to the government. As conditions of this loan usually were better than

In the PIS, the government would not buy any crops from farmers. Rather, for a certain guarantee period it would ex ante fix an "insured price" per ton of rice (of various types), based on production costs with a profit margin of 20 to 25 percent. Roughly following market prices it would then announce "benchmark prices" every two weeks during the guarantee period. If these benchmark prices were lower than the insured price, farmers who had registered with the program were eligible to receive as a payment the price difference per ton of rice they had "insured". The insured amount of rice was calculated by applying a notional expected yield per acre (also fixed by government) to the area which farmers had registered to the program. Farmers could only claim compensation once per season, but were free to choose the point in time. Farmers decided themselves whether, when and to whom to sell their crops; this way the program attracted also small farmers who mainly produce for own consumption. Payouts would be based on the ex-ante determined notional yields, irrespective of actual yields or sales.

The latter feature makes the PIS a decoupled program. The PIS does neither provide price insurance for market transactions nor does it compensate for other crop-related income shocks due to, e.g., adverse weather conditions or crop pest damage. Rather, it adds a stochastic lump-sum component to registered farmers' incomes.[7]

Eligibility and registration. Eligible for the PIS were farmers who own farm land – or tenants of such land, provided that the owner had approved and not registered himself.[8] The agriculture administrations of districts maintain land registries that collect data on land ownership of farm land (plot sizes) for different crops.

market conditions, farmers mostly would not redeem their rice, causing massive rice stocks to build up at the government's (World Bank, 2010).

[7]The literature discusses various degrees of "decoupling". In the strict understanding advocated by Goodwin and Mishra (2006), the PIS would count as *partially* rather than *fully* decoupled since its payments are not fixed and guaranteed but depend on ex-post realizations of market conditions (prices). In the taxonomy of agricultural insurance by Mahul and Stutley (2010), the PIS is a mixture between yield-based crop insurance (it uses some predetermined yield to calculate indemnities – but ignores actual yields) and crop revenue insurance (its payouts arise regardless of selling the crop).

[8]Anecdotal evidence suggests that this requirement was not always enforced consistently. In some places, also the family members of land title holders were able to register.

Participating land owners had to register their land with the program. Registration was costless but required some paperwork and the personal presence of the owner. Registration had to be done at a local branch of the (government-owned) *Bank for Agriculture and Agricultural Cooperatives (BAAC)*. The BAAC also administered payouts. For each crop a notional yield per rai (= 1,600 m^2) was officially fixed, roughly reflecting the expected average yield. Authorities recorded this *anticipated* quantity of produce based on the size of the registered land, capping it by a fixed maximum per household, depending on the rice variety (e.g., maximally 14 tons of jasmine rice, 16 tons of glutinous varieties, and 25 tons of other paddy per household).

Payouts. Before the planting season, the government fixed an "insured" price per ton for each crop for the whole harvest period. In 2010, the guarantee price ranged from 9,500 Baht ($\sim$ 300 US-\$, as of August 2010) per ton of glutinous rice to 15,300 Baht ($\sim$ 482 US-\$) per ton of jasmine rice. During the harvest period, the Thai Ministry of Commerce announced so-called "benchmark prices" bi-weekly, roughly tracking market prices. When claiming payments, a registered household was paid, via the BAAC, the difference between the insured price and the benchmark price at this point in time, multiplied by the amount of tons of notional crop registered with the program. If the benchmark price exceeded the insured price, farmers could not claim anything. The choice of the point in time when a farmer could cash in on the BAAC payment was – within broad limits – up to the farmer himself (for rice in Northeastern Thailand: between November and March). In particular, the farmer could delay claiming payments if he expected the benchmark price to fall in the future.

As shown in Figure 1, for most of the guarantee period the insured rice price was above the benchmark prices, which roughly tracked market prices and varied quite substantially over time.

The PIS based payments on *registered* tons of crops, not on actual harvests (or even seeded farmland). Farmers could keep their produce for own consumption as well as choose to sell it.

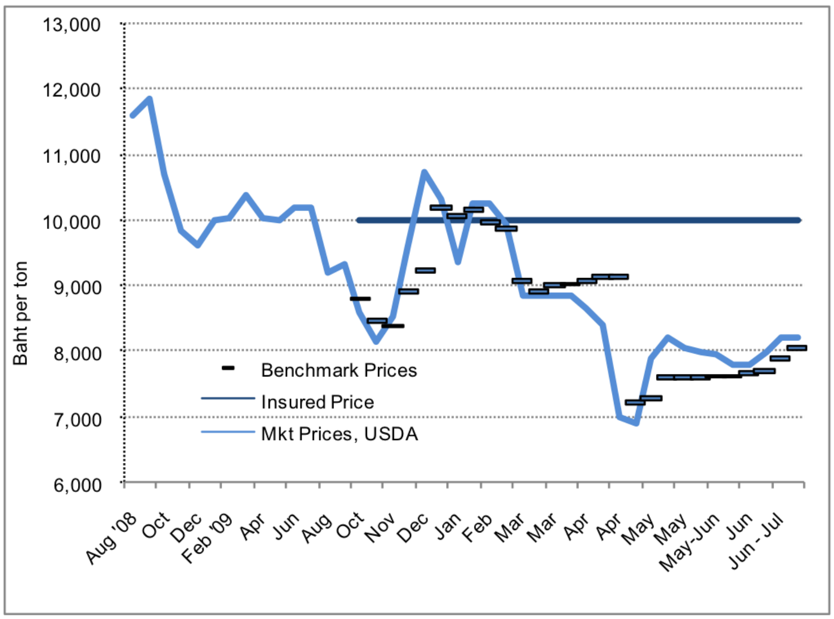

Figure 1: Insured, benchmark and actual rice prices, 2008-2010.
Source: World Bank (2010, p. 35)

4 Conceptual Framework

This section sets up a simple and stylized decision problem and theoretically predicts some of the effects of the Thai PIS.

4.1 Decision problem

We consider a single residual-claimant rice farmer with strictly monotonic preferences over wealth and access to some non-rice income opportunities. The farmer decides how much to invest in rice cultivation. "Investments", denoted by x, is meant generically and can represent expenditures for seeds or fertilizer, the size of his land used to grow rice, or the time or labor devoted to growing rice. The farmer also engages in another income-generating activity, denoted by z. This activity is unrelated to rice farming and could capture other agricultural activities (different crops, hunting, logging etc.) as well as wage employment or off-farm self-employment. Investments in rice and the other activity have joint (direct and opportunity) costs, $C(x, z)$: direct expenses, foregoing immediate consumption or leisure, reducing the time and resources available for other unmodelled activities etc. We assume that the cost function is strictly increasing and strictly convex in (x, z). I.e., $C_w(x, z) > 0$ and $C_{ww}(x, z) > 0$ for $w = x, z$. We do not make any assumption on the cross-effects, C_{xz}, allowing for other activities to affect the marginal opportunity costs of rice production in any direction.[9]

Investments in rice generate yields, $Y(x)$, where the yield function Y is strictly increasing and concave in investments x. The other activity earns income, $\pi(z)$, where π is strictly increasing and concave in z. Both yield functions and the cost function are non-stochastic; the only source of uncertainty is the rice price, p. The harvest has monetary value $p \cdot Y(x)$.

[9] All cases are conceivable: if activities x and z are not connected with one another (say, buying the seeds for two different crops), then $C_{xz} = 0$. If, however, x and z are uses of the farmer's time for different activities, then spending more time on activity x may increase the opportunity costs of the time spent on z, implying $C_{xz} > 0$. Conversely, if expanding activity x increases the farmer's skills also for doing z, this can be captured by $C_{xz} < 0$.

Assuming that the farmer is an expected-utility maximizer, his investment problem reads as:

$$\max_{x,z} V_0(x,z) := \int u\left(p \cdot Y(x) + \pi(z) - C(x,z)\right) \mathrm{d}F(p).$$

Here, $u = u(c)$ is a strictly increasing (vNM) utility index over consumption or final wealth (denoted by c) and $F(p)$ is the distribution of the rice price. In line with the literature (Moschini and Hennessy, 2001, Mahul and Stutley, 2010, Just, 2011), we assume that farmers are risk averse: $u''(c) < 0$ for all c. Denote the optimal decisions in the above problem by (x_0, z_0) and the attending utility level by $V_0^* = V_0(x_0, z_0)$.

We now introduce a stylized version of the PIS. Payouts from the PIS for a (registered) farmer are denoted by I (= "indemnity"). Denoting the insured price by $\bar{p}$ and the notional yield, calculated on the basis of registered land, by $\bar{y}$, the regulations of PIS, as outlined above, stipulate the indemnity I as follows:

$$I = \max\{\bar{p} - p, 0\} \cdot \bar{y}. \tag{1}$$

We shall henceforth suppress in notation the dependence of I on notional yield and the fixed insured price; both are exogenous (once registered) and invariant.

While (1) mimicks the Thai PIS, our predictions generalize to all support programs with the following properties:

- Payouts only vary with the price are decoupled from the yield Y or its driver x. Formally, $I = I(p)$.
- Payouts are non-negative: $I(p) \geq 0$ for all p.
- Payouts weakly decrease in price: $I'(p) \leq 0$.

For a farmer registered in the PIS the investment problem reads as:

$$\max_{x,z} V_1(x,z) := \int u\left(p \cdot Y(x) + \pi(z) - C(x,z) + I(p)\right) \mathrm{d}F(p).$$

Denote the optimal solution to this problem by (x_1, z_1) and the attending utility level by $V_1^* = V_1(x_1, z_1)$.

4.2 Predictions

Formally, for any given (x, z), the PIS induces a first-order stochastic dominance (FSD) shift in the probability distribution of the farmer's income. A couple of predictions on the effects of PIS participation can be derived from the theory of decisions under risk; the proofs of results (2) to (5) below are relegated to Appendix A.

Registration. Since the PIS would dole out non-negative payments under all circumstances and guarantees strictly positive payments in some states of the world, *not* to register for the program is at odds with having non-satiated preferences: it violates the basic first-order stochastic dominance rule.

