# Essay on Economic Development and Poverty Reduction

Achmad Tohari
M.Sc. Economics and Social Sciences, Utrecht University
B.Sc. Economics, Universitas Airlangga

THE UNIVERSITY OF WESTERN AUSTRALIA

This thesis is presented for the degree of Doctor of Philosophy of
The University of Western Australia
Economics
UWA Business School
May 2020

## DEDICATION

To my beloved family: my dearest wife Anna Retnawati, my daughter Taaj Riretna Amaraduhita, and my son Ganesha Rarendra Amaradipa

# ABSTRACT

This thesis is a collection of three empirical essays on poverty targeting and alleviation programs in Indonesia. The first paper aims to evaluate the benefits of unified program eligibility, conducting the first judicious evaluation of multiple concurrent programs in unison for the first time. Specifically, this paper examines how the benefits of social programs aimed at reducing poverty, complement one another, in the context of the introduction of Indonesia's Unified Targeting System (UDB). Introducing a new method of evaluation under the condition of complementary programs, this study shows that the probability of targeted households receiving all three programs increased by 117 percent. Further analysis shows that households receiving all three complementary programs have at least 30 percentage points higher per capita expenditure than those receiving none. The results highlight the need to account for program complementarities and provide support for unified program eligibility.

The second paper evaluates the impact of the KPS (Social Protection Card) and in tandem an information campaign on the receipt of two of Indonesia's largest social programs, the *Raskin* (rice for the poor) and the BLSM (temporary unconditional cash transfers). This paper also investigates a potential mechanism through which information influences the level of benefits received. Exploiting the design of the *Raskin* program, this study implements a (normalised) fuzzy regression discontinuity methodology across 482 Indonesian districts, using program eligibility as an instrument for having received the information treatment. Further corroborating the results with semi-parametric and parametric techniques, this chapter shows that the information treatment increases the amount of rice received under the *Raskin* program by around 30 percentage points. In terms of the BLSM, we further show that the information treatment reduces the likelihood of elite capture by local leaders by around 25 percentage points. This study also provides evidence that understanding the information treatment is crucial for poor household's outcomes, since fully informed households receive their full entitlement of rice.

The third paper conducts the first judicious evaluation of Capital Fundamentalism. In other words, this paper seeks to assess whether an initial injection of capital, across all sectors - with the notable exception of infrastructure – can catalyse subsequent economic development, through the mechanism of structural transformation. The setting for the analysis is the Government of Indonesia's Inpres Desa Tertinggal (IDT or Left Behind Village) Program, which was originally planned to be implemented between 1994 and 1997. By exploiting the official village 'scores' of the IDT program along with their provincial thresholds, this study adopts a (fuzzy) regression discontinuity design. The IDT program significantly increased household welfare in Java, Sumatra and Bali and Nusa Tenggara as households exited agriculture in favour of more productive activities. This paper finds no evidence of the program affecting structural transformation in Kalimantan, Sulawesi or Papua. The effects of the program were larger for villages with access to better quality infrastructure. This evidence suggests that structural transformation was a necessary condition for injections of capital to foster regional development.

# THESIS DECLARATION

I, Achmad Tohari, certify that:

This thesis has been substantially accomplished during enrolment in this degree.

This thesis does not contain material which has been submitted for the award of any other degree or diploma in my name, in any university or other tertiary institution.

In the future, no part of this thesis will be used in a submission in my name, for any other degree or diploma in any university or other tertiary institution without the prior approval of The University of Western Australia and where applicable, any partner institution responsible for the joint-award of this degree.

This thesis does not contain any material previously published or written by another person, except where due reference has been made in the text and, where relevant, in the Authorship Declaration that follows.

This thesis does not violate or infringe any copyright, trademark, patent, or other rights whatsoever of any person.

Signature: [redacted]

Date: 12/02/2020

## AUTHORSHIP DECLARATION: CO-AUTHORED PUBLICATIONS

This thesis contains work that has been published and/or prepared for publication.

| |
|---|
| Details of the work:<br>Tohari, A., Parsons, C. and Rammohan, A., 2019. Targeting poverty under complementarities: Evidence from Indonesia's unified targeting system. *Journal of Development Economics,* 140: 127-144. |
| Location in thesis: Chapter 2 |
| Student contribution to work:<br>I am responsible for the preparation of datasets, developing and conducting estimation strategy, interpretation of the results, and completion of the draft. |
| Co-author signatures and dates:<br>[redacted] (12-2-20) (ANU RAMMOHAN)<br>(12-2-20) (CHRIS PARSONS) |

| |
|---|
| Details of the work:<br>Tohari, A., Parsons, C. and Rammohan, A., 2017. Does Information Empower the Poor? Evidence from Indonesia's Social Security Card (No. 11137). *IZA Discussion Papers.* |
| Location in thesis: Chapter 3 |
| Student contribution to work:<br>I am responsible for the preparation of datasets, developing and conducting estimation strategy, interpretation of the results, and completion of the draft. |
| Co-author signatures and dates:<br>[redacted] (12.2.20) (ANU RAMMOHAN)<br>(12-2.20) (CHRIS PARSONS) |

| |
|---|
| Details of the work:<br>Tohari, A., Parsons, C. and Rammohan, A., 2019. Capital Fundamentalism and Structural Transformation |
| Location in thesis: Chapter 4 |
| Student contribution to work:<br>I am responsible for the preparation of datasets, developing and doing estimation strategy, interpretation of the results, and completion of the draft. |
| Co-author signatures and dates:<br>[redacted] (12.2.20) (ANU RAMMOHAN)<br>2-20) (CHRIS PARSONS) |

# TABLE OF CONTENTS

## LIST OF TABLES

# LIST OF FIGURES

## ACKNOWLEDGEMENTS

First and foremost, I would like to thank my supervisors, Prof. Anu Rammohan and A/Prof. Christopher Parsons, whose constant support and encouragement has been invaluable. I owe much more to them than what is reflected in this thesis.

I also gratefully acknowledge generous funding from the Australian government through the Department of Foreign Affairs and Trade for the Australian Award Scholarship (AAS). I would also extend my sincere gratitude to Mrs Debra Basanovic and Ms Celia Shah, Liaison Officers of the AAS, who have kindly assisted me in addressing various matters.  I am also sincerely grateful to the National Team for the Acceleration of the Poverty Reduction (TNP2K) for providing data support.

I am grateful to Bambang Widianto, Sudarno Sumarto, Elan Satriawan, Aufa Doarest, Priadi Asmanto, Gracia Hadiwidjaya, Mohammad Purnagunawan, Adam Latief, (TNP2K), Vivi Alatas, Hendratno Tuhiman (*late*) and Taufik Hidayat (World Bank) for their comments and helps. I would also like to thank Samuel Bazzi (Boston University), Ken Clements (UWA), Benjamin Olken (MIT) as well as seminar participants in TNP2K, the University of Western Australia, and PhD Conference as to anonymous referees for their valuable comments and suggestions.

I would like to thank my fellow students and friends: Riznaldi Akbar, Noor Syaifudin, Sigit Perdana, Nugraha Adi, Taufan Pamungkas, Troy Barry, Emiliano Carlevaro, Harsha Paranavitha, Harsha Konara, Long Vo, Lily Vu, Hoi Minh Chu, Qing Li, Thomas Favoury, Tom Simpson, Riko Stevens, Jill Trinh, Mohammad Farhad, and Rafat Mahmood for many helpful conversations over the years. I also sincerely grateful for Isabela Banea, Maryann Eventts, and Ha Le, for their kind assistance in making my life at UWA go smoothly.

Finally, for my parents and parents in law, I never thank you enough for caring and protecting me and my family from the things we shouldn’t do.

# Chapter 1

# Introduction

## 1.1 Introduction

This thesis is a collection of three empirical essays on poverty targeting and alleviation programs in Indonesia. As in other developing countries, poverty reduction and a reduction in inequality have become central policy issues in Indonesia. The most challenging task in delivering targeted poverty alleviation programs is the issue of how to differentiate between the poor and the rich. With regards to the implementation of targeting methods, Indonesia has experimented with several targeting methods to reach the poor, such as geographical targeting, community-based targeting, and proxy-means testing (PMT) (World Bank, 2012). The first experience in targeting was in 2005-2006, when the temporary unconditional cash transfer, *Bantuan Langsung Tunai* (BLT) program used community-based nominations and other data to identify prospective beneficiary households. This census database of poor households was also known as PSE05 (*Pendataan Sosial Ekonomi Penduduk 2005*, or Socio-economic Data Collection of the Population) (see Hastuti, et al., 2006).

In 2008-2009, the GoI updated the database identifying poor households based on an updated list from PSE05, with community verification. This database was previously used to identify eligible households for previous social transfers such as the BLT 2008-2009 and was also known as PPLS08 (*Pendataan Program Lindungan Sosial* 2008, or Data Collection for Targeting Social Protection Programs). However, it has been argued that PPLS08 was similar to PSE05 and there continued to be errors related to targeting that had the potential to stimulate social unrest (Widjaja, 2009; Cameron & Shah, 2014). To address the imperfections in previous targeting systems, in 2011, the GoI through the TNP2K (for *Tim Nasional Percepatan Penanggulangan Kemiskinan* or the Team for the Acceleration of the Poverty Reduction) and the BPS developed the UDB (for Unified Targeting System or *Basis Data Terpadu* - BDT), the primary aim of which was to standardise program eligibility. Using the setting of the introduction of the UDB, the first paper of this thesis aims to evaluate the benefits of unified program eligibility, conducting the first judicious evaluation of multiple concurrent programs in unison for the first time. Specifically, this paper examines how the benefits of social programs aimed at reducing poverty, complement one another, in the context of the introduction of Indonesia’s Unified Targeting System (UDB).

Following the implementation of the UDB, in the first quarter of 2013 the GoI also issued a card, the Social Security Card – *Kartu Perlindungan Sosial* (KPS), covering 25% of the poorest households or 15.5 million poor and vulnerable households. The KPS card was the first attempt by the GoI to confirm the eligibility status of households. Accompanying the KPS card was additional information on how to use the card for accessing the benefits of poverty programs, and also provided an indication of the size of benefits from each program. These efforts are in line with the World Bank's campaign for greater dissemination of information on various poverty programs among social welfare recipients (World Bank 2004). The second chapter of the thesis aims to evaluate the impact of the KPS and information campaign on the receipt of two of Indonesia's largest social programs, the *Raskin* (rice for the poor) and the *BLSM* (temporary unconditional cash transfers). This paper also investigates a potential mechanism through which information influences the level of benefits received.

Finally, in view of capital fundamentalism, the best way to promote economic growth and economic development is simply by increasing investment. Differences in individual or national stocks of capital were the major determinants of differences in the levels of income. A straightforward piece of advice on development problems is that government intervention is advocated to ensure economies break free from vicious cycles of under-development (Harrod, 1939; Domar, 1946; Lewis, 1954; Rostow, 1960), and simultaneous investments across many industries Rosenstein-Rodan (1943). The neoclassical growth model and growth accounting research in later years, however, indicated that differences in the patterns of investment were not the factors behind the differences in living standard in the long run (Solow, 1957; Denison, 1962, 1967). Despite the strength of opinions on both sides of the debate, the underlying ethos of Capital Fundamentalism has yet to be judiciously tested. The third paper of this thesis conducts the first judicious evaluation of Capital Fundamentalism. In other words, this paper seeks to assess whether an initial injection of capital, across all sectors - with the notable exception of infrastructure – can catalyse subsequent economic development, through the mechanism of structural transformation. The setting for the analysis is the Government of Indonesia's *Inpres Desa Tertinggal* (IDT or Left Behind Village) Program, which was originally planned to be implemented between 1994 and 1997. The overarching aim of the IDT program was to inject capital into the economies of poor households in selected villages. The program was abruptly curtailed however due to the Asian Financial Crisis, meaning that the last year of implementation was 1996.

## 1.2 Description of Thesis

The data used in the first two papers come from several sources, including the analysis draws on the National Socioeconomic Survey (SUSENAS), the Social Protection Survey (SPS), the Village

Potential Census (PODES) and the Proxy Means Test (PMT) coefficients and cut-offs for all 471 Indonesian municipalities as well as individual household PMT scores.

The first two papers utilize data from the 2005, 2009 and 2014 waves of the SUSENAS survey to: (1) measure the benefit incidence from poverty programs and their targeting performance relative to previous efforts; (2) predict the poverty level of each household; and (3) estimate the relationship between poverty, social protection eligibility and household characteristics, particularly using the 2014 SUSENAS survey.[1] The second dataset used in the analysis is the 2014 Social Protection Survey (SPS). This survey was implemented from the first quarter of 2013 to the first quarter of 2014 and was specifically aimed at examining the performance of poverty targeting under the implementation of the UDB. A question pertaining to the KPS was only asked in the last two rounds. Therefore, this study uses data from the first quarter of 2014 since it was the period just after the implementation of the KPS. This paper uses this survey to obtain information about the implementation of KPS related to the benefits received by poor households from the poverty targeting. The third source of data is the 2014 PODES, which provides information on all villages/*desa* in Indonesia. The village census covers a sample of around 80,000 villages and was fielded around periodic censuses. It includes useful information on village characteristics, including the main sources of income, population and labor force characteristics, socio-culture, type of village administration and other relevant village-level information. The last and most important dataset is the Proxy Means Test (PMT) coefficients and cut-offs for all 471 Indonesian municipalities as well as individual household PMT scores. This data was used by the Government of Indonesia, through the National Team for the Acceleration of Poverty Reduction (TNP2K), to select the beneficiaries of the poverty program from 2012 to 2014.