Well-being. With the PIS, farmers are better off than without. This is an immediate implication of the monotonicity of u and the FSD feature of the FIPG:

$$V_1^* > V_0^*. \tag{2}$$

Rice production. In one-dimensional decision problems, behavioral responses with respect to FSD shifts in the distribution of payoffs with a single risk have been characterized by Ormiston (1992). The necessary conditions for unambiguous comparative statics are restrictive even then – and even more so in a two-dimensional decision problem such as ours. As in Ormiston (1992, Theorem 3), decreasing absolute risk aversion (DARA; $-u''(c)/u'(c)$ is decreasing in c) turns out to be a powerful sufficient condition for plausible responses. DARA is generally thought to be a reasonable assumption concerning preferences and allows for a wide range of utility functions (for an application to decoupling, see Serra, 2006).

For our framework we obtain that if preferences exhibit DARA, then

$$x_1 > x_0, \tag{3}$$

i.e., farmers covered by PIS should invest more in rice: increase the land devoted to rice cultivation, devote higher expenditure to rice farming etc.

Other income-generating activities. Increasing production activities and investment for rice may have repercussions on other components of farmers' income portfolios (other crops or livestock, off-farm activities or wage employment). As we assume that these alternative income-generating activities are risk-free, the PIS effects on them depend on the marginal opportunity cost of rice farming. In particular, provided that (3) holds, the model predicts that

$$z_1 \geq z_0 \quad \text{iff} \quad C_{xz}(x, z) \leq 0. \tag{4}$$

I.e., activities x and z will move in parallel [in opposite directions] upon participation in PIS if they decrease [increase] the marginal opportunity cost of one another (see Footnote 9).

If the income-generating activities other than rice cultivation have risky returns themselves, the PIS constitutes a (possibly correlated) background risk. The comparative statics of background risks vary considerably with the economic setting and depend, in general, on risk attitudes of higher order than just risk aversion and its monotonicity (see, e.g., Schlee and Gollier, 2006, Franke et al., 2011). We therefore refrain from any theoretical predictions (which, due to missing data on higher-order risk-attitudes, could not be verified in our sample anyway).

Incomes. Farmers who registered for the PIS will experience higher expected gross incomes and consumption levels:

$$Ec_1 > Ec_0. \tag{5}$$

Risk aversion. The transfers paid out by PIS might affect risk attitudes, although in a theoretically unclear way. It is well-known that DARA alone does *not* suffice for the farmer to become less risk-averse when experiencing a *stochastic* increase in wealth (as with PIS). Rather, risk vulnerability plays a crucial role. The dependence on the crop price, which enters multiplicatively, further complicates things, as now *relative* risk aversion and its monotonicity properties matter. It is unclear – and therefore largely an empirical question – whether farmers who invest and earn more end up with higher or lower risk-aversion.[10]

Dynamic effects. In an intertemporal framework, the static effects discussed so far propagate over time. For instance, if the additional investment predicted in (3) cannot be financed from own wealth, farmers would have to take up additional loans. To the extent that the income-generating activities (x, z) go to finance assets that do not depreciate immediately, participation in the PIS will result in a higher stock of physical assets. The effect on financial assets is, however, not clear: if savings are a normal good, then farmers will save more when they experience a FSD shift in their incomes. However, there might be offsetting effects from a lower necessity to build financial buffers through precautionary saving. The same applies to buffer goods like stored crops or livestock.

5 Data

Time frame and sampling. For the empirical analysis, we use three waves (labelled W2, W3, and W4) from an extensive panel data set representative for rural

[10] For CRRA utilities, Franke et al. (2011, Lemma 2) show that (in our terms) if the non-negative risk generated by the PIS is "small" or "large" then derived relative risk aversion, defined for V_D^* (with $D = 0, 1$) is increasing and concave in wealth, but may decrease in the intermediate range.

households in the relatively poor Northeast of Thailand. Data collection started in 2007 and covered 2,200 (mostly rice-farming) households in 220 villages from three Northeastern provinces of Ubon Ratchathani, Buriram, and Nakhon Phanom. These provinces were purposely selected for the survey on the basis of their low per-capita incomes, the great importance of agriculture, a low agricultural potential, geographical remoteness, and their variation in agro-ecological conditions and development status (Hardeweg et al., 2013). Due to a three-stage cluster sampling procedure on sub-district, village and household level, the household sample is representative for the rural areas of the three provinces.

The survey instrument was a comprehensive questionnaire with detailed information on all household members, composition of income, financial situation, agricultural production, assets, shock experience etc.[11]

To generate a homogenous and relevant sample for our analysis we dropped households who do not cultivate rice crops in 2008 (before the start of the program) or for whom information on PIS registration status was missing (about 7 percent of the full sample), which leaves us with 1,482 farm households.[12]

The ad-hoc nature and short implementation period of the PIS in combination with the three panel waves provide us with the unique opportunity to control for pre-implementation farm(er) characteristics and farmer fixed effects when analyzing the impact of the program. Further, we can estimate whether program effects persist after the PIS had been suspended. Wave W2 of the TVSEP household panel had been conducted before the farmer income guarantee program became active. Waves W3 and W4 were conducted when the PIS was active for one year and two years after it had been suspended, respectively. Table 1 describes the time line of data coverage and program status.

[11] The surveys were carried out in the project “Impact of shocks on the vulnerability to poverty – consequences for the development of emerging Southeast Asian economies”, sponsored by the German Research Foundation (DFG FOR 756) and continued now as the Thailand Vietnam Socio-Economic Panel (TVSEP). The full questionnaire is available at https://www.tvsep.de/.

[12] The PIS also applies to cassava and corn farmers. We focus on rice since the sampled region is dominantly used for rice cultivation. Most of the excluded households were dropped because they do not farm at all.

Table 1: Panel waves and program status

Panel Wave	Data Period	Policy Status
Wave 1 (W1, not used)	May 2006 - April 2007	Pledging scheme
Wave 2 (W2)	May 2007 - April 2008	Pledging scheme
not covered	May 2008 - April 2009	Pledging scheme
Wave 3 (W3)	May 2009 - April 2010	PIS
not covered	May 2010 - April 2011	PIS (fragmented)
not covered	May 2011 - April 2012	Pledging scheme
Wave 4 (W4)	May 2012 - April 2013	Pledging scheme

Sample characteristics. Columns *Raw Sample* of Table B.1 in Appendix B report descriptive statistics on farm household characteristics, farming activities and land use, wealth (debt and assets), labor supply choices and income sources as well as experienced economic shocks and expectations of the sampled farm households.

Some features of our data set are noteworthy. First, the majority of the farmed land is owned by the household that cultivates it (76 percent on average). Ownership status is relevant as production effects of decoupled payments may also work through wealth effects by altering land rent or value. Second, farms in our sample are quite small with an average rice acreage of 3.4 Rai (slighlty more than half a hectare) in the base year, 2008. This focus on small-scalers is a novel ingredient of our study. Third, households are quite poor with respect to income and wealth even by Thai standards.

Take-up and its drivers. About 60 percent of the farm households in our sample registered for PIS in 2009, while the remaining farmers did not. The rate of non-take-up in our sample[13] is substantial and, in view of the give-away structure of the PIS, requires discussion.

[13]For the whole of Thailand, the BAAC registered 3.5 million eligible farmers (95 percent of all farmers and a five-fold increase over the rice-pledging scheme which the PIS replaced. The main reason for this success was the ability of small-scale farmers to register (USDA, 2010).

Table 2: Self-reported reasons for not-registering for PIS

Reason	Frequency	Percent
No or wrong information about the program	253	39.3
Registration is too much effort or too complicated	117	18.2
Not satisfied with government policies in previous years or does not trust government	54	8.4
Forgot to register	42	6.5
Does not have a land title or owner registered himself	16	2.5
Cannot remember or did not reveal reason for not registering	162	25.2
Total	644	100

First, the theoretical prediction of full take-up requires that farmers are correctly informed about the program's existence and registration formalities. Moreover, transaction costs must be negligible. Since registration involved contact to the next branch of the BAAC and some paper work, distance to BAAC as well as reading and writing skills might be important for registration decisions. Eligibility for the program officially had to be proven by land tenure status, although implementation strictness of this rule seemed to vary locally.

To understand motivational determinants of non-take-up, we asked all non-registered eligible farmers in an open interview question of the 2013 household survey to recall their reasons for not registering. The answers are categorized in Table 2. They suggest that it is likely that registered and non-registered farmers differ in unobserved characteristics like overall motivation, proneness to procrastination, or hesitance. In terms of accessing correct information, social networks or membership in organizations might play a role. Some of these characteristics might not only have influenced registration decisions but also have an impact on risk attitude and investment behavior, as well as farming and labor supply choices and outcome.

Differences between participants and non-participants. As the descriptives in columns *Raw Sample* of Table B.1 show, registered and unregistered farmers have almost identical pre-treatment risk attitudes: 4.20 and 4.23, respectively, on a scale from 0 ("try to avoid risks") to 10 ("feel fully prepared to take risks"). Yet, they differed markedly in several other characteristics that might be relevant for investment behavior and risk-taking.

Registered households are slightly more likely to be headed by a male. On average, they used more land (and, thus, can be expected to benefit more from the program), own more agriculture-related assets and cultivated more rice in the pre-registration periods of our panel. They earned higher incomes from crop cultivation in both periods – which did not consistently translate into higher total incomes. Furthermore, registered farmer on average lost, and feared to lose, more income due to agricultural shocks. They hold more livestock, savings and stored crops, more loans related to agricultural investment or production expenses, and more loans in total.

6 Empirical Method

Our objective is to estimate the causal effects of PIS participation on investment behavior, income generating activities, household incomes and risk attitudes. The analysis needs to take into account that registration is based on self-selection and PIS-farmers differ markedly from non-registered farmers in observed (and possibly also in unobserved) characteristics that might mutually influence registration and outcome variables.

Method. We employ a propensity score matching augmented by a first-difference model (Heckman et al., 1997, Smith and Todd, 2005) in order to establish credible estimates of the program impact. Particularly, we estimate the treatment effect on the treated by an average nearest k-neighbor matching estimator, ATT, on differenced outcomes, ΔY, after and before registration. The estimator is defined by

$$\widehat{ATT} = \frac{1}{n_1} \cdot \sum_{i \in S_1} \left(\Delta Y_{1i} - \frac{1}{k} \sum_{j \in C_0(p_i)}^{k} \Delta Y_{0j} \right) \tag{6}$$

(see Heckman et al., 1997, Smith and Todd, 2005). Here, S_1 and S_0 denote the treatment ($D = 1$) and the non-treatment ($D = 0$) group, i.e., the sets of registered and non-registered farmers with group sizes n_1 and n_0. Variable p_i is the propensity score, i.e., the probability of any i to register to PIS. $C_0(p_1) \subset S_0$ is the set of comparison units (non-registered farmers), matched to treated farmer $i \in S_1$. The neighborhood $C_0(p_i)$ for each registered farmer i is defined as the set of the k nearest neighbors,

$$C_0(p_i) = \left\{ j \in S_0 : |p_i - p_j| = \min_{k \in S_0} \{|p_i - p_k|\} \right\},$$

where k is a pre-specified number of units to be matched to each individual i

To specify the propensity score,

$$p = p(X) = Prob(D = 1|X),$$

we use an advanced semi-automatic algorithm suggested in Imbens (2015). Via likelihood-ratio tests the algorithm selects those characteristics X from a large set of relevant baseline variables that are best suited to generate a counter-factual group that does not differ significantly from the group of registered farmers in relevant observable characteristics as well as our outcome variables before program launch. For a comprehensive description of the algorithm, see Section B.1 in the Appendix.

In (6), the difference in outcomes $\Delta Y_{1i} = Y_{1i,t} - Y_{0i,t-1}$ after and before the intervention of each registered farmer $i \in S_1$ is matched with a weighted average of differences in outcomes $\Delta Y_{0j} = Y_{0j,t} - Y_{0j,t-1}$ of neighboring non-registered farmers. Differencing the outcome variable precludes potential remaining biases due to time-invariant unobserved characteristics.

Procedures and diagnostics. Appendix B provides a detailed documentation of the matching procedures we ran with our sample. A credible identification of outcome differences between PIS-participants and (matched) non-participants using a propensity score requires certain conditions. In particular, outcomes have to be independent of PIS participation, given farmer characteristics (so-called *conditional independence*) and farmers with identical characteristics have positive probability of both being registered or not-registered (so-called *overlap*). Diagnostic tests, reported in Appendices B.2 and B.3, suggest that these conditions are met by our data. Hence, the estimated differences-in-differences in the outcomes between treated and matched control group, which we present in Section 7 and Appendix C, can indeed be attributed to participation in the PIS program.

7 Results and discussion

For various outcome variables, Tables 3 to 6 report first-difference estimates of average treatment effects on the treated for registered versus non-registered households. The tables only contain the results for the specification that performed best with respect to the propensity score matching (this was "Specification 1 with $k = 10$ neighbors"; see Appendix B). Results from two other specifications as well as for matching with $k = 1$ and $k = 5$ neighbors are presented in Tables C.1 to C.4 in Appendix C.

Each of the tables here and in Appendix C contains two panels, labelled A and B. Both panels take the pre-treatment wave W2 from 2008 as its base. Panels A use wave W3 from 2010 as the follow-up wave, which was run while the PIS was in effect. Panels A, thus, present estimates for the short-term differences between participant and non-participants. By contrast, Panels B use wave W4 from 2013 as the follow-up wave, three years after the PIS was abandoned. Effects here are interpreted as the medium-term impact.

Tables C.1 to C.4 show that our results remain essentially unaffected by different model specifications. We therefore confine the interpretation of our results to Tables 3 to 6.

7.1 Rice production and sale

We measure the impact of the PIS on rice production by three input factors – expenditures used for production, cultivated area, and durable agricultural assets – as well as by the total production of the insured rice crops in kg. We report the effects in Table 3.

Both instantaneously and in the medium run, we observe a substantial and significant difference between PIS-participants and non-participants in the percentage changes of cultivated area and rice cultivation expenditures, which consist of expenditure on fertilizer, pesticides, seeds, labor, tractor rental, and other rice cultivation inputs (Columns 1 and 2). Registered farmers use more land and more variable inputs for rice production in the short and the medium run. The effects tend to be larger in the medium run.

For investments in durable agricultural production factors, registered farmers did not experience significantly different asset growth in the short run: the change in agricultural assets during the PIS program does not significantly differ from the non-registered group. Yet, this changes in the medium term: registered farmers experience a larger increase of assets used for agricultural production than their non-registered counterparts (Column 3). The positive impacts of PIS on rice production is also visible in the output measure: the increases in inputs lead to faster growth of rice produce both immediately and in medium terms (Column 4).

To counter concerns of multiple testing, we built an index of the four variables in Columns (1) to (4). This index shows a positive and significant effect and thus confirms that rice production grew faster among PIS farmers, compared to non-PIS farmers (Column 5).

Finally, participation in the PIS also translates into higher rice sales. Since many farmers in our sample are subsistence farmers, this is not an automatic conclusion. Yet, our results in Column 6 show that sales go up both instantaneously and in the medium term, suggesting that the PIS affects the amount of rice supplied on the Thai rice market.

Table 3: PIS effects on rice production

	(1)	(2)	(3)	(4)	(5)	(6)
	△ Rice production				△	△
	(Log) Expenditures (PPP-$)	(Log) Area (Rai)	(Log) Agri. assets (Value)	(Log) Total produce (Kg)	Production index, based on (1) to (4)	(Log) Produce sold (Kg)
Panel A: Short-term effects (2010 vs. 2008)						
Spec.1, $k = 10$	0.664***	0.293***	0.206	0.696***	0.631***	0.402*
	(0.11)	(0.05)	(0.15)	(0.13)	(0.11)	(0.22)
Panel B: Medium-term effects (2013 vs. 2008)						
Spec.1, $k = 10$	1.048***	0.427***	0.388**	1.107***	0.990***	0.839***
	(0.13)	(0.06)	(0.19)	(0.14)	(0.12)	(0.22)

Notes: Heteroscedasticity-consistent standard errors adjusted for clustering at the village level in parentheses. *Expenditures* are given in PPP-$ (constant, 2005) and include expenditures on fertilizer, pesticides, seeds, labor, tractor rental, and other input factors related to rice cultivation. *Agri. assets* sums up the assets a farmer uses in agricultural production. *Production index* is given by standardizing variables in Columns (1) to (4) by calculating z-scores, taking the average of the four z-scores, and again transforming the average into a z-score. Standardization is based on the means and standard deviationd of the variables in the non-registered group at baseline. ***,**, * indicate significance at 1, 5 and 10%.

Section 4. They confirm that decoupling payouts to farmers does not imply neutrality. Our observations also suggest that decoupled payouts are a promising policy instrument to boost production activities and investment. In Northeastern Thailand, such programs may help to remedy the under-investment problem that plagues the region (Hohfeld and Waibel, 2013).

7.2 Possible channels

Participation in the PIS may have affected production decisions through at least three channels: the initial change in income, changes in risk attitude, and credit constraints. Table 4 reports to what extent such changes occurred.

Unsurprisingly, the PIS significantly affected farmers incomes through transfer payments instantaneously – but not in the medium term (Column 1).[14] Yet, while the actual difference over time in income from public transfers (including PIS payments) is higher for registered farmers, it seems to play a limited role only, compared to total baseline income (see Table B.1).[15] Therefore, the observed strong impact of PIS on production is not a mere income effect.

The program *ceteris paribus* triggered a reduction in risk-aversion in the short run (Column 2). In the medium run this effect ebbed off. Together with the moderate short-term investment effects in rice production, this suggests that changes in risk attitude precede changes in investment behavior. In line with the assumption of DARA, the remaining (non-significant) difference in risk aversion in the medium term might be due to the stronger increase in overall wealth among the participants of the program.

Finally, we find evidence that participation in the PIS loosens credit constraints: program-farmers are significantly more likely than non-participants to hold a loan related to agricultural expenses or investments (Column 3).

[14]The difference across groups in public transfers between 2008 and 2013 is negligible as the program was no longer active in 2013.

[15]This has three reasons. First, the average benchmark price set by the government was around 9,000 Baht per ton of rice during the major harvesting period from October till December 2009 (World Bank, 2010). As the insured price was 10,000 Baht, farmers could on average only reap a meagre compensation payment of 1,000 Baht (approx. 56 PPP-$ (constant, 2005)) per registered ton of produce (on average, farmers harvested approximately four tons of produce). Second, the benchmark price was higher than the insured price from mid-December 2009 till the end of March 2010. Farmers who did not file their claim before mid of December, hence, did not receive any compensation before the end of the surveyed period. Third, some farmers who had staked their claims early reported that payments were delayed and might not have arrived by the time of the interview in April 2010.

Table 4: Possible effect channels

	(1) $\triangle$ Income from public transfers (incl. PIS)	(2) $\triangle$ Risk attitude	(3) $\triangle$ Agri. loans (Yes=1)
Panel A: Short-term effects (2010 vs. 2008)			
Spec.1, $k = 10$	113.628***	0.302*	0.079**
	(20.39)	(0.16)	(0.03)
Panel B: Medium-term effects (2013 vs. 2008)			
Spec.1, $k = 10$	13.719	0.207	0.094***
	(16.78)	(0.17)	(0.03)

Notes: Heteroscedasticity-consistent standard errors adjusted for clustering at the village level in parentheses. *Risk Attitude* is determined by asking the respondent on a scale between 0 and 10 whether he usually tries to avoid risk or feels fully prepared for taking risks. *Agri. loans* is an indicator equal to one if farmer took up loan for investments or expenditures related to agricultural production. *Income from public transfers* includes payments from PIS as well as income form other government social assistance programs like the universal pension scheme, scholarships, food aid etc. ***,**, * indicate significance at 1, 5 and 10%.

7.3 Mix of Income-Generating Activities

We now turn to the effects from PIS participation on the labor portfolio. We capture the composition of the labor portfolio by the number of income-generating activities a household is engaged in. Further, we look at the share of land the household uses for rice cultivation as well as the fraction of household members who temporarily migrate to look for or take up job opportunities.