The first paper published in the Journal of Development Economics (Tohari, Parsons & Rammohan (2019) introduces a new method of evaluating poverty targeting performance under the condition of multiple concurrent programs, which *a priori* are expected to complement one another. Since we are able to observe over time whether eligible and ineligible households took receipt of any of the three programs, we analyse if there have been improvements in targeting performance, between 2005 and 2014. In other words, relative to the existing literature, which used covariates to estimate whether a household was eligible or not, this study is able to observe, across the entire nationally representative

[1] The National Socioeconomic Survey (SUSENAS) is an annual cross-sectional, nationally representative dataset, initiated in 1963-1964 and fielded once every year or two since then. In 2011, however, the BPS changed the survey frequency to quarterly. This covers some 300,000 individuals and 75,000 households quarterly.

sample, whether households were eligible for programs and then of those programs to which they are eligible, which households actually received those programs. This paper uses a matching approach to evaluate the impact on household welfare of moving to a unified targeting system. The matching approach allows us to estimate the difference in household outcomes, between households that received every combination of social program.

The second paper exploits the programs' designs to establish a causal inference of the impacts of information provision as well as individuals' understanding of information on the intensive margins of the benefit received from two of Indonesia's largest social welfare programs, namely Raskin and BLSM. These are the only two welfare programs that can be examined in this context due to the design and specific questions asked in the Social Protection Survey (SPS). Using all 482 official Proxy Mean Test (PMT) thresholds (i.e. PMT coefficients)[2] and cut-offs used by the Government of Indonesia (GoI) to identify households' eligibility, this study subsequently exploits the resulting discontinuity using a range of parametric, semiparametric and non-parametric methods.

In order to conduct a judicious assessment of the role of capital fundamentalism in fostering structural transformation, the third paper uses the regression discontinuity design to exploit the specificities of the selection mechanism of the IDT program in order to provide causal estimates of the program. This paper combines several data sources from village census datasets, administrative data and night light intensity data from the National Oceanic and Atmospheric Administration (NOAA). The first dataset used is the Government of Indonesia's administrative dataset, comprising of actual village and provincial IDT scores, those used to select villages into the IDT program from 1994 to 1996. The second data source is the administrative triennial village census or PODES (for *Potensi Desa* or Village Potential Censuses), which comprises the universe of villages in Indonesia. PODES collects a plethora of data including physical and administrative characteristics, infrastructure and social organizations and amenities. This paper employs data from the 1990, 1993 and 1996 PODES for a variety of purposes: i) reconstruct the IDT village and province scores from IDT94 as a robustness check to test the fidelity of the aforementioned administrative data on the IDT program. ii) use data from PODES 1993 for the construction of some of our pre-treatment baseline measures and iii) conversely exploit data from 1996 PODES to construct some of our post-treatment

[2] Proxy means testing is often used for targeting poverty programs in developing countries. The method assigns a score to all potential participants as a function of observed characteristics. When strictly applied, the program is assigned if and only if a unit's score is below some critical level, as determined by the budget allocation of the scheme (Ravallion, 2007).

outcomes. The third data used is the administrative village censuses. Due to the importance of the IDT program, the GoI, through the BPS, conducted additional censuses in two village in 1994 and 1995. In 1994, the GoI collected additional information on village characteristics, including details on the POKMAS (community groups) within villages. These data were used to construct both the village and province scores for IDT95 and given our privileged access to these data, they were first employed to double-check the construction of the official IDT95 scores. This paper further employs administrative data from the 1994 village census to construct a number of our baseline measures. Finally, this paper incorporates night light intensity data from the National Oceanic and Atmospheric Administration (NOAA) into the analysis. This paper uses luminosity data as a proxy for productivity for both 1993 and 1996 to represent the periods before and after the implementation of IDT.

## 1.3 Contribution of Thesis

The first paper makes several contributions to the economic literature. The first contribution is in the area of evaluation of poverty targeting programs by introducing a new method of evaluating poverty targeting performance under the condition of multiple concurrent programs, which a priori are expected to complement one another. Whereas poverty programs are nearly always delivered alongside one another (Grosh et al. 2008), previous evaluations of the poverty programs have studied single programs in isolation (Cornia and Steward, 1995; Jayne et al, 2002; Schultz, 2004; Galasso and Ravallion, 2005; Ravallion, 2008, 2009; Angelucci & De Giorgi, 2009; De Janvry et al., (2012), Niehaus et al (2013) and Brown et al (2018). If the benefits of poverty programs are complementary, in the sense that the marginal benefits of individual programs in the presence of complementary programs are positive, then there are cases to be made for unified program eligibility *and* for the concurrent evaluation of complementary programs on efficiency and accuracy grounds.

The first paper also contributes to the evaluation of poverty targeting and programs in Indonesia. Indonesia's targeting system has been the subject of evaluations using field experiments (Alatas et al. 2012; Alatas, et al. 2016) restricted to fairly small samples, raising fears of external validity. Others have used nationally representative data to focus on single programs, for example the *Askeskin* and *Jamkesmas* programs (Sparrow 2008; Sparrow et al. 2013) or the *Raskin* program (Sumarto et al., 2003; Olken 2005). Bah et al (2018) represent an exception since those authors evaluate both the *BLT* and *Jamkesmas* programs, but they do so separately from one another and focus on the process of targeting as opposed to targeting outcomes using a restricted sab-sample of the overall population.

The second paper adds to a growing body of research on the impact of an information intervention on social welfare programs. Despite the potentially crucial importance of information provision for successful targeting of social programs to the poor, the existing literature focuses almost exclusively on analysing the provision of information in alternative contexts. Their results have largely been inconclusive. Studies by Reinikka and Svensson (2004) in Uganda, and Pandey, and Goyal and Sundararaman (2009) in India, for example, find that access to information on these programs contributed positively to education-related outcomes. Others such as Banerjee et al. (2010) in India, Pradhan et al. (2014) and Ravallion et al. (2013) in Indonesia, and Lieberman and Posner and Tsai (2014) in Kenya, fail to uncover any statistically significant impact of information provision on the quality of children's schooling. Olken's (2007) study from Indonesia finds that disseminating information locally reduced leakage from road project funds. However, he also notes that increased public participation in monitoring had no discernible impact on the same outcome. It remains unclear why some information-based interventions succeed in improving service delivery, while others do not. One possible explanation relates to the extent to which information is understood by eligible households (Fox, 2007). To the best of my knowledge, there are only two studies, Ravallion et al. (2013) in India and Banerjee et al. (2018) in Indonesia, that evaluate information-based interventions in poverty programs, both of which use field experiments and their results contradict one another. Previous research, with the exception of Ravallion et al. (2013), assumes that targeted households fully understand the information content provided to them.

This paper differs from Banerjee et al.'s (2018) study from Indonesia in several ways: (1) this study evaluates two programs nationwide as opposed to a single program using a smaller sample; (2) this paper provides evidence of an alternative causal mechanism through which information interventions affect poor household's outcomes; and finally (3) this paper is able to gauge the impacts of both information provision and understanding the content of the information provided.

The third paper is at the intersection of several branches of the economic literature, above all, the literature that examines the determinants of structural transformation as part of the process of economic development. This literature is essentially founded on the notion of 'dualism' first introduced by Lewis (1954), according to which, areas of differential productivity exist within countries, which provide opportunities for improvements in efficiency. Productivity wedges, between, for example, agricultural and non-agricultural areas, mean that the reallocation of labour between sectors can yield (aggregate) productivity gains (Gollin et al, 2002; Lagakos and Waugh, 2013; Bryan et al, 2014; Gollin et al 2014; Au and Henderson, 2016; Munshi and Rosenzweig, 2016).

An expansive literature explores factors that both expedite and impede the process of structural transformation and thus economic development. These include labour regulation (Fallon and Lucas, 1993; Besley and Burgess, 2004; Manning, 2014), labour mobility costs (Nickell et al., 2002, Lee and Wolpin, 2006; Messina, 2006 and Hayashi and Prescott 2008) and goods mobility (Herrendorf et al, 2012; Adamopolous, 2011 and Gollin and Rogerson, 2010). This paper contributes to these literatures by examining the role of Capital Fundamentalism, the role of a pure injection of capital, in catalysing structural transformation, as captured by households exiting the agricultural sector.

This paper also speaks directly to the literature that examines the role of *rural* infrastructure in facilitating structural transformation (Gollin and Rogerson, 2010; Adamapoulos, 2011; Herrendorf et al., 2012; Asher and Novosad, 2019). Crucially, since infrastructure is the only form of capital that recipient villages are *unable* to spend IDT funds on, and since those villages located within our RDD cut-off envelope have access to varying transport links, this study is able to additionally provide causal estimates of the role of rural infrastructure for those villages that receive IDT funds. In doing so, this study provides causal evidence on the role of initial conditions in infrastructure on the degree of structural transformation.

Finally, the third paper also contributes to the literature that examines the relationship between structural transformation and welfare. The role of structural change in reallocating factors of production to explain countries' growth performance is well-known (Chenery et al, 1986; Syrquin, 1995). Most studies (e.g. Nelson and Pack, 1999; and Ngai and Pissarides 2007) find a positive effect of structural change on economic performance, although Caselli (2005) argues that such effects are negligible. Some measures of welfare used in this study include productivity (as captured through nightlight data), enrolment rates, infant mortality, livestock numbers, a measure of poverty, namely the number of poor households, as well as a variable capturing the number of Small and Micro size Enterprises (SMEs).

This page is intentionally left blank

**Chapter 2**

# Targeting Poverty under Complementarities: Evidence from Indonesia's Unified Targeting System

Tohari, A., Parsons, C. and Rammohan, A., 2019. Targeting poverty under complementarities: Evidence from Indonesia's unified targeting system. *Journal of Development Economics*, 140, pp.127-144.

Journal of Development Economics 140 (2019) 127–144

Contents lists available at ScienceDirect

Journal of Development Economics

journal homepage: www.elsevier.com/locate/devec

# Targeting poverty under complementarities: Evidence from Indonesia's unified targeting system[☆]

Achmad Tohari[a,b], Christopher Parsons[a,*], Anu Rammohan[a]

[a] University of Western Australia, Perth, Australia
[b] Fakultas Ekonomi dan Bisnis, Universitas Airlangga, Jl. Airlangga 4-6, Surabaya 60286, Indonesia

ABSTRACT

Developing countries are increasingly moving to unified targeted systems to better identify the poor and improve their outcomes. While social programs are nearly always delivered alongside one another however, the evaluations of these programs typically occur in isolation. Combining nationally representative administrative and survey data, we evaluate Indonesia's three largest social programs in unison. The setting for our evaluation is the launch of Indonesia's Unified Targeting system, an innovation developed to unify program eligibility, reduce targeting errors and increase program complementarities. Introducing a new method of evaluation under the condition of complementary programs, we show that the probability of targeted households receiving all three programs increased by 117 percent. Our analysis shows that households receiving all three complementary programs have at least 30 percentage points higher per capita expenditure than those receiving none. Our results highlight the need to account for program complementarities and provide support for unified program eligibility.

*"I can live for two months on a good compliment"*

Mark Twain

Targeted poverty programs represent important interventions to reduce poverty in developing countries. Recent years have witnessed a proliferation of unified poverty targeting systems, based on single consolidated registries. 92 countries are currently implementing or preparing to roll out unified targeting systems, which cover almost two billion people (Honorati et al., 2015, Bah et al 2018). Whereas poverty programs are nearly always delivered alongside one another however (Grosh et al., 2008), the evaluations of these programs typically occur in isolation.[1] If the benefits of poverty programs are complementary, in the sense that the marginal benefits of individual programs in the presence of complimentary programs are positive, then there is a case to be made for unified program eligibility *and* for the concurrent evaluation of complimentary programs on efficiency and accuracy grounds. Indeed multi-faceted programs have been shown to have a significantly positive and persistent impact on the chances of 'ultra-poor' households escaping poverty (Banerjee et al., 2015). Since the vast majority of unified targeting programs are still being developed however, it is timely to evaluate their efficacy both in terms of their targeting performance and their impact on household welfare.