Registered farmers use a larger share of their land for rice cultivation (Column 1). The PIS, further, affects the mix of other income-generating activities (Columns 2 to 5). Registered farmers engage significantly more in income-generating activities related to livestock and, in the medium run, to off-farm wage employment. They also reduce their self-employment activities in the medium term. In addition, registered households send a significantly larger share of household members away for job opportunities in the medium run compared to their non-registered counterparts

(Column 7).

To summarize all shifts in the labor portfolio, we built an activity index that adds the numbers of all non-crop related income activities from Columns 2 to 5. For registered households, this index increases faster, suggesting an enlarged portfolio of non-crop related income-generating activities in the medium run (Column 6).

Given the potential of off-farm activities to contribute to rural development and poverty alleviation in Thailand (Brünjes et al., 2013), the decoupled PIS seems to be a promising policy intervention: it promotes diversification of income sources away from farming.

In terms of prediction (4) from our theoretical model, a positive [negative] sign in Columns (2) to (5) together with the positive effect in Column (1) suggest that the corresponding activity decreases [raises] the marginal opportunity costs of rice cultivation. Specifically, households would then view self-employment as an activity that reduces, at the margin, the net benefit from rice cultivation – while wage employment increases it.

7.4 Income and its sources

In line with the findings on income-generating activities, Table 6 reports an upward shift in incomes from crop cultivation and life-stock products for PIS-participants both in the short and the medium run; income from self-employment is substantially reduced among registered farmers (Columns 1, 2, and 5). Moreover, in the medium run incomes from wage employment increase significantly (Column 4). Remittances and incomes from resource extraction activities are not affected by PIS participation (Columns 3 and 6).

The estimates for the difference in total household incomes do not suggest any positive income shift for registered farmers in the short term (Column 7). In the medium run, the effects are positive, yet not significant. The reduction of income from self-employment is canceled out by higher incomes from agricultural activities as well as wage employment.

Table 5: Income-generating activities

	(1) △ Land used for rice cultivation (share)	(2) △ Number of income generating activities in ... Livestock products	(3) Resource extraction	(4) Wage employment	(5) Self-employment	(6) △ Activity index, based on (2) to (5)	(7) △ HH members temp. gone for job/job search (share)
Panel A: Short-term effects (2010 vs. 2008)							
Spec.1, $k = 10$	0.067***	0.089**	0.054	0.025	-0.042	0.126	0.000
	(0.01)	(0.03)	(0.11)	(0.07)	(0.04)	(0.15)	(0.01)
Panel B: Medium-term effects (2013 vs. 2008)							
Spec.1, $k = 10$	0.131***	0.126***	0.076	0.243***	-0.083**	0.362***	0.031**
	(0.03)	(0.04)	(0.05)	(0.07)	(0.04)	(0.10)	(0.01)

Notes: Heteroscedasticity-consistent standard errors adjusted for clustering at the village level in parentheses. *Land used for rice cultivation (share)* is the area of land used for rice cultivation as a share of total used land. *Resource extraction* refers to all income generating activities related to fishing, logging, collecting, and hunting. *Self-employment* refers to all kinds of income generating non-farm business activities. *Activity index* adds up the *Number of income generating activities* in columns (2) to (5). ***,**, * indicate significance at 1, 5 and 10%.

Registered farmers appear to have used the PIS as a vehicle to change their portfolio of income-generating activities. Within the temporal confines of our study it is impossible to tell whether this will eventually pay off in terms of higher total incomes in the long run. Notwithstanding, the changes may increase well-being in other ways than via expected incomes. For example, wage employment may give farmers more stable income streams, compared to self-employment, which individuals in developing country contexts often use to temporarily bridge times of un(der)employment.

8 Conclusion

Understanding how subsidy and income support programs influence farmers' investment behavior is important for well-informed agricultural policy making and, potentially, for the economic development of rural areas. The analysis is often complicated by the fact that payments from such programs are state-contingent and correlated

Table 6: Income effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	△ Income (PPP$)						
	Crop cultivation	Life-stock/life-stock products	Resource extraction	Wage employment	Self-employment	Remit-tances (family/relatives)	Total
Panel A: Short-term effects (2010 vs. 2008)							
Spec.1, $k = 10$	429.598***	84.310**	-21.999	-57.795	-646.902***	106.604	-89.096
	(130.06)	(40.93)	(14.66)	(336.38)	(225.83)	(70.24)	(453.54)
Panel B: Medium-term effects (2013 vs. 2008)							
Spec.1, $k = 10$	473.563**	276.068**	0.550	917.115**	-1528.914***	36.490	451.682
	(187.77)	(125.04)	(7.04)	(431.87)	(473.73)	(55.06)	(581.82)

Notes: Heteroscedasticity-consistent standard errors adjusted for clustering at the village level in parentheses. *Incomes* are given in PPP$ (constant, 2005). *Income from crop cultivation* is the sum of income obtained from the cultivation of subsidized and non-subsidized crops. *Income from resource extraction* is the sum of income obtained from fishing, logging, collecting, and hunting activities. *Income from self-employment* includes income from all kinds of non-farm self-employment. *Total income* includes incomes reported in columns (1) to (6), income from public transfers (incl. PIS payments), as well as all other types of household income. ***,**, * indicate significance at 1, 5 and 10%.

with the risks that farmers face. The overall effect of such programs on farmers' incomes and behavior is, thus, not clear *a priori*.

We investigate the Thai Price Insurance Scheme (PIS), a decoupled subsidy program for rice farmers that was active from 2009 till 2010 (effectively). Analyzing such a voluntary program is plagued by potential selection issues: registration for the program is not random and the sample is highly unbalanced in relevant co-variates between registered and non-registered farmers. We applied a propensity score matching combined with first-difference estimators to balance the sample and to estimate the genuine impact of the program on farm households' production portfolios and related indicators.

We find that decoupling does not leave production choices unaffected. Registered farmers in our sample do invest in, produce, and sell more rice compared to their non-registered counterparts. While this may seem like bad news for WTO regulations which classify decoupled programs as "green box" (i.e. not distortionary for market prices), it may be good news for WTO ambitions to support the UN Sustainable Development Goals (SDG). WTO has committed itself particularly to supporting UN attempts by reducing trade (particularly export) barriers for poor countries. Yet, our study shows that the role of the WTO in fostering inclusive growth, reducing inequality (across and within countries), and eliminate poverty (which are all established goals in the SDG curriculum) can go beyond trade liberalization. Paying attention to the needs of disadvantaged and marginalized populations, it may be advisable to link program regulations to regional development levels.

Possibly unintentionally, the Thai PIS investigated in this paper did affect channels that are known to spur rural development. Three important mechanisms stand out: an effect on risk aversion, a relieve of credit constraints, and a shift from non-farm self-employment to wage employment activities. For the short run, we find that farmers became less risk-averse and that the PIS leads to increases in total sum of agriculture-related loans. Both increased risk-aversion and credit constraints are known to hinder investments in poor contexts, which in turn is an important prerequisite for growth. Moreover, the PIS led to shifts in the portfolio of income generating activities and household incomes. These shifts not only to result from expanding the cultivation of the subsidized crop but also from changes in non-farm related activities. Particularly, the PIS program made households shift from non-farm, small-scale business activities in self-employment to wage employment, which arguably generates more stable income streams.[16]

Importantly, the effects of the Thai PIS last beyond the active phase of the program. Such programs may, therefore, be effective tools to improve rural development. Their evaluation should look beyond the immediate distortions of production and prices.

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[16] This would be in line with the view of self-employment as a "last resort", i.e., as subsistence activity that underemployed households use to make ends meet (Falco and Haywood, 2016).

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Appendices

A Proofs for Section 4

This Appendix proves the theoretical predictions (2) to (5).

Proof of (2): Evidently,

$$V_0^* = V_0(x_0, z_0) < V_1(x_0, z_0) \leq V_1(x_1, z_1) = V_1^*.$$

The first inequality comes from the FSD improvement through I, conditional on (x, z). The second (weak) inequality is by the maximum property of (x_1, z_1).

Proof of (3): Denote by

$$c_0 = pY(x_0) + \pi(z_0) - C(x_0, z_0) \quad \text{and} \quad c_1 = pY(x_1) + \pi(z_1) - C(x_1, z_1) + I(p).$$

the final wealth levels with and without the PIS. The curvature properties of u, Y, π, and C imply that the first-order conditions (FOC)

$$\int (pY'(x_D) - C_x(x_D, z_D)) \cdot u'(c_D) \mathrm{d}F(p) = 0 \tag{A.1}$$

$$\pi'(z_D) - C_x(x_D, z_D) = 0 \tag{A.2}$$

(with $D = 0, 1$) are necessary and sufficient for optimal decisions (x_0, z_0) and (x_1, z_1).[17] Equations (A.1) and (A.2) can be solved sequentially: Condition (A.2) implicitly defines the optimal z_D *contingent* on x: $z_D = Z(x)$. Specifically, applying the implicit function theorem to (A.2),

$$Z'(x) = \frac{\mathrm{d}z_D}{\mathrm{d}x} = \frac{C_{xz(x,z)}}{\pi''(z) - C_{zz}(x, z)}, \tag{A.3}$$

[17] Condition (A.2) follows from the fact that π and C are non-stochastic.

which is opposite in sign to $C_{xz}(x, z)$. Setting

$$H(x) := \pi(Z(x)) - C(x, Z(x)),$$

we can interpret the farmer's decision problem as mono-variate, i.e.,

$$\begin{aligned} x_0 &= \arg\max_x \int u(pY(x) + H(x))\mathrm{d}F(p) \\ x_1 &= \arg\max_x \int u(pY(x) + H(x) + I(p))\mathrm{d}F(p). \end{aligned}$$

The FOCs for $D = 0, 1$ then read as

$$\int (pY'(x) + H'(x)) \cdot u'(c_D)\mathrm{d}F(p) = 0. \tag{A.4}$$

Due to the strict concavity of u, we get that $x_0 < x_1$ if, and only if, the LHS of (A.4) for $D = 1$ is positive when evaluated at x_0.

Evaluating the LHS of (A.4) for $D = 1$ at x_0 and expanding by $u'(c_0)$ under the integral, we obtain:

$$\int (pY'(x_0)+H'(x_0))\cdot u'(pY(x_0)+H(x_0)+I(p))\mathrm{d}F = \int (pY'(x_0)+H'(x_0))\cdot u'(c_0)\cdot\psi(p)\mathrm{d}F$$

with

$$\psi(p) := \frac{u'(pY(x_0) + H(x_0) + I(p))}{u'(pY(x_0) + H(x_0))}.$$

By Chebyshev's Algebraic Inequality, if ψ is strictly increasing [strictly decreasing] in p, then

$$\begin{aligned}
&\int (pY'(x_0) + H'(x_0)) \cdot u'(c_0) \cdot \psi(p) \mathrm{d}F \\
&\quad > [<] \quad \int (pY'(x_0) + H'(x_0)) \cdot u'(c_0) \mathrm{d}F \cdot \int \psi(p) \mathrm{d}F = 0,
\end{aligned} \tag{A.5}$$

where the final equality is due to the FOC-property of x_0 for $D = 0$. Setting $c_+ := pY(x_0) + H(x_0) + I(p)$, verify that

$$\psi'(p) = \frac{1}{u'(c_0)^2} \cdot [u'(c_0)u''(c_+)(Y(x_0) + I') - u'(c_+)u''(c_0)Y(x_0)]$$

is positive for all p if and only if

$$-\frac{u''(c_+)}{u'(c_+)} \cdot \frac{Y(x_0) + I'(p)}{Y(x_0)} < -\frac{u''(c_0)}{u'(c_0)}.$$

Since $c_+ > c_0$, $u''(c) < 0$, and $I'(p) \leq 0$ for all p, DARA ensures that this holds. Hence, the $>$-sign holds in (A.5). Consequently, $x_0 < x_1$.

Proof of (4): Recall that $z_D = Z(x_D)$. The claim then follows from (A.3) together with (3).

Proof of (5): We will show that expected *gross* incomes (i.e., $E(pY(x) + H(x))$) already are higher under PIS. Adding the non-negative PIS payouts $I(p)$ reinforces this effect, implying higher levels of expected net income (consumption).

We will first show that $pY(x) + H(x)$ is strictly concave in x. Verify that

$$\begin{aligned}
H'(x) &= Z'(x)(\pi' - C_z) - C_x; \\
H''(x) &= Z''(x)(\pi' - C_z) + Z'(x)^2(\pi'' - C_{zz}) - C_{xx} - 2C_{xz}Z'(x).
\end{aligned}$$

Here, $\pi' - C_z = 0$ from (A.2). Moreover, $\pi'' - C_{zz} < 0$ and $-C_{xx} < 0$ by assumption. From (A.3), we get that $C_{xz}Z'(x) > 0$. Hence, $H''(x) < 0$. Since $Y''(x)$ is negative, the concavity of $pY(x) + H(x)$ follows.

Using this and (3) we get that, for given p,

$$p \cdot (Y(x_1) - Y(x_0)) + H(x_1) - H(x_0) \geq (pY'(x_1) - H'(x_1)) \cdot (x_1 - x_0).$$

By risk-aversion, the FOC (A.4) for x_1 implies that $E[pY'(x_1) + H'(x_1)]$ is strictly positive. Hence,

$$E[p \cdot (Y(x_1) - Y(x_0)) + H(x_1) - H(x_0)] \geq (x_1 - x_0)E[pY'(x_1) + H'(x_1)] > 0.$$

B Propensity Score Matching

This Appendix presents the propensity score matching we conducted. Finding a suitable counterfactual group for the registered farmers hinges on a well informed propensity score. Particularly, the propensity score model should include as many characteristics X as possible that could be correlated with the registration decision as well as with potential non-treatment outcomes. Wave W2 of TVSEP (our household panel) contains data for a large set of such potential characteristics. Since the wave was sampled 16 months before the registration to the PIS started (see Table 1), respondents could not have been affected by the program or its anticipation at the point of data collection (the PIS was only announced in July 2009, a couple of months before registration started). Descriptive statistics on all raw variables are reported in Columns *Raw Sample* of Table B.1.

B.1 Algorithm

Following Imbens (2015), we choose specifications of the propensity score model in three different ways. Specification 1 linearly includes a large number of relevant characteristics X and Y_{t-1}, i.e., the first-order lags of the outcome variables in levels. Specifications 2 and 3, further, allow for non-linear relationships and covariate interactions. In Specification 2, given the variables X and Y_{t-1}, we employ an algorithm suggested in Imbens (2015), which applies likelihood ratio tests for all first and possible second-order terms (quadratic and interaction) in multiple loops. It selects those variables for inclusion into the propensity score model which improve the fit by more than a certain threshold. Specification 3 follows the same logic but pre-selects eleven variables to be automatically included linearly before running the algorithm. Pre-selected variables are chosen because they can be expected to affect the likelihood to register for the PIS as well as the outcomes strongly; we use indicators on land size and rice production, risk attitude, anticipated future severity of income loss due to agricultural risks, and several household demographics (education, age, and gender of household head; household size and composition). We use logit models for all three specifications.

The model-fit statistics of the three specifications for the raw sample are presented in Table B.2. In Specification 1, all 36 variables listed in Table B.1 are included. In Specification 2 the algorithm selects 33 variables to be included linearly and 129 second-order terms. In Specification 3 the algorithm selects 19 variables in addition to the 11 preselected characteristics to be included linearly and 100 second-order terms. Table B.2 reveals that, the value of the log-likelihood function, the pseudo-R^2 and Chi^2 are much higher in Specification 2 (and 3) than in Specification 1.

Before we can use the propensity score for matching and estimating program impacts, we need to ensure that farmers of the two groups are not too different. In the presence of large pre-matching differences, regressions will be sensitive to the choice of specification and outliers. Looking at Table B.1 we observe modest standardized differences for most household characteristics across groups in the raw sample. Yet, several covariates, including some lagged outcome variables, show standardized mean differences greater than 0.25 in absolute value. To arrive at more robust estimates we follow Heckman et al. (1997) and trim the sample before matching, using a trimming parameter of 0.1 at each extreme of the propensity score, as recommended by Crump et al. (2009). Based on the diagnostics in Table B.2, we choose the propensity score generated from Specification 2 for our trimming exercise and drop observations from

Table B.1: Covariate balance before and after matching

Covariate	Raw Sample						Trimmed Sample		Matched Sample			
	Control		Treatment						Spec.1, $k = 10$		Spec.3, $k = 5$	
	Mean	SD	Mean	SD	SDiff$_p$	Diff (t-test)	SDiff$_p$	Diff (t-test)	SDiff$_p$	Diff (t-test)	SDiff$_p$	Diff (t-test)
W2, Rice produce total (kg)	2888.43	2469.89	4585.47	3222.86	0.59	1697.04***	0.34	870.19***	0.00	−1.70	0.02	60.80
W2, Rice produce sold (kg)	1008.24	1608.34	2023.06	2150.59	0.53	1014.82***	0.30	522.00***	−0.02	−28.60	−0.02	−36.40
W2, Used land (rai)	2.77	2.16	3.78	2.38	0.45	1.01***	0.26	0.57***	0.02	0.04	−0.02	−0.04
W2, Income from public transfers	101.27	178.02	116.13	194.55	0.08	14.86	0.01	2.36	−0.02	−3.39	0.02	4.03
W2, Risk attitude	4.17	2.88	4.18	2.77	0.00	0.01	0.00	0.01	−0.01	−0.03	−0.09	−0.25
W2, Average anticipated severity of income loss due to agricult. risks	0.61	0.46	0.73	0.47	0.27	0.13***	0.16	0.07***	0.02	0.01	0.05	0.02
W2, HH head has primary education or lower	0.74	0.44	0.74	0.44	0.01	0.01	−0.04	−0.02	−0.03	−0.01	−0.02	−0.01
W2, Age of HH head	55.14	13.04	54.62	12.26	−0.04	−0.52	−0.06	−0.71	−0.02	−0.30	−0.01	−0.14
W2, # children of age <6 years in HH	0.41	0.63	0.41	0.62	0.01	0.01	0.02	0.02	−0.02	−0.01	−0.03	−0.02
W2, Gender of HH head	0.71	0.45	0.80	0.40	0.20	0.09***	0.10	0.04*	0.04	0.02	0.00	0.00
W2, HH nucleus size	4.01	1.56	4.27	1.59	0.17	0.26***	0.08	0.13	0.01	0.02	0.04	0.06
W2, # of agricult. related shocks in ref. period	1.02	1.10	1.00	1.08	−0.02	−0.02	−0.01	−0.01	0.01	0.01	0.00	0.00
W2, Average severity of agricult. related shocks in ref. period	1.43	1.26	1.46	1.28	0.02	0.03	0.03	0.04	0.02	0.03	0.00	−0.01
W2, Income loss due to agri. related shocks in ref. period	313.85	638.85	529.58	928.45	0.27	215.73***	0.16	106.07***	0.00	−1.72	0.03	17.69
W2, If you won 100,000 Baht, how much would you invest?	2594.40	1425.01	2611.87	1453.55	0.01	17.46	−0.01	−14.60	0.02	34.10	−0.03	−36.40
W2, # of agricult. related risks anticipated for future 5 years	8.33	6.00	9.20	5.92	0.15	0.87***	0.06	0.33	0.00	0.03	0.02	0.14
W2, Average anticipated severity of asset loss due to agricult. risks	0.32	0.42	0.42	0.50	0.22	0.10***	0.10	0.04*	0.00	0.00	0.05	0.02
W2, HH savings (value)	471.62	985.16	548.62	1086.51	0.07	77.00	0.03	30.93	0.01	10.94	−0.02	−19.32
W2, Travel time to BAAC	26.45	12.78	24.80	12.01	−0.13	−1.64***	−0.10	−1.21*	0.00	0.04	−0.01	−0.16
W2, How many days you need to get 60,000 Baht if you needed them?	13.98	17.61	12.06	16.13	−0.11	−1.92**	−0.06	−1.01	0.03	0.51	−0.03	−0.46
W2, Expenditures related to rice cultivation	487.76	410.89	769.12	555.21	0.58	281.36***	0.33	148.45***	−0.03	−12.10	0.01	3.51
W2, Agricultural assets (value)	878.70	1184.13	1140.22	1253.36	0.21	261.52***	0.16	176.27***	−0.01	−7.50	0.00	−5.60
W2, HH has loan(s) related to agri. investment	0.47	0.50	0.55	0.50	0.16	0.08***	0.05	0.03	0.00	0.00	0.02	0.01
W2, HH members temp. gone for job/job search (share)	0.03	0.11	0.02	0.08	−0.16	−0.02***	−0.08	−0.01	−0.03	0.00	0.04	0.00
W2, Total household income	8579.22	8204.62	9086.16	7988.52	0.06	506.94	0.03	223.46	0.02	112.40	−0.04	−252.90
W2, Land used for rice cultivation (share)	0.95	0.35	1.00	0.45	0.13	0.05**	0.02	0.01	−0.01	0.00	0.08	0.03
W2, Income from crop production	951.47	2089.61	1546.59	2635.13	0.25	595.12***	0.08	159.23	−0.02	−38.70	−0.05	−95.50
W2, Income from lifestock/livestock product	145.98	701.88	257.21	816.31	0.15	111.23***	0.06	39.99	0.00	−1.85	−0.01	−4.57
W2, Income from resource extraction	190.10	301.17	189.41	280.37	0.00	−0.70	0.03	7.54	0.03	7.56	0.01	2.11
W2, Income from wage employment	5320.93	6323.99	5374.30	6050.14	0.01	53.37	−0.03	−152.89	0.02	95.40	−0.05	−290.70
W2, Income from self-employment	1774.08	7086.33	1284.60	4134.23	−0.08	−489.48*	0.07	223.19	0.03	94.20	0.04	133.69
W2, Remittances	459.84	997.94	486.99	1001.27	0.03	27.15	−0.01	−7.86	0.00	3.08	0.05	48.48
W2, Livestock products (# of IGA)	0.34	0.57	0.48	0.66	0.22	0.14***	0.08	0.05	0.00	0.00	0.01	0.01
W2, Resource extraction (# of IGA)	3.23	2.41	3.36	2.37	0.05	0.13	0.09	0.21	0.02	0.04	0.02	0.05
W2, Wage employment (# of IGA)	1.78	1.52	1.75	1.38	−0.03	−0.04	−0.05	−0.08	0.03	0.05	−0.05	−0.07
W2, Self-employment (# of IGA)	0.38	0.67	0.35	0.60	−0.05	−0.03	−0.03	−0.02	0.00	0.00	0.03	0.02