Traditionally, unified targeting systems have been implemented in developed rather than developing countries, which lack complete information on household welfare (Grosh et al., 2008). Recently there has been a proliferation in developing country uptake and program development however, due to relaxed budget constraints and the timely collection of better information on household welfare. The underlying philosophy of unified targeting is to consolidate beneficiary lists so as to standardise the target population (World Bank 2012a, 2012b). If differing and potentially complementary social programs adopt inconsistent beneficiary lists, then there will likely exist households that receive program A and not program B, and others that receive program B and not program A. Efforts, such as unified targeting, which therefore seek to unify uptake but do not change the overall incidence of uptake, will therefore necessarily yield better outcomes along the extensive

☆ Achmad Tohari's PhD studies have been generously funded by Australia's Department of Foreign Affairs (DFAT) and data support came from Goverment of Indonesia's TNP2K. We are also grateful to the Editor Andrew Foster, Bambang Widianto, Sudarno Sumarto, Elan Satriawan, Aufa Doarest, Priadi Asmanto, Gracia Hadiwidjaja (TNP2K), Vivi Alatas, Hendratmo Tuhiman, Taufik Hidayat (World Bank), Samuel Bazzi (Boston University), Ken Clements (UWA) and Benjamin Olken (MIT) as well as seminar participants both in TNP2K and the University of Western Australia as well as to an anonymous referees for their valuable comments and suggestions.

* Corresponding author.
*E-mail addresses:* ach.tohari@feb.unair.ac.id (A. Tohari), christopher.parsons@uwa.edu.au (C. Parsons), anu.rammohan@uwa.edu.au (A. Rammohan).

1 Examples include: Cornia and Stewart (1995), Jayne et al. (2002), Schultz (2004), Galasso and Ravallion (2005), Ravallion (2008, 2009), Angelucci and De Giorgi (2009), De Janvry et al. (2012), Niehaus et al. (2013) and Brown et al. (2018).

https://doi.org/10.1016/j.jdeveco.2019.06.002
Received 30 April 2018; Received in revised form 23 May 2019; Accepted 5 June 2019
Available online 12 June 2019
0304-3878/

margin. Evaluating complementary programs in isolation relying on outcome variables that may be affected by more than one program, may therefore lead to upward biases, since a household's outcomes might otherwise be driven by omitted programs.

In this paper, we evaluate the benefits of unified program eligibility in a developing country context, conducting the first judicious evaluation of multiple concurrent programs in unison for the first time.[2] Specifically, we examine how the benefits of social programs aimed at reducing poverty, complement one another, in the context of the introduction of Indonesia's Unified Targeting System (UDB), the primary aim of which was to standardise program eligibility.

Indonesia's targeting system has been the subject of evaluations using field experiments (Alatas et al., 2012; Alatas et al., 2016) restricted to fairly small samples, raising fears of external validitiy. Others have used nationally representative data to focus on single programs, for example the *Askeskin* and *Jamkesmas* programs (Sparrow, 2008; Sparrow et al., 2013) or the *Raskin* program (Sumarto et al., 2003; Olken, 2005). Bah et al (2018) represents an exception since those authors evaluate both the Unconditional Cash Transfers (*Bantuan Langsung Tunai* or *BLT*) and the Health insurance for the poor (*Jamkesmas)* programs, but they do so independently of each another, and focus on the process of targeting as opposed to targeting outcomes using a restricted sub-sample of the overall population.

Our focus is instead on Indonesia's three largest social welfare programs operating in unison. Together these welfare programs account for 87% of Indonesia's social expenditure. We exploit rich nationally representative administrative and survey data, which includes privileged access to the Proxy Means Test (PMT) coefficients and cut-offs for all 471 Indonesian municipalities as well as individual household PMT scores.[3] Introducing a new method of evaluating poverty targeting performance under the condition of multiple concurrent programs, which *a priori* are expected to complement one another, we first document the improvements in targeting performance, between 2005 and 2014; since we are able to observe over time, whether eligible and ineligible households took receipt of any of the three programs. In other words, relative to the existing literature, which used covariates to estimate whether a household was eligible or not,[4] we are able to observe, across the entire nationally representative sample, whether households were eligible for programs, and then among eligible households, which households actually received those programs. We show that the introduction of the UDB significantly increased the targeting performance of social programs in Indonesia. The probability of targeted households receiving all three programs increased by 117 percent compared to previous targeting efforts.

We continue by evaluating the impact on household welfare of moving to a unified targeting system. Our matching approach, allows us to estimate the difference in household outcomes, between households that received every combination of social program. We exploit the design of the anti-poverty programs, which has been argued to be first best when analysing social programs that target poverty (Ravallion, 2007). Specifically, we are able to match individual households using their PMT scores, using the optimal bounds procedure suggested by Crump et al. (2009). We subsequently show that this procedure yields far superior results than using covariates alone, by providing a much larger and better distributed common support from which to match treated and untreated units.

We compare the difference in the benefits various households receive, in terms of per capita expenditures, between the introduction of the UDB in 2011, (when the baseline data were collected) and 2014, a suitable period to follow-up in since all households were eligible for all three programs in the intervening period including when the Government of Indonesia provided Unconditional Cash Transfers to households in 2013, following their decision to reduce the nationwide oil price subsidy. In our preferred empirical specification, we use a control function with the PMT score entering the first stage regression. We therefore generate estimates of the marginal benefits of receiving Indonesia's three flagship social programs conditional on the receipt of either zero, one or else combinations of two other programs.[5] Households receiving all three programs, experienced an increase in household expenditure of at least 30 percentage points compared to those that received no programs, and household expenditure increased between 16 and 19 percentage points for households receiving all three programs compared to households that received only one or two programs. Our results highlight the tangible benefits of the introduction of the UDB, in other words of unified program eligibility.

## 1. Background

### 1.1. History of Indonesian poverty programs

The majority of Indonesians hover around the national poverty threshold (World Bank, 2012a) with approximately half the population living below IDR15,000 per day (around PPP USD 2.25 a day). Marginal shocks therefore have profound effects on household welfare in Indonesia (Pritchett et al., 2000; Suryahadi et al., 2003). This has made poverty and vulnerability central policy issues for successive governments.

Indonesia has a long history of targeted social programs, and since 2005, the Indonesian government has experimented with several methods to identify and access vulnerable groups, while implementing several complimentary social programs. Alatas et al. (2012) and Cameron and Shah (2014) however, show that a significant proportion of poor households in Indonesia do not benefit from targeted poverty programs. To address these concerns, the Government of Indonesia (GoI) developed a Unified Targeting System, called the *Basis Data Terpadu* or Unified Database (UDB), through the establishment of TNP2K[6] under the auspices of the Office of the Vice-President of Indonesia and the Indonesian Central Bureau of Statistics (BPS), which was introduced in 2011.

The primary objectives of the UDB are: (i) to provide detailed socioeconomic information on the poor and most vulnerable households by name, and by address; (ii) to improve the targeting of social welfare programs; and (iii) to ensure that the social protection programs better complement one another. To achieve these objectives, efforts were made to unify program eligibility through the development of Proxy Means Test coefficients, *such that the poorest 25% of the population should be eligible for all three of Indonesia's flagship social welfare programs.* In so doing, the GoI aimed to reduce targeting errors and ensure that poor households received the benefits from multiple complimentary programs (TNP2K, 2015). Indonesia's three flagship programs are: Health Insurance for the Poor (*Asuransi Kesehatan untuk Keluarga Miskin*, or *Askeskin*, later renamed *Jamkesmas*), Rice for the Poor (*Beras Miskin*, or *Raskin*) and

[2] While Brière and Lindert (2005) and Castaneda and Fernandez (2005) pertain to unified eligibility in Brazil and Colombia respectively, both are descriptive in nature and neither provides a comparison of the effectiveness of targeting performance of unified targeting programs relative to single programs and neither examine the welfare benefits of unified targeting systems.

[3] The only other paper we are aware of that implements the administrative PMT scores is Bah et al (2018), who rely on the PMT coefficients from only six municipalities.

[4] See for example: Jalan and Ravallion (2003), Godtland et al. (2004), Hoddinott and Skoufias (2004) Galasso and Ravallion (2005), Pradhan et al. (2007) van de Walle and Mu (2007) and Bazzi, S. et al. (2015).

[5] Household welfare is measured using per capita expenditure. The administrative data also prove vital for estimating household per capita expenditure in 2011, which is calculated by applying observable 2014 data to the 2011 PMT coefficients, in order to produce a measure of the change in household welfare between 2011 and 2014.

[6] *Tim Nasional Percepatan Penanggulangan Kemiskinan* or the National Team for Accelerating Poverty Reduction.

Unconditional Cash Transfers (*Bantuan Langsung Tunai*, or BLT, later renamed BLSM).[7] Of the GoI's overall allocation of around 11.5 percent of total expenditure in 2016 on social programs, 87% was allocated to these three flagship programs.

The GoI introduced social security programs for the first time following the Asian Financial Crisis (Grosh et al., 2008; Sumarto and Bazzi, 2011).[8] These, the first generation of Indonesia's social protection programs, called *Jaring Pengaman Sosial* (JPS), were implemented under President Habibie's Administration in 1999/2000 (Widjaja, 2009). The JPS sought to protect chronically poor households from falling further into poverty while eliminating vulnerable households' exposure to risk (Sumarto et al., 2002).[9] The JPS was tasked with ensuring, among other duties, the availability of affordable food through the OPK (*Operasi Pasar Khusus* or special market operation program). In 2002, the GoI changed the OPK to become one of the largest social protection programs named *Raskin* (*Beras untuk Keluarga Miskin* or Rice for the Poor), which aimed to reduce household spending on food, especially on rice.

The second generation of social protection programs were implemented between 2005 and 2008 to alleviate the financial burden on households from rising oil prices. To mitigate the negative effects, especially on poor and near-poor households, the GoI launched the Fuel Subsidy Reduction Compensation Program, namely *Program Kompensasi Pengurangan Subsidi Bahan Bakar Minyak* (World Bank, 2006; Yusuf and Resosudarmo, 2008; Rosfadhila et al., 2011). Under this scheme, an Unconditional Cash Transfer program was introduced to complement the BLT (for *Bantuan Likuiditas Tunai* or Direct Cash Assistance). This program was subsequently renamed BLSM (for *Bantuan Langsung Sementara Masyarakat* or Temporary Unconditional Cash Transfer program) in 2013.[10] From July to September 2005, the GoI through Statistics Indonesia (*Badan Pusat Statistik* or BPS) conducted a census of poor households for the first time, with the aim of effectively implementing the BLT program. The database was also known as PSE05 (*Pendataan Sosial Ekonomi Penduduk*, 2005, or Socio-economic Data Collection of the Population).[11]

Due to concerns about the poor performance of the PSE05,[12] in 2008–2009 the GoI once again restructured the nationwide programs, by updating the list of program beneficiaries. At this time the government's three main flagship program were the BLT, *Raskin* and *Jamkesmas*. From the perspective of budget disbursement, BLT spending constitutes 40 percent of total social assistance expenditure, *Raskin* accounts for 34 percent and Jamkesmas for 13 percent (Jellema and Noura, 2012). This updated version, was known as the PPLS08 (*Pendataan Program Lindungan Sosial*, 2008, or Data Collection for Targeting Social Protection Programs). As with PSE05, this database was primarily used to identify eligible households for unconditional cash transfers. Due to time constraints however, the problems associated with PPLS08 were similar or worse than those of the PSE05 and errors in targeting continued (Rosfadhila et al., 2011). Some argue that targeting errors catalysed social unrest (Widjaja, 2009; Cameron and Shah, 2014).[12]

### 1.2. Introduction of the UDB

The UDB, first introduced in 2011,[13] was developed to harmonise social program eligibility, by standardising the list of intended beneficiaries, such that the bottom 25% of the households, were eligible for all three social programs. The introduction of the UDB therefore represents an ideal testing ground to evaluate the benefits of unified program eligibility in developing countries and for examining the role of complimentary social program benefits.[14] The poorest 40 percent of the population was first identified for inclusion in social assistance programs through proxy means testing.[15] Although the bottom 40% of the population are eligible for *Jamkesmas*, only the bottom 25% of households are eligible for *Raskin* and the *BLT* (see Fig. 1). Harmonising social program eligibility through the introduction of the UDB was expected to improve targeting outcomes and improve welfare through lowering targeting errors and by increasing complementarities between social assistance programs, which failed to occur under the previous targeting regime (TNP2K, 2015).

In comparison to the previous targeting system, a number of improvements were introduced, including: (1) an increase in the number of indicators used to measure household welfare (26 as opposed to 14) from the 2011 poverty census, namely PPLS11;[14] (2) greater coverage of households in PPLS11, reaching 40 percent of the population surveyed or approximately 24 million households; (3) the implementation of a two-stage targeting process in the data collection of PPLS11;[15] and (4) a PMT model to measure targeting thresholds based on 471 district-specific models, as opposed to using a single national threshold (TNP2K, 2015). Fig. 2 details the development of UDB and the use of the database for selecting poor beneficiaries of the poverty programs.