Notes: SDiff$_p$ is the standardized difference, i.e. the difference in means or proportions divided by pooled standard deviation. Column *Diff* reports differences between registered and non-registered farmers. IGA = income-generating activities. ***,**, * indicate significance at 1, 5 and 10% from t-test.

the sample with an assigned propensity score greater than 0.9 or smaller than 0.1. This means discarding 103 observations from the control group and 318 observations from the treatment group. As shown in Table B.1, the covariate balance of the (still unmatched) sample is much improved after trimming. Though moderate biases persist for a few variables, the remaining bias is much reduced with all standardized differences below 0.35 in absolute value.

For the trimmed sample, we recalculate the propensity score specifications following the procedure described above. For Specification 2 [Specification 3], the algorithm now includes 22 [19] first-order and 31 [31] second-order terms. In all specifications the log-likelihood is improved while the degrees of freedom are the same or substantially smaller, respectively. Choice is still difficult, though: Specification 3 has the highest log-likelihood – it is even higher than in Specification 2 despite the lower number of degrees of freedom "invested". Yet, Specification 1 invests substantially less degrees of freedom, while its log-likelihood is only lower by 40 and 43 points, respectively. For a clearer assessment which of the models is preferable for matching, we run further diagnostic tests below.

B.2 Overlap

To ensure that a suitable match can be found for all treated farmers, we assess the *overlap* of the propensity score distributions of the two groups. The condition of overlap requires that farmers with identical characteristics have positive probability both of being registered or not-registered. Using the notation of Section 6, it must be true for all i that $0 < p(X) < 1$. We assess overlap graphically by studying the kernel density functions of the propensity score distributions by groups.

As Figure B.1 shows, the two distributions largely overlap after trimming, indicating that *overlap* holds. This is particularly true for the propensity score based on Specification 1. However, a small share of registered farmers at the upper end of the distribution does not have a very close counterfactual. Limiting the sample to the region of common support does not essentially change our results.

Table B.2: Propensity score model statistics (Raw and trimmed samples)

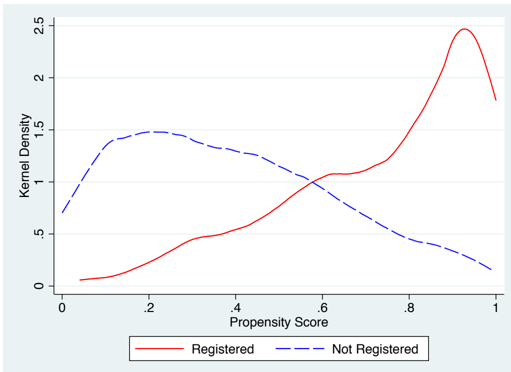
Raw Sample	# 1st order terms	# 2nd order terms	LL	df	Chi^2	$p > Chi^2$	pseudo R^2	AIC	BIC
Spec. 1	36	0	-935	36	260.93	0.00000	0.12242	-9494	1.231
Spec. 2	33	129	-733	162	666.13	0.00000	0.31252	-8971	1.134
Spec. 3	30	100	-773	130	584.55	0.00000	0.27424	-9125	1.145
Trimmed Sample									
Spec. 1	36	0	-761	36	64.71	0.00232	0.04901	-6395	1.377
Spec. 2	22	31	-721	53	154.04	0.00000	0.09829	-6353	1.338
Spec. 3	19	31	-718	50	147.88	0.00000	0.10295	-6382	1.326

Notes: LL is the value of the log-likelihood function; *df* denotes the degrees of freedom. AIC and BIC measure, resp., the Akaike and the Bayesian information criterion.

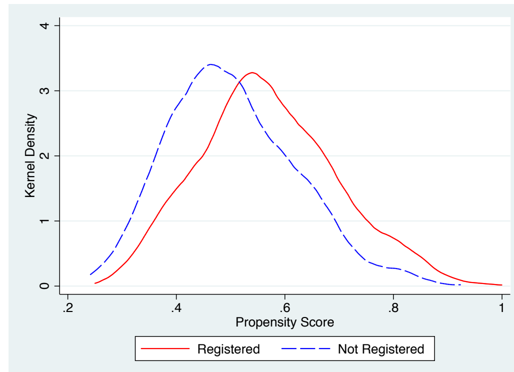
B.3 Matching quality and conditional independence

The condition of *conditional independence* demands that, conditional on characteristics X, the differenced outcomes of selected non-registered farmers have the same distribution as registered farmers would have experienced had they not registered. Formally, $E(\Delta Y_0|p(X), D = 1) = E(\Delta Y_0|p(X), D = 0)$ must hold. Although this assumption can never be truly tested, the balance of the pre-treatment outcome variables across groups in the matched sample indicates whether it is reasonable to assume conditional independence in our sample. In the actual matching, as described in Section 6, we match on $k = 1$, 5 and 10 neighbors. Table B.3 summarizes in which of the matched samples the balance in the pre-treatment covariates has improved most. The indicators suggest that matching on ten neighbors performs best to reduce the bias in the pre-treatment covariates in Specifications 1 and 2, while in Specifications 3 matching on five and ten neighbors leads to a comparable performance. Of all tested models, matching with ten nearest neighbors based on the

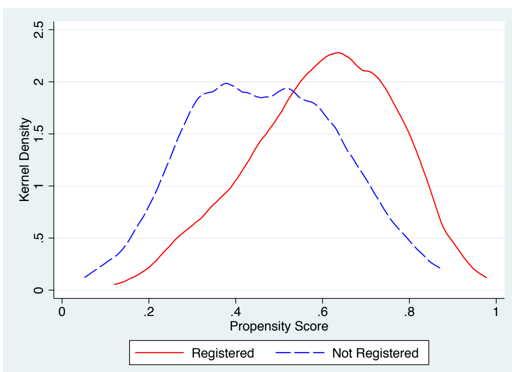
Figure B.1: Kernel density of propensity score before and after trimming



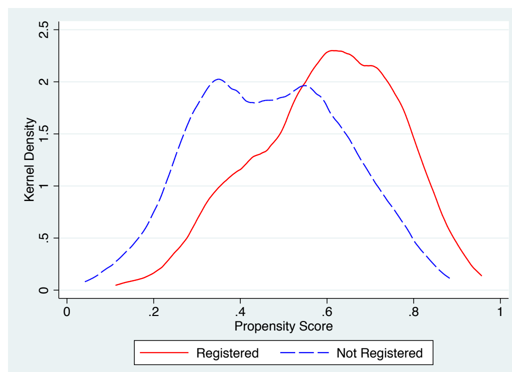
(a) Raw Sample



(b) Trimmed Sample, Spec. 1



(c) Trimmed Sample, Spec. 2



(d) Trimmed Sample, Spec. 3

propensity score from Specification 1 shows the best overall performance to reduce bias in the linear characteristics. Further, according to the *t*-statistics in the covariate balance of Table B.1, none of the covariates significantly differs across groups. All standardized differences are below 0.05 with a mean of 0.016, indicating that the sample is well-balanced. For Specification 3 (the preferred specification given the objective model selection criteria above), the balancing performance is almost as good as in Specification 1. According to the *t*-tests non of the differences between groups are statistically significant. When looking at the more conservative

Table B.3: Propensity score model statistics (Trimmed sample)

Trimmed Sample	pseudo R^2	Chi^2	$p > Chi^2$	Mean of SDiff
Unmatched	0.049	77.95	0.000	8.7
Spec. 1, $k = 1$	0.030	52.35	0.038	5.4
Spec. 1, $k = 5$	0.005	9.14	1.000	2.3
Spec. 1, $k = 10$	0.004	6.82	1.000	1.6
Spec. 2, $k = 1$	0.033	57.05	0.014	5.5
Spec. 2, $k = 5$	0.020	35.36	0.499	5.0
Spec. 2, $k = 10$	0.012	20.37	0.980	2.9
Spec. 3, $k = 1$	0.025	43.93	0.171	4.7
Spec. 3, $k = 5$	0.009	15.98	0.998	2.8
Spec. 3, $k = 10$	0.010	17.02	0.997	2.8

measure of standardized differences, we see slightest differences in two characteristics: share of land used for rice cultivation and risk attitude. The overall mean of standardized differences across covariates is 0.028, indicating a reasonably-balanced sample. In addition, Specifications 3 (and 2) balance a number of interaction and quadratic terms (which are not shown here). Based on both, *overlap* and *conditional independence*, we choose Specification 1 ($k = 10$) as our preferred one (reported in the main text). Estimates based on nearest neighbor matching with one, five, and ten neighbors for all specification are reported in Appendix C. Our results remain essentially unaffected by choice of specification and number of matched neighbors.

C Further specifications

This Appendix presents estimates for specifications of the propensity score matching other than the one reported in the main text. As a short summary, the estimates are very similar across specifications.

Table C.1: Rice production

	(1)	(2)	(3)	(4)	(5)	(6)
	△ Rice production				△	△
	(Log) Expenditures (PPP$)	(Log) Area (rai)	(Log) Agri. assets (value)	(Log) Total produce (kg)	Production index, based on (1) to (4)	(Log) Produce sold (kg)
Panel A: Short-term effects (2010 vs. 2008)						
OLS, trimmed sample	0.516***	0.253***	0.020	0.660***	0.528***	0.215
	(0.11)	(0.05)	(0.14)	(0.12)	(0.10)	(0.20)
Spec.1, $k = 1$	0.739***	0.319***	0.243	0.665***	0.660***	0.066
	(0.14)	(0.06)	(0.18)	(0.16)	(0.12)	(0.28)
Spec.1, $k = 5$	0.739***	0.320***	0.239	0.776***	0.701***	0.462**
	(0.13)	(0.06)	(0.16)	(0.16)	(0.12)	(0.23)
Spec.1, $k = 10$	0.664***	0.293***	0.206	0.696***	0.631***	0.402*
	(0.11)	(0.05)	(0.15)	(0.13)	(0.11)	(0.22)
Spec.2, $k = 1$	0.423***	0.176***	-0.137	0.335*	0.320**	0.289
	(0.15)	(0.07)	(0.21)	(0.20)	(0.15)	(0.27)
Spec.2, $k = 5$	0.592***	0.264***	-0.045	0.519***	0.495***	0.429*
	(0.08)	(0.04)	(0.17)	(0.08)	(0.06)	(0.24)
Spec.2, $k = 10$	0.578***	0.256***	-0.036	0.577***	0.510***	0.509***
	(0.07)	(0.04)	(0.15)	(0.05)	(0.05)	(0.18)
Spec.3, $k = 1$	0.535***	0.292***	0.376*	0.579***	0.570***	0.697**
	(0.15)	(0.07)	(0.20)	(0.19)	(0.16)	(0.28)
Spec.3, $k = 5$	0.509***	0.250***	0.206	0.577***	0.518***	0.515**
	(0.11)	(0.05)	(0.16)	(0.13)	(0.11)	(0.20)
Spec.3, $k = 10$	0.557***	0.269***	0.184	0.591***	0.544****	0.536***
	(0.11)	(0.05)	(0.15)	(0.13)	(0.11)	(0.17)
Panel B: Medium-term effects (2013 vs. 2008)						
OLS, trimmed sample	0.995***	0.395***	0.276	1.138***	0.955***	0.646***
	(0.13)	(0.06)	(0.17)	(0.15)	(0.12)	(0.23)
Spec.1, $k = 1$	1.247***	0.528***	0.540**	1.295***	1.190***	0.654**
	(0.19)	(0.09)	(0.24)	(0.22)	(0.17)	(0.30)
Spec.1, $k = 5$	1.133***	0.470***	0.442**	1.217***	1.085***	0.854***
	(0.15)	(0.06)	(0.20)	(0.16)	(0.13)	(0.23)
Spec.1, $k = 10$	1.048***	0.427***	0.388**	1.107***	0.990***	0.839***
	(0.13)	(0.06)	(0.19)	(0.14)	(0.12)	(0.22)
Spec.2, $k = 1$	1.335***	0.451***	0.151	1.321***	1.137***	1.216***
	(0.30)	(0.10)	(0.24)	(0.35)	(0.26)	(0.39)
Spec.2, $k = 5$	1.110***	0.489***	0.129	1.128***	1.012***	1.179***
	(0.14)	(0.06)	(0.21)	(0.16)	(0.13)	(0.24)
Spec.2, $k = 10$	1.000***	0.429***	0.108	1.046***	0.916***	1.052***
	(0.11)	(0.05)	(0.20)	(0.12)	(0.10)	(0.21)
Spec.3, $k = 1$	1.132***	0.528***	0.330	1.285***	1.122***	1.386***
	(0.18)	(0.08)	(0.22)	(0.21)	(0.17)	(0.28)
Spec.3, $k = 5$	0.849***	0.403***	0.254	0.920***	0.830***	0.882***
	(0.13)	(0.05)	(0.18)	(0.14)	(0.11)	(0.22)
Spec.3, $k = 10$	0.868***	0.405***	0.290*	0.925***	0.843***	0.932***
	(0.12)	(0.05)	(0.17)	(0.14)	(0.11)	(0.21)

Notes: Heteroscedasticity-consistent standard errors adjusted for clustering at the village level in parentheses. Specifications are as explained in Appendix B.1; k is the number of nearest neighbors. *Expenditures* are given in PPP$ (constant, 2005) and include expenditure on fertilizer, pesticides, seeds, labor, tractor rental, and other input factors related to rice cultivation. *Agri. assets* sum up those assets a farmer uses in the agricultural production process. ***,**, * indicate significance at 1, 5 and 10%.

Table C.2: Possible channels

	(1) △ Income from public transfers (incl. PIS)	(2) △ Risk attitude	(3) △ Agri. loans (Yes=1)
Panel A: Short-term effects (2010 vs. 2008)			
OLS, trimmed sample	140.889***	0.248	0.087**
	(22.78)	(0.21)	(0.04)
Spec.1, $k = 1$	114.014***	0.384	0.027
	(28.62)	(0.24)	(0.04)
Spec.1, $k = 5$	111.977***	0.320*	0.080**
	(22.13)	(0.17)	(0.03)
Spec.1, $k = 10$	113.628***	0.302*	0.079**
	(20.39)	(0.16)	(0.03)
Spec.2, $k = 1$	97.340***	0.683**	0.066
	(33.14)	(0.27)	(0.06)
Spec.2, $k = 5$	111.427***	0.357*	0.084***
	(19.43)	(0.19)	(0.03)
Spec.2, $k = 10$	111.970***	0.324*	0.081***
	(20.67)	(0.17)	(0.03)
Spec.3, $k = 1$	90.705***	-0.003	0.088*
	(26.71)	(0.32)	(0.05)
Spec.3, $k = 5$	89.012***	0.442*	0.065
	(22.23)	(0.25)	(0.04)
Spec.3, $k = 10$	86.854***	0.394	0.075*
	(22.77)	(0.25)	(0.04)
Panel B: Medium-term effects (2013 vs. 2008)			
OLS, trimmed sample	15.337	0.178	0.105***
	(17.86)	(0.22)	(0.04)
Spec.1, $k = 1$	28.204	0.208	0.112***
	(24.27)	(0.27)	(0.04)
Spec.1, $k = 5$	18.973	0.189	0.105***
	(18.28)	(0.18)	(0.03)
Spec.1, $k = 10$	13.719	0.207	0.094***
	(16.78)	(0.17)	(0.03)
Spec.2, $k = 1$	7.804	0.381	0.138**
	(24.13)	(0.36)	(0.06)
Spec.2, $k = 5$	15.640	0.337**	0.115**
	(20.41)	(0.15)	(0.05)
Spec.2, $k = 10$	15.406	0.260**	0.092**
	(18.22)	(0.10)	(0.04)
Spec.3, $k = 1$	40.570	0.184	0.062
	(25.46)	(0.34)	(0.05)
Spec.3, $k = 5$	24.645	0.259	0.065
	(17.07)	(0.28)	(0.04)
Spec.3, $k = 10$	14.773	0.327	0.076*
	(18.25)	(0.30)	(0.04)

Notes: Heteroscedasticity-consistent standard errors adjusted for clustering at the village level in parentheses. Specifications are as explained in Appendix B.1; k is the number of nearest neighbors. *Risk Attitude* is determined by asking the respondent on a scale between 0 and 10 whether he usually tries to avoid risk or feels fully prepared for taking risks. *Agri. loans* is an indicator equal to one if farmer took up loan for investments or expenditures related to agricultural production. *Income from public transfers* includes payments from PIS as well as income form other government social assistance programs like the universal pension scheme, scholarships, food aid etc. ***, **, * indicate significance at 1, 5 and 10%.