### 1.3. Introduction of the KPS

Following improvements in targeting, in the third quarter of 2013, the GoI introduced the Social Security Card (*Kartu Perlindungan Social - KPS)*. This card aimed to cover the bottom 25 percent of households or 15.5 million poor and near-poor households. The names of these households, derived from the UDB, entitled households to *Raskin*, temporary unconditional cash transfers (BLSM) and financial assistance for students of those family members (TNP2K, 2015). According to an ad-hoc committee established to diseminate information with regards to oil price subsidy reduction (Tim Sosialisasi Penyesuaian Subsidi Bahan Bakar Minyak, 2013), this card could also be used to access the Jamkesmas program. This is reasonable since, as shown in Fig. 1, the coverage of Jamkesmas is far higher than the coverage of the KPS. To ensure that every eligible household received the card without disruption, the GoI employed the postal mail service and cards were delivered

[7] We are unable to evaluate Indonesia's smaller social programs such as scholarship for the poor (Bantuan Siswa Miskin, or BSM), the Conditional Cash Transfer program (Program Keluarga Harapan, or PKH) and community block grants for education and development (Widianto, 2013), since their coverage is not nationwide and since their targeting is not based on the UDB but is rather based on the old targeting regime based on the PPLS08 else based on nominations by teachers, or school-based targeting.

[8] Please refer to in the Appendix, which summarizes the evolution of social safety net in Indonesia from 1997 to 2008.

[9] The GoI disbursed IDR3.9 trillion directly to JPS programs out of a total development budget of IDR14.2 trillion, with financial support from international donors including the World Bank and the Asian Development Bank (Sumarto and Bazzi, 2011).

[10] Under this program, the targeted household received cash transfers delivered via post office (Bazzi et al., 2015). The BLT cash benefit was IDR100,000 (roughly US$10) per month to each targeted recipient household and it was increased to IDR150,000 under the BLSM scheme.

[11] The data collection involved community-based nominations combined with other data to identify prospective beneficiary households based on fourteen selected indicators that represented the well-being of poor households, see Hastuti et al. (2006) for further details.

[12] Previous studies by Hastuti et al. (2006), Widjaja (2009) and World Bank (2012a), assert that the PSE05 and PPLS08 programs suffered from serious problems. They argue that since households who were nominated by sub-village heads were surveyed with the PMT questionnaire, many poor households were excluded.

[13] We take 2011 as our starting point, given that the baseline poverty census was conducted in that year.

[14] Pendataan Program Lindungan Sosial, 2011.

[15] The two-stage data collection involved (i) compiling lists of households using data from PPLS08 and the 2010 Population Census through poverty mapping; and (ii) complementing those data with the results of consultations with low-income groups and through impromptu discussions and general observations (Bah et al. 2018).

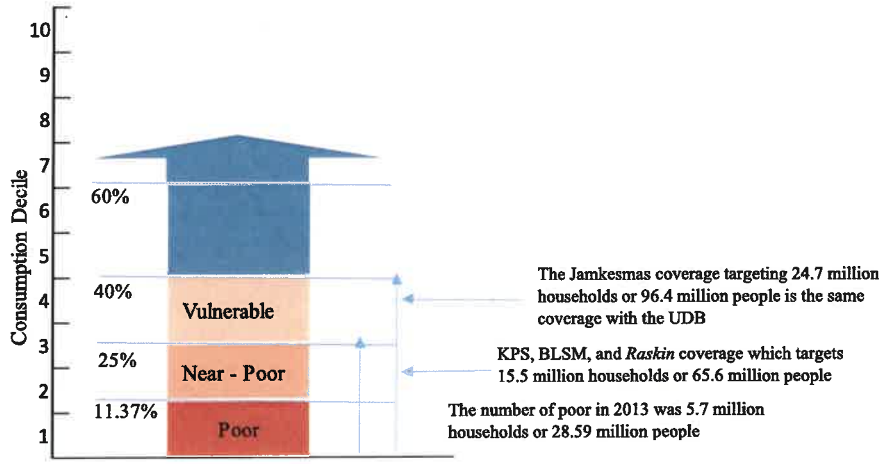



**Fig. 1.** The coverage of the UDB and Indonesia's three largest poverty programs.

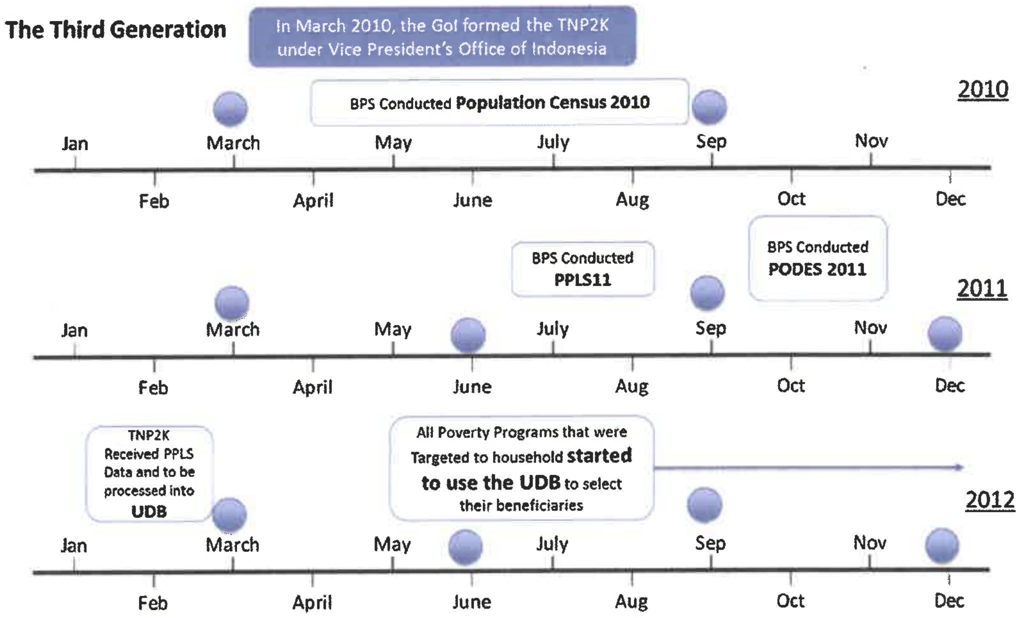



**Fig. 2.** Third generation of social protection programs and development of the UDB

directly to households where possible.[16] The overarching aim of the KPS, was to reinforce beneficiaries' rights to program entitlement, through receipt of the physical card as well as through the provision of an information pack that was delivered alongside the KPS. Given that the beneficiary list dervied from the UDB however, it is still possible that the Type I and Type II errors that remained features of the UDB were carried over to the disbursement of the KPS. These are described in further detail below.

### 1.4. *Targeting under complementarities*

The most popular indicators to measure targeting performance are: Type I errors (*undercoverage*) and Type II errors (*leakage*), although these have been developed along a number of dimensions (see: Coady et al., 2004, Galasso and Ravallion, 2005 and World Bank, 2012b). An important feature of all these performance measures is that they only evaluate the performance of single poverty programs. To evaluate the targeting performance of multiple programs simultaneously, we rather need to adopt an alternative approach, as shown in Table 1, wherein errors of inclusion and exclusion can be redefined under conditions of complementarities.

Following the notation and logic of Ravallion (1990), the three programs, BLT, *Raskin*, and *Jamkesmas* are abbreviated using (B), (R), and (J) respectively. Therefore, $B_B$ or $B_R$ or $B_J$ (the total number of beneficiaries in each program) is equal to P (the total number of individuals deemed poor). Similarly, the total number of non-beneficiaries under each program is denoted by NP. The term $ee_T$ refers to the share of poor households that do not receive any programs relative to the total number of poor households (i.e. errors of exclusion), and can formally be written as:

$$ee_T = \frac{E2_B}{P} + \frac{E2_R}{P} + \frac{E2_J}{P} + = \frac{E2_B + E2_R + E2_J}{P} \quad (1)$$

[16] According to the TNP2K (2015), between June and November 2013, the GoI sent the KPS card to 15, 530, 897 beneficiaries. At the end of the period, however, PT Pos reported that only 402,861 (i.e. 2.6% of the total) had been returned.

**Table 1**
Targeting matrix of the complementary multiple programs.

| | | Poverty Status | | Total |
|---|---|---|---|---|
| | | Poor | Non-poor | |
| Beneficiaries status of program BLT | Beneficiary | Correct inclusion ($C1_B$) | Error of Inclusion ($E1_B$) | $B_B$ |
| | Non- beneficiary | Error of Exclusion ($E2_B$) | Correct Exclusion ($C2_B$) | $NB_B$ |
| Beneficiaries status of program *Raskin* | Beneficiary | Correct inclusion ($C1_R$) | Error Inclusion ($E1_R$) | $B_R$ |
| | Non- beneficiary | Error of Exclusion ($E2_R$) | Correct Exclusion ($C2_R$) | $NB_R$ |
| Beneficiaries status of program *Jamkesmas* | Beneficiary | Correct inclusion ($C1_J$) | Error of Inclusion ($E1_J$) | $B_J$ |
| | Non- beneficiary | Error of Exclusion ($E2_J$) | Correct Exclusion ($C2_J$) | $NB_J$ |
| | | P | NP | T |

This table represent an extension of the standard matrix used in evaluation the performance of poverty targeting. The information about the standard matrix can be found in studies by Coady et al. (2004).

**Table 2**
Joint and marginal probabilities of poor households receiving poverty programs.

| | Joint probability | Marginal (BLT) | Marginal (*Raskin*) | Marginal (*Jamkesmas*) | Total |
|---|---|---|---|---|---|
| (1) | (2) | (3) | (4) | (5) | |
| BLT only | $(C_{B=1,R=0,\ J=0}/P)$ | $(C_{B=1,R=0,\ J=0}/P)$ | – | – | |
| *Raskin* only | $(C_{B=0,R=1,\ J=0}/P)$ | – | $(C_{B=0,R=1,\ J=0}/P)$ | – | |
| *Jamkesmas* only | $(C_{B=0,R=0,\ J=1}/P)$ | – | – | $(C_{B=0,R=0,\ J=1}/P)$ | |
| BLT and *Raskin* only | $(C_{B=1,R=1,\ J=0}/P)$ | $(C_{B=1,R=1,\ J=0}/P)$ | $(C_{B=1,R=1,\ J=0}/P)$ | | |
| BLT and *Jamkesmas* only | $(C_{B=1,J=1,\ R=0}/P)$ | $(C_{B=1,J=1,\ R=0}/P)$ | – | $(C_{B=1,J=1,\ R=0}/P)$ | |
| *Raskin* and *Jamkesmas* only | $(C_{R=1,\ J=1,\ B=0}/P)$ | – | $(C_{R=1,\ J=1,\ B=0}/P)$ | $(C_{R=1,\ J=1,\ B=0}/P)$ | |
| BLT, *Raskin* and *Jamkesmas* | $(C_{B=1,R=1,J=1}/P)$ | $(C_{B=1,R=1,J=1}/P)$ | $(C_{B=1,R=1,J=1}/P)$ | $(C_{B=1,R=1,J=1}/P)$ | |
| None | $(C_{B=0,R=0,\ J=0}/P)$ | – | – | – | $ee_T$ |
| Total | 100 | $C1_B/P$ | $C1_R/P$ | $C1_J/P$ | |

This table is constructed using information from Table 1 to measure the degree of complementarity of each program with respect to the others. For example, under perfect complementarities, the joint probability of poor households receiving three programs will be equal to the total marginal probability for all programs. This implies that under this condition, the joint probability for poor households receiving either one or two programs will be zero.

The error of inclusion $ei_T$, the ratio of non-poor beneficiaries to the total number of beneficiaries in each program is:

$$ei_T = \frac{E1_B}{B_R} + \frac{E1_R}{B_B} + \frac{E1_J}{B_J} = \frac{E1_B + E1_R + E1_J}{P} \quad (2)$$

To evaluate poverty targeting under program complementarities, we propose evaluation methods using probabilities that measure the likelihood of a poor household receiving either one, two, or all three programs simultaneously, else no program at all. Table 2 (column 2) shows the joint probabilities of poor households participating in one, two, all three programs, or no program at any given time. The marginal probabilities of poor households receiving each program are presented in Columns 3–5 of Table 2. Under conditions of perfect complementarities, the joint probability of poor households receiving all three programs will be equal to the sum of the constituent marginal probabilities.[17]

Using the information in Table 2, we further measure the degree of complementarity of each program with respect to the others. For example, the complementarity between BLT and *Raskin* is measured by:

$$P(BLT = 1|Raskin = 1) = \frac{(C_{B=1,R=1,\ J=0}/P) + (C_{B=1,R=1,J=1}/P)}{C1_B/P} \quad (3)$$

Where $P(BLT = 1|Raskin = 1)$ denotes the conditional probability of poor households receiving the BLT, given that they also receive benefits from the *Raskin* program. The term $(C_{B=1,R=1,\ J=0}/P)$ represents the joint probability of receiving both BLT and *Raskin* programs and the expression $(C_{B=1,R=1,J=1}/P)$ is the joint probability of receiving all three programs. The denominator$C1_B/P$, refers to marginal probability of receiving the BLT program.

The complementarity of the BLT program with respect to the two other programs can be assessed using:

$$P(BLT = 1|Raskin = 1, Jamkesmas = 1) = \frac{(C_{B=1,R=1,J=1}/P)}{((C_{B=1,R=1,J=1}/P) + (C_{R=1,\ J=1,\ B=0}/P))} X\ 100 \quad (4)$$

Where $P(BLT = 1|Raskin = 1, Jamkesmas = 1)$ measures the likelihood of a poor household receiving BLT given that they also participate in the other two programs. The term $(C_{B=1,R=1,J=1}/P)$ represents the joint probability of poor households participating in those three programs, while $(C_{R=1,\ J=1,\ B=0}/P)$ is the joint probability of the poor households receiving both *Raskin* and *Jamkesmas* programs.