Table C.3: Income-generating activities

	(1) △ Land used for rice cultivation (share)	(2) △ Number of income generating activities in ...	(3)	(4)	(5)	(6) △ Activity index, based on (2) to (5)	(7) △ HH members temp. gone for job/job search (share)
		Livestock products	Resource extraction	Wage employment	Self-emlpoyment		
Panel A: Short-term effects (2010 vs. 2008)							
OLS, trimmed sample	0.064***	0.070*	-0.098	0.085	-0.005	0.052	0.005
	(0.02)	(0.04)	(0.16)	(0.08)	(0.03)	(0.20)	(0.01)
Spec.1, $k = 1$	0.092**	0.093*	-0.058	0.016	-0.091*	-0.040	0.001
	(0.04)	(0.05)	(0.18)	(0.10)	(0.05)	(0.26)	(0.01)
Spec.1, $k = 5$	0.071***	0.083**	-0.053	0.045	-0.041	0.034	0.001
	(0.02)	(0.04)	(0.14)	(0.08)	(0.04)	(0.19)	(0.00)
Spec.1, $k = 10$	0.067***	0.089**	0.054	0.025	-0.042	0.126	0.000
	(0.01)	(0.03)	(0.11)	(0.07)	(0.04)	(0.15)	(0.01)
Spec.2, $k = 1$	0.021	0.107*	0.181	0.112	-0.027	0.373	-0.001
	(0.04)	(0.06)	(0.27)	(0.17)	(0.05)	(0.38)	(0.01)
Spec.2, $k = 5$	0.036	0.062	0.102	0.106	-0.038	0.232	-0.003
	(0.02)	(0.05)	(0.14)	(0.11)	(0.03)	(0.20)	(0.01)
Spec.2, $k = 10$	0.036	0.091**	0.052	0.087	-0.046	0.184	-0.004
	(0.02)	(0.04)	(0.12)	(0.09)	(0.03)	(0.17)	(0.00)
Spec.3, $k = 1$	0.053*	0.109**	0.564**	0.054	-0.029	0.698**	-0.012**
	(0.03)	(0.05)	(0.23)	(0.13)	(0.04)	(0.30)	(0.01)
Spec.3, $k = 5$	0.039*	0.081**	0.075	0.035	-0.031	0.160	-0.003
	(0.02)	(0.04)	(0.05)	(0.09)	(0.03)	(0.12)	(0.01)
Spec.3, $k = 10$	0.039*	0.079**	0.070	0.072	-0.036	0.184*	-0.002
	(0.02)	(0.03)	(0.05)	(0.09)	(0.04)	(0.11)	(0.01)
Panel B: Medium-term effects (2013 vs. 2008)							
OLS, trimmed sample	0.143***	0.106**	-0.121	0.290***	-0.070*	0.205	0.023*
	(0.03)	(0.04)	(0.15)	(0.09)	(0.04)	(0.19)	(0.01)
Spec.1, $k = 1$	0.181***	0.107**	-0.099	0.212**	-0.106**	0.114	0.040**
	(0.07)	(0.05)	(0.17)	(0.10)	(0.05)	(0.21)	(0.02)
Spec.1, $k = 5$	0.142***	0.106***	0.009	0.271***	-0.072*	0.314**	0.030**
	(0.02)	(0.04)	(0.08)	(0.08)	(0.04)	(0.12)	(0.01)
Spec.1, $k = 10$	0.131***	0.126***	0.076	0.243***	-0.083**	0.362***	0.031**
	(0.03)	(0.04)	(0.05)	(0.07)	(0.04)	(0.10)	(0.01)
Spec.2, $k = 1$	0.160***	0.147**	0.240	0.385**	-0.061	0.711**	0.024
	(0.05)	(0.06)	(0.26)	(0.15)	(0.06)	(0.32)	(0.02)
Spec.2, $k = 5$	0.123***	0.118**	0.077	0.310***	-0.080**	0.425*	0.020
	(0.03)	(0.05)	(0.14)	(0.11)	(0.04)	(0.22)	(0.01)
Spec.2, $k = 10$	0.109***	0.150***	0.020	0.280***	-0.058	0.392**	0.011
	(0.02)	(0.05)	(0.11)	(0.10)	(0.04)	(0.20)	(0.01)
Spec.3, $k = 1$	0.136***	0.184***	0.469***	0.224	-0.030	0.847***	0.027
	(0.03)	(0.05)	(0.15)	(0.14)	(0.05)	(0.23)	(0.02)
Spec.3, $k = 5$	0.086***	0.126***	-0.028	0.250**	-0.093**	0.254*	0.028*
	(0.02)	(0.04)	(0.08)	(0.10)	(0.04)	(0.15)	(0.02)
Spec.3, $k = 10$	0.089***	0.122***	0.020	0.333***	-0.099**	0.376***	0.025*
	(0.02)	(0.04)	(0.05)	(0.10)	(0.04)	(0.13)	(0.01)

Notes: Heteroscedasticity-consistent standard errors adjusted for clustering at the village level in parentheses. Specifications are as explained in Appendix B.1; k is the number of nearest neighbors. *Land used for rice cultivation (share)* is the area of land used for rice cultivation as a share of total used land. *Resource extraction* refers to all income generating activities related to fishing, logging, collecting, and hunting. *Self-employment* refers to all kinds of income generating non-farm business activities. *Activity index* adds up the *Number of income generating activities* in columns (2) to (5). ***, **, * indicate significance at 1, 5 and 10%.

Table C.4: Income effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	△ Income (PPP$)						
	Crop cultivation	Life-stock/life-stock products	Resource extraction	Wage employment	Self-employment	Remittances (family/relatives)	Total
Panel A: Short-term effects (2010 vs. 2008)							
OLS, trimmed sample	412.740***	70.486	-15.624	28.934	-588.804***	70.072	-0.771
	(143.27)	(50.59)	(20.15)	(351.64)	(216.13)	(71.30)	(434.82)
Spec.1, $k = 1$	348.904*	176.485***	-14.242	147.452	-799.581***	65.276	-55.451
	(195.77)	(60.79)	(22.55)	(488.08)	(301.11)	(87.64)	(632.46)
Spec.1, $k = 5$	466.600***	85.173*	-15.828	149.811	-676.009**	98.768	126.198
	(146.78)	(46.72)	(14.75)	(362.18)	(271.99)	(73.78)	(529.22)
Spec.1, $k = 10$	429.598***	84.310**	-21.999	-57.795	-646.902***	106.604	-89.096
	(130.06)	(40.93)	(14.66)	(336.38)	(225.83)	(70.24)	(453.54)
Spec.2, $k = 1$	291.042	164.701**	-7.795	237.103	-725.987**	42.424	4.201
	(187.11)	(73.92)	(36.71)	(516.49)	(363.39)	(76.70)	(684.52)
Spec.2, $k = 5$	414.898***	95.731**	15.142	147.868	-809.058***	63.965	-60.405
	(129.50)	(41.34)	(24.26)	(387.44)	(301.82)	(62.58)	(501.53)
Spec.2, $k = 10$	493.670***	80.697**	5.358	36.017	-873.814***	62.563	-180.355
	(124.50)	(39.34)	(18.88)	(364.34)	(313.61)	(61.93)	(484.88)
Spec.3, $k = 1$	446.253***	93.671	26.988	255.846	-823.749**	-7.636	1.911
	(171.09)	(65.24)	(30.16)	(509.25)	(419.81)	(85.00)	(665.19)
Spec.3, $k = 5$	358.097***	101.219	-20.632	-92.514	-614.623***	36.195	-205.149
	(125.83)	(63.22)	(19.34)	(398.63)	(153.58)	(68.99)	(458.83)
Spec.3, $k = 10$	367.299***	77.102	-14.068	-5.552	-688.565***	29.233	-210.365
	(126.28)	(55.01)	(18.94)	(378.95)	(231.09)	(66.51)	(484.83)
Panel B: Medium-term effects (2013 vs. 2008)							
OLS, trimmed sample	493.806***	146.798*	-1.224	974.159**	-1184.182***	70.101	729.690
	(186.11)	(86.38)	(17.24)	(433.42)	(363.40)	(75.21)	(575.45)
Spec.1, $k = 1$	311.395	310.162**	-6.602	1367.964**	-1592.883***	-27.342	605.532
	(262.60)	(125.76)	(16.62)	(575.96)	(523.83)	(101.12)	(711.46)
Spec.1, $k = 5$	471.455**	253.170***	-0.648	1033.487**	-1447.898***	33.634	613.773
	(187.27)	(91.76)	(8.89)	(428.71)	(527.62)	(58.35)	(657.57)
Spec.1, $k = 10$	473.563**	276.068**	0.550	917.115**	-1528.914***	36.490	451.682
	(187.77)	(125.04)	(7.04)	(431.87)	(473.73)	(55.06)	(581.82)
Spec.2, $k = 1$	447.996*	263.718**	9.741	1344.200**	-1264.147**	41.667	966.650
	(241.81)	(104.87)	(29.09)	(601.91)	(567.14)	(94.71)	(763.99)
Spec.2, $k = 5$	509.556***	188.462**	32.714*	1017.167**	-1122.598***	15.853	801.246
	(172.70)	(86.42)	(16.80)	(418.11)	(405.02)	(76.95)	(571.76)
Spec.2, $k = 10$	586.331***	187.689**	22.860*	1143.429***	-1127.033***	29.069	981.134
	(179.51)	(80.28)	(13.82)	(426.01)	(374.29)	(81.98)	(598.00)
Spec.3, $k = 1$	562.989*	258.479**	45.046*	1524.749***	-1171.200**	94.679	1487.534*
	(318.28)	(109.33)	(25.53)	(565.83)	(526.70)	(92.80)	(793.82)
Spec.3, $k = 5$	499.431**	166.023	-4.301	1460.186***	-1035.592***	52.511	1267.624**
	(198.20)	(109.55)	(14.72)	(499.88)	(325.71)	(86.48)	(577.68)
Spec.3, $k = 10$	560.692***	178.477*	4.272	1534.241***	-1051.431***	20.476	1372.530**
	(188.35)	(103.62)	(14.80)	(469.53)	(358.43)	(83.66)	(570.68)

Notes: Heteroscedasticity-consistent standard errors adjusted for clustering at the village level in parentheses. Specifications are as explained in Appendix B.1; k is the number of nearest neighbors.

Incomes are given in PPP$ (constant, 2005).

Income from crop cultivation is the sum of income obtained from the cultivation of subsidized and non-subsidized crops.

Income from resource extraction is the sum of income obtained from fishing, logging, collecting, and hunting activities.

Income from self-employment includes income from all kinds of non-farm self-employment.

Total income includes incomes reported in columns (1) to (6), income from public transfers (incl. PIS payments), as well as all other types of household income.

***,**, * indicate significance at 1, 5 and 10%.