## 2. Data

To evaluate the performance of poverty targeting under the UDB, the analysis draws on data from the National Socioeconomic Survey (SUSENAS), the Social Protection Survey (SPS) and the Village Potential Census (PODES) described in detail below. Fig. 3 provides a time-line of the various data collection activities.

### 2.1. SUSENAS surveys

In this paper, we utilize data from the 2005, 2009 and 2014 waves of the SUSENAS survey to: (1) measure the benefit incidence from poverty programs and their targeting performance relative to previous efforts; (2) predict the poverty level of each household; and (3) estimate the relationship between poverty, social protection eligibility and household characteristics, particularly using the 2014 SUSENAS survey.[18]

[17] Under this condition, the joint probability for poor households receiving either one or two programs will therefore be zero.

[18] The National Socioeconomic Survey (SUSENAS) is an annual cross-sectional, nationally representative dataset, initiated in 1963–1964 and fielded once every year or two since then. In 2011, however, the BPS changed the survey frequency to quarterly. This covers some 300,000 individuals and 75,000 households quarterly.

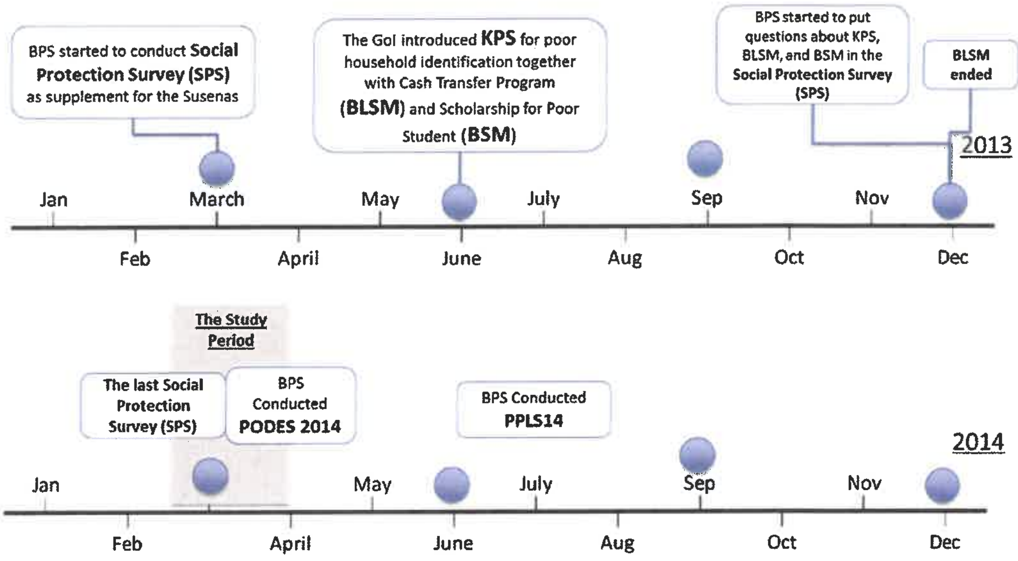



**Fig. 3.** Time horizon of data collection in the periods between 2013 and 2014.

**Table 3**
Observed joint and marginal probabilities of the poor household receiving the poverty programs.

| Targeting Methods → | 2005[a] | | | | 2009[a] | | | | 2014[b] | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Probabilities → | Joint | Marginal Probabilities | | | Joint | Marginal Probabilities | | | Joint | Marginal Probabilities | | |
| Programs ↓ | | BLT | *Raskin* | *Jamkesmas* | | BLT | *Raskin* | *Jamkesmas* | | BLT | *Raskin* | *Jamkesmas* |
| BLT only | 7.89 | 7.89 | | | 5.30 | 5.30 | | | 3.90 | 3.90 | | |
| *Raskin* only | 18.28 | | 18.28 | | 23.22 | | 23.22 | | 19.26 | | 19.26 | |
| *Jamkesmas* only | 0.93 | | | 0.93 | 1.75 | | | 1.75 | 4.42 | | | 4.42 |
| BLT and *Raskin* only | 30.96 | 30.96 | 30.96 | | 24.78 | 24.78 | 24.78 | | 9.60 | 9.60 | 9.60 | |
| BLT and *Jamkesmas* only | 1.73 | 1.73 | | 1.73 | 1.66 | 1.66 | | 1.66 | 8.36 | 8.36 | | 8.36 |
| *Raskin* and *Jamkesmas* only | 2.93 | | 2.93 | 2.93 | 3.29 | | 3.29 | 3.29 | 9.22 | | 9.22 | 9.22 |
| BLT, *Raskin* and *Jamkesmas* | 15.66 | 15.66 | 15.66 | 15.66 | 12.49 | 12.49 | 12.49 | 12.49 | 27.34 | 27.34 | 27.34 | 27.34 |
| None | 21.62 | | | | 27.51 | | | | 17.91 | | | |
| Total | 100.00 | 56.24 | 67.83 | 21.23 | 100.00 | 44.23 | 63.78 | 19.20 | 100.00 | 49.19 | 65.41 | 49.33 |

This table presents the joint and marginal probability of poor households receiving either one, two or all three programs, measured using the formula presented in Table 2. Source: Authors' calculation. Note: a) measured using SUSENAS 2006 and 2009; b) measured using SUSENAS and Social Protection Survey (SPS) 2014.

### 2.2. Social Protection Survey (SPS)

The second dataset used in the analysis is the 2014 Social Protection Survey (SPS). This survey was implemented from the first quarter of 2013 to the first quarter of 2014 and was specifically aimed at examining the performance of poverty targeting under the implementation of the UDB. A question pertaining to the KPS was only asked in the last two rounds. Therefore, we use data from the first quarter of 2014 since it was the period just after the implementation of the KPS. We use this survey to obtain information about the implementation of KPS relating to the benefits received by poor households from the poverty targeting.

### 2.3. Village census (PODES)

The last source of data is from the 2014 PODES, which provides information on all villages/*desa* in Indonesia. This village census covers a sample of around 80,000 villages and is fielded around periodic censuses. It includes useful information on village characteristics, including the main sources of income, population and labor force characteristics, socio-culture, type of village administration and other relevant village-level information.

### 2.4. Merging the datasets

Since 2011 the BPS has not published the village and subdistrict codes for the SUSENAS dataset, making the process for merging these datasets challenging. In meeting this challenge, we construct our data as follows:

i) We merge the Quarter 1 2014 SPS with Quarter 1 2014 SUSENAS using the household ID that is available in both datasets. In all, we merge 70,336 households of the SPS sample to the total 71,051 sample of the SUSENAS.
ii) We merge those two datasets with the 2014 pooled SUSENAS data to obtain village and sub-district IDs using a 'bridging code' shared privately with us.[19]
iii) Finally, we merge the resulting dataset with the PODES data using the village ID to obtain village level variables. After merging with the PODES data, we are able to identify 67,118 households as well as details of their expenditure, social protection and village

[19] We are grateful to a staff member of the TNP2K targeting team who provided us with this bridging code.

information that can be combined with the official PMT coefficients in order to obtain individual household PMT scores (see below).

In addition to the merging, the administrative data were relied upon to estimate household per capita expenditure in 2011. This was calculated first by applying the 2011 UDB district-specific coefficients to the 2014 SUSENAS household data comprising all variables used to calculate the PMT score (please refer to Table A5) to generate an estimate of per capita household expenditure in 2011. This was then adjusted for CPI inflation during the first quarter of 2011 so as to make per capita household expenditure as close as possible to the pre-treatment conditions in the second and the third quarter of 2011. To validate our estimates of real per capita expenditure at the district level, we compared them to the real per capita expenditure data from SUSENAS, 2011. No significant differences were found. This is unsurprising since the PMT coefficients used in the UDB were developed using data from SUSENAS, 2011. Nevertheless, our recovery of the 2011 household per capita expenditures raises the spectre of measurement error in our dependent variable, although ceteris paribus this should not affect our coefficient estimates but rather widen our confidence intervals. All the variables used in this study are presented in Tables A1 and A2 in the Appendix.

## 3. The implementation of the UDB, targeting errors and complementarities

In this section, using our nationally representative data, we document the evolution of targeting outcomes in Indonesia under the condition of complementarities between 2005 and 2014.[20] The poor performance of poverty targeting based on the PSE05 is confirmed in the 2005 panel (Table 3), which presents the joint and marginal probabilities of receiving different program combinations in that year. The probability of a poor household receiving *Raskin* was 67.83 percent, significantly higher than the 56.24 percent for BLT and 21.25 percent for *Jamkesmas*, respectively. Another striking feature is with regards to program complementarities. For example, as shown in the first column of Table 3, only 15.66 percent of eligible poor households received all three programs, while 21.62 percent of eligible households received none.[21]

The results of targeting based on the PPLS08 for the 2009 panels are presented in Tables 3 and 4 respectively. The joint probability of poor households receiving all three programs based on the PPLS08 targeting method is slightly lower than targeting based on PSE05 (12.49 percent as opposed to 15.66 percent). Table 4 shows that in 2009 the complementarities of the three programs were almost identical, albeit a little worse, to the previous targeting regime. For example, among poor households that were *Raskin* recipients, only 58.43 percent received BLT transfers and 24.75 percent received benefits from the *Jamkesmas* program, respectively.

The performance of poverty targeting after the introduction of the UDB in 2011, under unified program eligibility, is significantly better than the targeting based on the PSE05 and PPLS08, as illustrated in the 2014 panels of Tables 3 and 4 There was no significant improvement in the marginal probabilities of receiving *Raskin* or BLT compared to previous targeting efforts, although *Jamkesmas* participation more than doubled. Importantly, from the perspective of program complimentarities, the *joint* probability of participation in all three programs more than doubled between 2009 and 2014, from 12.49 percent to 27.34 percent; while the proportion of poor households that did not receive any program decreased from 27.51 percent to 17.91 percent over the same period. In Table A3, we further show that all these improvements are statistically significant.

Program complementarities dramatically improved following the introduction of the UDB, as shown in Table 4. Among poor households who benefited from the BLT for example, 75.09 percent were also *Raskin* recipients, while 72.56 percent also received *Jamkesmas* benefits. These figures are significantly higher than the unconditional probabilities of receiving *Raskin* (65.41 percent) and *Jamkesmas* (49.33 percent). In 2014, 72.35 percent of *Jamkesmas* beneficiaries from poor households also received BLT and 74.10 percent also received *Raskin*. Overall, in terms of the complementarities with other programs, we observe that access to *Jamkesmas* improved significantly. Prior to the implementation of the UDB, for example, only 33.58 percent and 33.52 percent of poor households in 2005 and 2009 respectively that received *Raskin* and *BLT* had access to *Jamkesmas*. Following the implementation of the UDB however, this percentage increased to 74.01. This improvement can be explained by the fact that prior to the implementation of the UDB, *Jamkesmas* was delivered based on self-targeting through the use of a poverty statement (*Surat Keterangan Miskin*) issued by local leaders (World Bank, 2012a, 2012b).

### 3.1. Did the KPS improve poverty targeting and poverty programs complementarities?

While our previous analysis highlights the improvements made in poverty targeting and program complementarities following the introduction of the UDB, in this section we further examine the impact of the introduction of the KPS on these outcomes.

Table 5 compares the joint and marginal probabilities of participating in the poverty programs comparing poor households that received the KPS (KPS holders) to those that did not (Non-KPS holders). From columns (5) and (9) we observe that the joint probability of participating in all three programs for KPS holders is significantly higher than for non-KPS holders (56.64 percent as opposed to 3.78 percent). Conversely, the joint probability of not receiving any of the three programs for a KPS holder is significantly lower than for a non-KPS holder (0.45 percent compared to 30.83 percent). The marginal probabilities are also much higher for KPS holders. For example, the probability of receiving BLT is 96.25 percent for KPS holders, while it is only 11.45 percent for non-KPS holders. We document these improvements in Table A4 in Appendix, which shows that the differences in joint probabilities over time are statistically significant.

Table 6 demonstrates that the introduction of the KPS also improved the complementarities between poverty programs. Among KPS holders, for example, the likelihood of receiving BLT for those who also received *Raskin* and *Jamkesmas* is much higher than for Non-KPS holders, (97.57 percent as compared with 19.8 percent). Similarly, the probability of KPS holders to receive *Jamkesmas*, while also being BLT and *Raskin* beneficiaries is 77.24 percent, while it is only 48.91 percent for non-KPS holders.

This evidence complements the findings of Banerjee et. al (2018) in the context of the *Raskin* program, since those authors find that eligibility status and information provision significantly increased subsidies received by beneficiaries. While the present study focuses on the extensive margin, we further show that receiving the KPS increases the probability of poor households receiving additional programs.

[20] The sample of households we use for this analysis is the bottom 11.37% of the distribution of households i.e. 'poor' households. This is because, as outlined in World Bank (2012a) the definition of the 'near-poor' proved inconsistent in the time periods before and after the introduction of the Unified Database. In the first part of our analysis therefore, we only document the receipt of programs for households that are eligible for all three programs over the entire period.

[21] The conditional probabilities of participating households in the 2005 panel are provided in Table 4, which can also be used to measure the complementarities between social assistance programs. For example, the probability of a poor household receiving *Raskin*, given that they are a recipient of both BLT and *Jamkesmas* is higher than 90 percent, while the probability of a poor household participating in both BLT and *Raskin* to also receive the *Jamksemas* program is 33.6 percent.

**Table 4**
Observed conditional and unconditional probabilities of poor households receiving poverty programs based on different targeting methods.

| Targeting Methods → | 2005[a] | | | 2009[a] | | | 2014[b] | | |
|---|---|---|---|---|---|---|---|---|---|
| Probabilities → | BLT | *Raskin* | *Jamkesmas* | BLT | *Raskin* | *Jamkesmas* | BLT | *Raskin* | *Jamkesmas* |
| Programs ↓ | | | | | | | | | |
| P (.) | 56.24 | 67.83 | 21.23 | 44.23 | 63.78 | 19.20 | 49.19 | 65.41 | 49.33 |
| P (. \|BLT = 1) | 100.00 | 82.89 | 30.91 | 100.00 | 84.26 | 32.00 | 100.00 | 75.09 | 72.56 |
| P (. \|*Raskin* = 1) | 68.73 | 100.00 | 27.40 | 58.43 | 100.00 | 24.75 | 56.47 | 100.00 | 55.88 |
| P (. \|*Jamkesmas* = 1) | 81.85 | 87.51 | 100.00 | 73.74 | 82.23 | 100.00 | 72.35 | 74.10 | 100.00 |
| P (. \|*Raskin* = 1, *Jamkesmas* = 1) | 84.25 | 100.00 | 100.00 | 79.14 | 100.00 | 100.00 | 74.79 | 100.00 | 100.00 |
| P (. \|BLT = 1, *Jamkesmas* = 1) | 100.00 | 90.07 | 100.00 | 100.00 | 88.25 | 100.00 | 100.00 | 76.59 | 100.00 |
| P (. \|BLT = 1, *Raskin* = 1) | 100.00 | 100.00 | 33.58 | 100.00 | 100.00 | 33.52 | 100.00 | 100.00 | 74.01 |

This table presents conditional and unconditional probabilities measured based on information in Table 3. The number on each cell of the table is derived using formula presented in either Equations (1)–(3), or 4 depending its condition. Note: a) are measured using SUSENAS 2006 and 2009; b) is measured using SUSENAS and Social Protection Survey (SPS) 2014.

**Table 5**
Observed joint and marginal probabilities of the poor household receiving the poverty programs in 2014 (with or without KPS).

| Classification → | Poor Households - All Sample | | | | Poor Households - with KPS | | | | Poor Households - without KPS | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Probabilities → | Joint | Marginal Probabilities | | | Joint | Marginal Probabilities | | | Joint | Marginal Probabilities | | |
| Programs ↓ | | BLT | *Raskin* | *Jamkesmas* | | BLT | *Raskin* | *Jamkesmas* | | BLT | *Raskin* | *Jamkesmas* |
| BLT only | 3.90 | 3.90 | | | 6.37 | 6.37 | | | 1.95 | 1.95 | | |
| *Raskin* only | 19.26 | | 19.26 | | 0.62 | | 0.62 | | 34.87 | | 34.87 | |
| *Jamkesmas* only | 4.42 | | | 4.42 | 1.27 | | | 1.27 | 7.08 | | | 7.08 |
| BLT and *Raskin* only | 9.60 | 9.60 | 9.60 | | 16.69 | 16.69 | 16.69 | | 3.95 | 3.95 | 3.95 | |
| BLT and *Jamkesmas* only | 8.36 | 8.36 | | 8.36 | 16.55 | 16.55 | | 16.55 | 1.78 | 1.78 | | 1.78 |
| *Raskin* and *Jamkesmas* only | 9.22 | | 9.22 | 9.22 | 1.41 | | 1.41 | 1.41 | 15.77 | | 15.77 | 15.77 |
| BLT, *Raskin* and *Jamkesmas* | 27.34 | 27.34 | 27.34 | 27.34 | 56.64 | 56.64 | 56.64 | 56.64 | 3.78 | 3.78 | 3.78 | 3.78 |
| None | 17.91 | | | | 0.45 | | | | 30.83 | | | |
| Total | 100.00 | 49.19 | 65.41 | 49.33 | 100.00 | 96.25 | 75.36 | 75.88 | 100.00 | 11.45 | 58.36 | 28.41 |

This Table presents probabilities measured as in Table 4 by dividing the sample whether the households received KPS or did not. Note: These probabilities are measured using SUSENAS and Social Protection Survey (SPS) 2014.

**Table 6**
Observed conditional and unconditional probabilities of the poor household receiving the poverty programs in 2014 (with or without KPS).

| Classification → | Poor Households - All Sample | | | Poor Households - with KPS | | | Poor Households - without KPS | | |
|---|---|---|---|---|---|---|---|---|---|
| Probabilities → | BLT | *Raskin* | *Jamkesmas* | BLT | *Raskin* | *Jamkesmas* | BLT | *Raskin* | *Jamkesmas* |
| Programs ↓ | | | | | | | | | |
| P (.) | 49.19 | 65.41 | 49.33 | 96.25 | 75.36 | 75.88 | 11.45 | 58.36 | 28.41 |
| P (. \|BLT = 1) | 100.00 | 75.09 | 72.56 | 100.00 | 76.19 | 76.05 | 100.00 | 67.49 | 48.52 |
| P (. \|*Raskin* = 1) | 56.47 | 100.00 | 55.88 | 97.31 | 100.00 | 77.03 | 13.24 | 100.00 | 33.49 |
| P (. \|*Jamkesmas* = 1) | 72.35 | 74.10 | 100.00 | 96.46 | 76.51 | 100.00 | 19.56 | 68.82 | 100.00 |
| P (. \|*Raskin* = 1, *Jamkesmas* = 1) | 74.79 | 100.00 | 100.00 | 97.57 | 100.00 | 100.00 | 19.34 | 100.00 | 100.00 |
| P (. \|BLT = 1, *Jamkesmas* = 1) | 100.00 | 76.59 | 100.00 | 100.00 | 77.39 | 100.00 | 100.00 | 68.02 | 100.00 |
| P (. \|BLT = 1, *Raskin* = 1) | 100.00 | 100.00 | 74.01 | 100.00 | 100.00 | 77.24 | 100.00 | 100.00 | 48.91 |

This table present probabilities measured as in Table 5 with dividing the sample becomes either the households received KPS or did not. These probabilities are measured using SUSENAS and Social Protection Survey (SPS) 2014.

## 4. Empirical estimation

While the introduction of the UDB and the KPS significantly improved poverty targeting and program complimentarities, in this section, we assess the impact of these improvements on household welfare.[22] To assess program complimentarities, an outcome measure that is affected by all three program is required, for which we use household per capita expenditures and a P1 measure of poverty.

For each household $h$, $h = 1, 2, \ldots .N$ in the sample, the triplet $(Y, R, X)$ is observed. $Y$ is the potential outcome, $R$ is a multilevel treatment variable, which takes an integer value between 0 and $P$. $X$ represents the vector of pre-treatment covariates, while $D_h^r(R_h)$ is the indicator of receiving treatment $r$ for household $h$:\

$$D_h^r(R_h) = \begin{cases} 1, & \text{if } R = r \\ 0, & \text{otherwise.} \end{cases}$$

For each household, there is a set of potential outcomes $(Y_h^0, \ldots, Y_h^P)$. $Y_h^r$ represents the potential outcome for each household $h$, for which $R = r$ where $r \in \mathbb{N}_0 = \{0, \ldots\ldots, P\}$ In this study, we are primarily interested in the average treatment effect on the treated (ATT), $\theta$, of participating in one or more of several poverty programs $R$, relative to the counterfactual of not receiving one or more of the programs, such that:

[22] Note that in this section we include the bottom 40% of households in our sample, in other words, all 'poor', 'near poor' and vulnerable households. The fact that 'vulnerable' households are only eligible for Jamkesmas is irrelevant for our analysis, since the prevalence of Type I and Type II errors in each strata of the propensity score provides sufficient counterfactual observations. Also note that due to our stratification of the propensity score, our matching process will likely never match and thus compare 'poor' and 'vulnerable' households since they will differ in their PMT score.

$$\theta_{\widetilde{rc}} \equiv \theta_r - \theta_c \equiv E[Y_h^r(\theta_r) - Y_h^c(\theta_c) \,|R=r] \tag{5}$$

for potential outcomes of household *h*. The different treatment level received by each household given pre-treatment variables is represented either by *r* or *c*. Our goal is to identify the parameter vector $\delta \equiv \theta_{\widetilde{rc}}$. We therefore denote the difference in per capita expenditure (PCE) as:

$$(PCE_{h+1}|R=r)e(PEC_{h,h+1}|R=c) = \theta_{rc+\varepsilon h,h+1} \tag{6}$$

where $\theta_{\widetilde{rc}} = \theta_r - \theta_c$ is the average-on-the-treated effect and $\varepsilon_{h.\ t+1}$ is the error term. Since our study relies on observational data, our aim is to ensure that $\varepsilon_{h.\ t+1}$ is as close as posssible to zero, such that our results equate as closely as possible to a quasi-experimental scenario.[23]

Taking into consideration the advantages of efficiency and practicality, following Hirano et al. (2003), Abadie (2005) and Bazzi et al. (2015), we implement a semiparametric reweighting estimator.[24,25]

### 4.1. Estimation of the propensity score

Propensity score estimation, which can be used to adjust for differences in pre-treatment variables, is a crucial step when matching is implemented as an evaluation strategy (Rosenbaum and Rubin, 1983, 1984). The underlying principle is that the pre-intervention variables that are not influenced by participation in the program should be included in the regression (Jalan and Ravallion, 2003).

Non-experimental estimators can benefit from exploiting the program design for identification.[26] The first-best solution is to estimate the propensity scores using both the PMT score generated from official coefficients used by the GoI as well as the underlying variables selected for the construction of the PMT score.[27,28] The PMT score for the poorest 40 percent in the UDB was measured using the district-specific models for the 471 Indonesian districts.[29] We apply these official district-specific coefficients, using data from the first quarter of 2014 to generate $\widehat{p}_h$, the probability that a household received the poverty program i.e. the PMT scores. We implement the procedure from Crump et al (2009) to calculate the optimal bounds. For the sake of comparison we use the same covariates that were used in the PMT model, as detailed in Table A5 of the Appendix.

The results are shown in Fig. 4. The estimation of the propensity score based on the PMT scores alone are shown in the left panel (A), while the estimation using the underlying covariates is shown in the right panel (B). The estimation based on the PMT score is demonstrably better in terms of the considerable overlap in the propensity score of treated (T = 1) and control (T = 0) units. We therefore select the PMT score-based estimates as inverse probability weights to rebalance recipient and non-recipient households along observable dimensions.

### 4.2. Balancing groups

Next we reweight the sample to ensure that the non-treated group is as comparable as possible to the treated group (in terms of the propensity score). As described by Abadie (2005), Smith and Todd (2005) and Busso et al. (2014), all estimators adjusting for covariates can be understood as different methods to weight the observed outcomes using weight, $\widehat{\omega}$.

Under the case of binary treatment, we can rewrite the average treatment effect on the treated as:

$$\widehat{\theta} = {}^1\!/_{N_1} \sum_{h=1}^{N} \widehat{D_h^r(R_h)}\widehat{\omega}_h Y_h^r - {}^1\!/_{N_0} \sum_{h=1}^{N}(1 - D_h^r(R_h))\widehat{\omega}_h Y_h^0 \tag{7}$$

$$N_1 = \sum_{h=1}^{N} \widehat{D_h^r(R_h)}, \qquad N_0 = N - N_1 \tag{8}$$

Where *N* represents the sample size of an i.i.d sample, $N_1$ denotes the size of the treated subsample and $\widehat{D_h^r(R_h)}$ the sample's predicted probability of receiving any poverty programs.

Following Busso et al. (2014), we normalize the weights such that: ${}^1\!/_{N_0} \sum_{h=1}^{N}(1 - \widehat{D_h^r(R_h)})\widehat{\omega}_h Y_h^0 = 1$. The contribution of the non-recipient to the counterfactual, $\widehat{\omega}$, can then be directly computed as proportional to their estimated odds of treatment, $\widehat{\omega_h} = \widehat{D_h^r(R_h)} \,/\, (1 - \widehat{D_h^r(R_h)})$.

Fig. 5 shows the distribution of the baseline PMT across treatment levels. Reassuringly, households receiving all three programs are on average relatively poor, compared to other households. Conversely, households that do not receive any program benefits (i.e. our control group) are relatively rich when compared to other groups. After reweighting however, the distribution of the control group moves substantially to the left, therefore significantly improving the overlap with the treatment groups.

### 4.3. Alternative estimators of the average treatment effect

Studies by Imbens and Wooldridge (2009) and Busso et al. (2014) discuss different estimators (beyond OLS) that are suitable under the reweighting approach. Following these, we consider (1) reweighting estimators using the estimated odds of treatment, $\widehat{\omega}$; (2) double robust estimation controlling the IPW estimators using either their propensity scores, $(\widehat{P}_h)$ or the PMT score $(PMT_h)$, as suggested by Scharfstein et al. (1999) and Lunceford and Davidian (2004)[30] (3) Control function

[23] This means that estimation of $\theta_{\widetilde{rc}}$ should satisfy several assumptions including (1) weak unconfoundedness which Imbens and Guido (2000) formally states as follows: $Y_h^r \perp D_h^r(R_h) \,|\, X_h,\ \forall r \in \mathbb{N}_0$. where $\perp$ denotes orthogonality or independence. Under this assumption, it requires that all determinants of treatment level and the outcome variable are observed. (2) complete overlap that can be formally stated as follows: $0 < \Pr[R_h = r\,|X_h = h],\ \forall r \in \mathbb{N}_0$ and $\forall x$ in the support of.*X*.

[24] Reweighting estimators often have better finite sample properties than common matching procedures (Busso et al., 2014), and given that, multiple treatments are considered, it is computationally less complicated.

[25] Despite our privileged access to administrative data, our empirical setting and our emphasis on program complementarities does not naturally lend itself to an RDD as is the case for example in Tohari et al., (2018). This is because in theory, 15% more of the population were eligible for *Jamkesmas* as when compared to *Raskin* and *BLT*, which in turn would mean that in an RDD setting in the case of *Jamkesmas*, we could only compute the ATE for households who received *Jamkesmas* with those that received nothing and *Jameskas* beneficiaries with households that received all three programs.

[26] We also attempted to merge the SPS data with the UDB database so as to estimate the PMT score for each household. Using KPS codes to facilitate the merge, however, we only managed to match 5669 households from the SPS sample of 70,336 and the UDB sample of 25.5 million households. Ultimately, the matched households all belonged to the same consumption decile and did not vary sufficiently in terms of their PMT score, number of poverty programs received and household characteristics. These matched data fail to generate a sufficiently large region of common support, or so-called "failure of common support" (Ravallion, 2007).

[27] We are grateful to TNP2K for providing us with access both to the PPLS 2011 database and the 471 district-specific coefficients for generating the UDB database.

[28] Most covariates attributed to the non-poor condition of households have a negative relationship with the probability of receiving poverty programs, inlcuding (1) the likelihood of male headed households the government programs; (2) the education level of the household head (3) households that have more assets (e.g. gas ≥12 kg; refrigerator; motorcycle).

[29] There are 482 districts in Indonesia, of which we use 471 in our analysis since 11 districts are dropped when we merge our data.

[30] Under this treatment, the estimation produces consistent estimators, while also potentially reducing bias due to any misspecification of the propensity score.

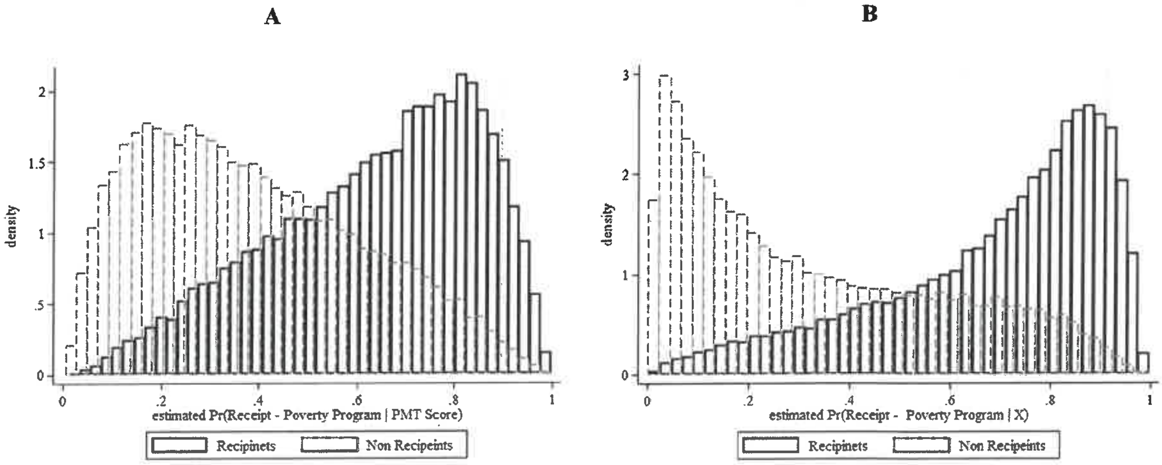



**Fig. 4.** Estimation of Propensity Score based on PMT Score and Underlying Covariates.

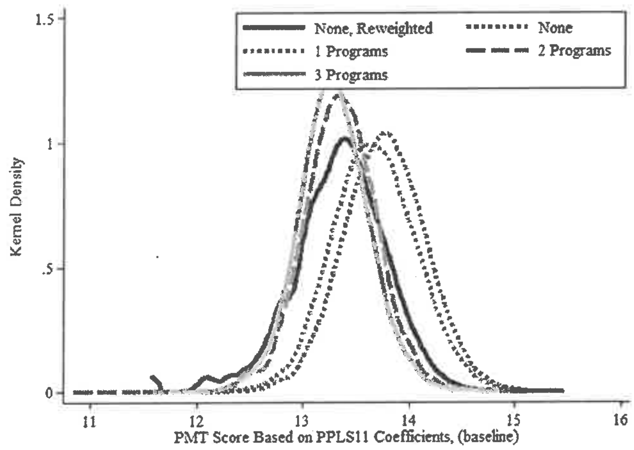



**Fig. 5.** Baseline of PMT score across treatment level.

estimation, following Rosenbaum and Rubin (1984), which stratifies the propensity score (which in turn is based on the PMT score) into five subclasses, while including the PMT score in the first stage regression. The average treatment effect on the treated is then measured within a specific stratum and is then weighted across strata.

## 5. Results

### 5.1. Household per capita expenditure

Table 7 presents the estimation of the ATT using as the dependent variable the difference, between 2011 and 2014 per capita expenditure (PCE) between households before and after treatment. This outcome variable is measured using the ratio of real per capita expenditure in 2014 and an estimate of real per capita expenditure, which is generated using 471 district-specific coefficients of the UDB.

Over the period of study, households that did not receive any poverty program experienced a decrease in their PCE of between 19 and 35 percentage points. Households that received all three programs experienced PCE growth of around 33 percentage points on average (Table 7). Similarly, poor households that received two poverty programs also experienced an increase in their PCE, though at a lower rate when compared to households that received all three. Relative to households that did not receive any program, households that received two programs experienced a rise in per capita expenditure of about 26 percentage points on average. Households that received only one program experienced negative growth in PCE of 13 percentage points on average. Comparing these households to the non-receiving group however, we observe that these households are still better off (by around 15 percentage points) relative to those households that did not receive any program.

Summing up, the implementation of multifaceted poverty programs are shown to significantly impact on per capita expenditures of poor households. A household that received only one program experienced a negative growth in PCE. This may be because during the study period, the GoI reduced the fuel price subsidy, which resulted in inflation in the basket of goods used by the poor (World Bank, 2006; Yusuf and Resosudarmo, 2008).

### 5.2. Robustness check: alternative outcome variable

As an alternative outcome variable, one which is affected by all three social programs that we are evaluating, we use a P1 measure of poverty, a normalised per capita poverty gap (Foster et al., 1984). These results confirm the monotonic increases of the impact of multifaceted programs, in other words households that received a greater number of programs experienced a larger decrease in the P1 measure of poverty. For example, households that receive all three programs (in the upper panel of Table 8) experience a decrease of around 0.9 percentage points on average. Concurrently, the poverty gap of the control group increases by almost 2.6 percentage points. Taken together, we observe that on average the poverty gap of those households that receive all three programs shrank by around 3.5 percentage points.

### 5.3. Robustness check: generalised propensity score

Taking into consideration the multilevel treatment and joint inference due to complementarities of the programs, next we discuss the robustness of our findings accounting for alternative approaches to deal with multiple treatments (see: Athey and Imbens, 2017). For example, Imbens and Guido (2000) and Hirano and Imbens (2004) propose the use of a Generalised Propensity Score (GPS) which is a generalization of the conventional binary-case matching estimation. Under the GPS, the conditional probability of receiving a specific level of treatment given pre-treatment variables is defined as:

$$g(r,x) \equiv \Pr[R_h = r \mid X_h = x] = E\left[D_h^r(R_h) \mid X_h = x\right]. \tag{9}$$

The average potential outcomes can also be identified, as in the binary treatment case, by weighting observed outcomes with the conditional probability of receiving treatment, as follows:

**Table 7**
Difference in per capita expenditures.

| Estimator | OLS | IPW | Double Robustness ($\hat{p}_h$) | Double Robustness ($PMT_h$) | Control Function |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *3 Programs vs. None* | | | | | |
| | 0.085 | 0.085 | 0.126 | 0.126 | 0.143 |
| | (0.012) | (0.012) | (0.012) | (0.012) | (0.012) |
| | −0.248 | −0.284 | −0.274 | −0.274 | −0.190 |
| | (0.009) | (0.010) | (0.009) | (0.009) | (0.011) |
| | **0.333** | **0.369** | **0.400** | **0.400** | **0.332** |
| | (0.013) | (0.014) | (0.013) | (0.014) | (0.013) |
| Reweighted | No | Yes | Yes | Yes | Yes |
| Propensity Score Control | No | No | Yes | No | Yes |
| PMT score control | No | No | No | Yes | No |
| Number of Households | 63,681 | 66,972 | 66,972 | 66,972 | 66,972 |
| | 0.154 | 0.159 | 0.178 | 0.178 | 0.184 |
| *2 Programs vs. None* | | | | | |
| | 0.036 | 0.034 | 0.053 | 0.052 | 0.058 |
| | (0.010) | (0.010) | (0.011) | (0.011) | (0.011) |
| | −0.256 | −0.293 | −0.287 | −0.287 | −0.204 |
| | (0.009) | (0.009) | (0.010) | (0.009) | (0.012) |
| | **0.292** | **0.327** | **0.340** | **0.339** | **0.262** |
| | (0.011) | (0.012) | (0.013) | (0.013) | (0.013) |
| Reweighted | No | Yes | Yes | Yes | Yes |
| Propensity Score Control | No | No | Yes | No | Yes |
| PMT score control | No | No | No | Yes | No |
| Number of Households | 63,681 | 66,972 | 66,972 | 66,972 | 66,972 |
| | 0.153 | 0.158 | 0.177 | 0.176 | 0.182 |
| *1 Program vs. None* | | | | | |
| | −0.068 | −0.064 | −0.104 | −0.105 | −0.130 |
| | (0.010) | (0.010) | (0.011) | (0.010) | (0.010) |
| | −0.300 | −0.334 | −0.353 | −0.352 | −0.276 |
| | (0.010) | (0.011) | (0.012) | (0.012) | (0.012) |
| | **0.232** | **0.270** | **0.248** | **0.248** | **0.146** |
| | (0.009) | (0.010) | (0.010) | (0.010) | (0.012) |
| Reweighted | No | Yes | Yes | Yes | Yes |
| Propensity Score Control | No | No | Yes | No | Yes |
| PMT score control | No | No | No | Yes | No |
| Number of Households | 63,681 | 66,972 | 66,972 | 66,972 | 66,972 |
| | 0.154 | 0.159 | 0.179 | 0.178 | 0.185 |

Notes: the dependent variable is the difference log total per capita expenditure between before and after treatment. The first column denotes the pure OLS estimation, while the next column is the results of IPW estimator. Column 3 and 4 are the double robustness estimation which is proposed by Scharfstein et al. (1999), and column 5 is the five-subclass estimation following Rosenbaum and Rubin (1984). The standard errors (presented in parentheses) in column 2–5 are clustered by the village and computed over the entire two-step using a block bootstrap with 500 repetitions following Cameron et al, 2008.

**Table 8**
Differences in poverty gap indices (FGT).

| Estimator | OLS | IPW | Double Robustness ($\hat{p}_h$) | Double Robustness ($PMT_h$) | Control Function |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *3 Programs vs. None* | | | | | |
| | −0.017 | −0.017 | −0.010 | −0.009 | −0.009 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| | 0.019 | 0.007 | 0.008 | 0.008 | 0.026 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) |
| | **−0.0358** | **−0.023** | **−0.018** | **−0.018** | **−0.035** |
| | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) |
| Reweighted | No | Yes | Yes | Yes | Yes |
| Propensity Score Control | No | No | Yes | No | Yes |
| PMT score control | No | No | No | Yes | No |
| Number of Households | 63,681 | 66,972 | 66,972 | 66,972 | 66,972 |
| | 0.057 | 0.0561 | 0.103 | 0.107 | 0.112 |
| *2 Programs vs. None* | | | | | |
| | −0.010 | −0.008 | −0.005 | −0.005 | −0.006 |
| | (0.001) | (0.002) | (0.002) | (0.002) | (0.001) |
| | 0.020 | 0.008 | 0.009 | 0.009 | 0.027 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) |
| | **−0.0298** | **−0.016** | **−0.014** | **−0.014** | **−0.032** |
| | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) |
| Reweighted | No | Yes | Yes | Yes | Yes |
| Propensity Score Control | No | No | Yes | No | Yes |
| PMT score control | No | No | No | Yes | No |
| Number of Households | 63,681 | 66,972 | 66,972 | 66,972 | 66,972 |
| | 0.054 | 0.0538 | 0.103 | 0.106 | 0.112 |
| *1 Programs vs. None* | | | | | |
| | 0.018 | 0.018 | 0.011 | 0.010 | 0.009 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| | 0.031 | 0.019 | 0.016 | 0.015 | 0.032 |
| | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) |
| | **−0.0137** | **−0.001** | **−0.005** | **−0.005** | **−0.023** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) |
| Reweighted | No | Yes | Yes | Yes | Yes |
| Propensity Score Control | No | No | Yes | No | Yes |
| PMT score control | No | No | No | Yes | No |
| Number of Households | 63,681 | 66,972 | 66,972 | 66,972 | 66,972 |
| | 0.060 | 0.0589 | 0.104 | 0.108 | 0.113 |

Notes: the dependent variable is the difference of Poverty Gap Index (FGT1) between 2011 and March 2014. All conditions used in the estimation can be seen in Table 7.

$$E\left[\frac{Y_h D_h^r(R_h)}{g(r, X_h)}\right] = E\left[Y_h^r\right]. \quad (10)$$

In the implementation of the GPS, $g(r,x)$ is usually unknown, but can be estimated using discrete response models if the multivalued treatment does not have a logical ordering, or by ordered response models if a natural ordering exists (Imbens and Guido, 2000). All methods that assume uncounfoudedness however depend on the selection of covariates used in both measuring the GPS and estimating the outcomes.

Under the case of multivalued treatments in the GPS approach, the current literature has classified the estimation approaches into three groups. The first is based on regression adjustment, under which the conditional mean function of the potential outcomes for households who received treatment $r$ can be defined as:

$$\theta_r = E\left[Y_h^r \,|X_h\right] = E[Y_h \,|R = r,\, X_h] = \gamma_0^r + X_h^{'}\gamma_h^r \,, \forall r \in \mathbb{N}_0 \tag{11}$$

The average treatment effects from two levels of treatment of the regression adjustment (RA) is then:

$$\widehat{\theta}_{rc}^{RA} = \frac{1}{N}\sum_{h=1}^{N}(\widehat{\gamma}_0^r + X_h^{'}\widehat{\gamma}_h^r) - (\widehat{\gamma}_0^c + X_h^{'}\widehat{\gamma}_h^c) \tag{12}$$

$$\theta_{rc}^{IPTW} = \frac{1}{N}\sum_{h=1}^{N}(\widehat{\theta}_r\,(X_h) - \widehat{\theta}_c(X_h))$$

Where $r$ and $c$ represent levels of treatment received by each household given pre-treatment variables. The implementation of regression adjustment should be conducted carefully however, since it can generate a biased treatment effect due to misspecifications of the functional form of the outcome model (Drake, 1993; Abadie and Imbens, 2011).

The second estimation method used under the GPS approach is based on weighting estimators; the most popular of which is to use the inverse probability of treatment weighting (IPW). Under this estimator, the average treatment effect sample counterpart of equation (10) is given as:

$$\widehat{\theta}_{\widetilde{rc}}^{IPW} = \frac{1}{N}\sum_{h=1}^{N}\frac{Y_h D_h^r(R_h)}{\widehat{g}(r,\, X_h)} - \frac{1}{N}\sum_{h=1}^{N}\frac{Y_h D_h^c(R_h)}{\widehat{g}(c,\, X_h)} = \widehat{\theta}_r - \widehat{\theta}_c \tag{13}$$

Where $\widehat{g}(r,\, X_h)$ is the estimated GPS. Following Busso et al. (2014), as in the binary treatment in equation (7), we normalize the weights such that:

$$\widehat{\theta}_{\widetilde{rc}}^{IPW} = \left[\sum_{h=1}^{N}\frac{Y_h D_h^r(R_h)}{\widehat{g}(r,\, X_h)} \Big/ \sum_{h=1}^{N}\frac{D_h^r(R_h)}{\widehat{g}(r,\, X_h)}\right] - \left[\sum_{h=1}^{N}\frac{Y_h D_h^c(R_h)}{\widehat{g}(c,\, X_h)} \Big/ \sum_{h=1}^{N}\frac{D_h^c(R_h)}{\widehat{g}(c,\, X_h)}\right] \tag{14}$$

Cattaneo (2010) shows that $\widehat{\theta}_{\widetilde{rc}}^{IPW}$ emerges from the generalised method of moments (GMM) representation of treatment effects. Despite its advantage that the degree of overlap in the distribution of covariates between treatment levels can be easily summerised in numeric forms, the IPW has limitations including (1) the treatment effect can become distorted when the overlap assumption is violated, and (2) poorly estimated coefficients can result when the weights for few variables are relatively large.

Another alternative to estimate causal effects under the condition of multiple treatments, is the Augmented IPTW (A-IPTW) which Cattaneo (2010) also terms the Efficient Influence Function (EIF). If the GPS is correctly specified, the unconditional mean can be estimated using (Cattaneo, 2010):

$$\widehat{\theta}_{\widetilde{rc}}^{EIF} = \frac{1}{N}\sum_{h=1}^{N}\left[\frac{Y_h D_h^r(R_h)}{\widehat{g}(r,\, X_h)} - \left\{\frac{D_h^r(R_h)}{\widehat{g}(r,\, X_h)} - 1\right\}\widehat{Y}_h(R_h)\right] \tag{15}$$

Where $\widehat{Y}_h$ is the predicted outcome that is obtained from regressing $Y_h$ on $X_h$ for those observations with $D_h^r(R_h) = 1$. GMM can then be utilized to estimate equation (15) and measure its standard errors (Cattaneo, 2010).

To simulataneously estimate the average treatment effect of targeted social programs under the condition of program complimentarities we therefore consider: (1) The Regression Adjustment estimator of the ATE i.e. equations (12) and (2) The IPW estimator i.e. equations (13), and (3) two double robust estimators including EIF (equation (15)) as well as the inverse probability weighted regression adjustment (IPW-RA) following Uysal (2015); the results of which are contained in Table 9.

**Table 9**
Difference on Per Capita Expenditure estimated by Multivalued Treatment Effects.

| Estimators | RA | IPW | Double Robustness | |
|---|---|---|---|---|
| | | | EIF | IPW-RA |
| | (1) | (2) | (3) | (4) |
| 1 Program vs None | 0.162 | 0.162 | 0.124 | 0.172 |
| | (0.007) | (0.010) | (0.008) | (0.008) |
| 2 Programs vs None | 0.259 | 0.236 | 0.197 | 0.264 |
| | (0.012) | (0.019) | (0.013) | (0.016) |
| 3 Programs vs None | 0.329 | 0.287 | 0.214 | 0.303 |
| | (0.015) | (0.024) | (0.016) | (0.021) |
| Covariates Control | Yes | Yes | Yes | Yes |
| PMT score control | Yes | Yes | Yes | Yes |
| Number of Households | 66,972 | 66,972 | 66,972 | 66,972 |

Notes: the dependent variable is the difference log total per capita expenditure between before and after treatment. All estimators are estimated under the multivalued approach using Generalised Propensity Score estimation. The estimation of average treatment effects use: the Regression Adjustment approach as in equation (12) in Column (1); the IPW estimator as in equation (13) in Column (2); and two double robust estimators including EIF as in equation (15) in Column (3) and inverse probability weighted regression adjustment (IPW-RA) following Uysal (2015) in Column (4). The standard errors are presented in parentheses.

As in the binary case, the multiple treatment approaches generate estimates of the average treatment effects that monotonically increase with the receipt of increased number of programs. The results in Table 9 are somewhat smaller in magnitude however, especially for the one vs. no program case.

### 5.4. Does the type of the program matter?

We also examine which type of program delivers the greatest impact on household per capita expenditure, thereby contributing to the debate on cash vs. in-kind transfers and the circumstances in which they apply (see for example: Lindert et al. (2007), Currie and Gahvari (2008), Khera (2014) and Hidrobo et al. (2014)). In Table 10, we compare the per capita expenditures of households in receipt of every combination of poverty program. The bottom rows of columns 9–11 show that the impact of receiving a single program is marginal and statistically insignificant. In the bottom row of column 10 for example, we can see that the impact on household expenditure of receiving either BLT or *Raskin* is statistically insignificant from one another. Even though the subsidy received from BLT (cash with amount IDR. 100.000 (or USD 10)) is slightly higher than from *Raskin* (IDR. 80.000 (or USD 8)). Interestingly, if we compare the benefit of receiving two programs, *Raskin* and *Jamkesmas*, there is no differential impact and the coefficients are statistically insignificant. We hypothesise that this may be because the benefits of either *Raskin* or BLT are marginal to the total household expenditure. Moreover, this evidence contradicts previous research by Hidrobo et al. (2014), who claim that cash is preferable if the objective of the transfers are to improve household welfare.

## 6. Conclusion

We contribute to the poverty targeting literature along two dimensions. First, we provide the first judicious evaluation of unified program eligibility, in the context of Indonesia's Unified Targeting System, which was introduced to reduce targeting errors while increasing complementarities between programs. Secondly, we account for program

**Table 10**
Matrix Comparison – Combination between Treatments and Controls using Control Function Estimation.

| | None | 3 Programs | 2 Program | 1 Program | BLT and *Raskin* only | BLT and *Jamkesmas* only | *Raskin* and *Jamkesmas* only | BLT only | *Raskin* only | *Jamkesmas* only |
|---|---|---|---|---|---|---|---|---|---|---|
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
| None | | 0.316 | 0.247 | 0.128 | 0.245 | 0.274 | 0.232 | 0.162 | 0.129 | 0.136 |
| | | (0.014) | (0.012) | (0.011) | (0.019) | (0.020) | (0.016) | (0.038) | (0.012) | (0.019) |
| 3 Programs | 0.316 | | 0.0731 | 0.184 | 0.071 | 0.0395 | 0.090 | 0.160 | 0.185 | 0.189 |
| | (0.014) | | (0.013) | (0.013) | (0.020) | (0.022) | (0.016) | (0.040) | (0.013) | (0.021) |
| 2 Programs | 0.247 | 0.073 | | 0.110 | | | | 0.0820 | 0.112 | 0.111 |
| | (0.012) | (0.013) | | (0.011) | | | | (0.039) | (0.012) | (0.020) |
| 1 Programs | 0.128 | 0.184 | 0.110 | | 0.112 | 0.145 | 0.092 | | | |
| | (0.011) | (0.013) | (0.011) | | (0.019) | (0.020) | (0.014) | | | |
| BLT and *Raskin* only | 0.245 | 0.071 | | 0.112 | | 0.052 | 0.019 | 0.084 | 0.114 | 0.114 |
| | (0.019) | (0.020) | | (0.019) | | (0.023) | (0.022) | (0.041) | (0.019) | (0.025) |
| BLT and *Jamkesmas* only | 0.274 | 0.040 | | 0.145 | 0.051 | | 0.033 | 0.117 | 0.148 | 0.143 |
| | (0.020) | (0.022) | | (0.020) | (0.023) | | (0.026) | (0.042) | (0.021) | (0.024) |
| *Raskin* and *Jamkesmas* only | 0.232 | 0.090 | | 0.0920 | 0.019 | 0.033 | | 0.068 | 0.093 | 0.095 |
| | (0.016) | (0.016) | | (0.014) | (0.022) | (0.026) | | (0.041) | (0.015) | (0.023) |
| BLT only | 0.162 | 0.160 | 0.082 | | 0.084 | 0.117 | 0.068 | | 0.029 | 0.028 |
| | (0.038) | (0.040) | (0.039) | | (0.041) | (0.042) | (0.041) | | (0.039) | (0.042) |
| *Raskin* only | 0.129 | 0.185 | 0.112 | | 0.114 | 0.148 | 0.093 | 0.029 | | 0.000 |
| | (0.012) | (0.013) | (0.012) | | (0.019) | (0.021) | (0.015) | (0.039) | | (0.020) |
| *Jamkesmas* only | 0.136 | 0.189 | 0.111 | | 0.114 | 0.143 | 0.095 | 0.028 | 0.000 | |
| | (0.019) | (0.021) | (0.020) | | (0.025) | (0.024) | (0.023) | (0.042) | (0.020) | |

Notes: the dependent variable is the difference log total per capita expenditure between before and after treatment. All estimations are conducted under five-subclass estimation following Rosenbaum and Rubin (1984).

complimentarities, both in terms of targeting outcomes and household welfare; since while social programs aimed at targeting poverty are typically rolled out as part of a broader program packages, they are almost exclusively evaluated in isolation.

Our results illustrate the tangible benefits realised as a result of the introduction of the Unified Targeting System. The proportion of households that benefited from all three social programs more than doubled, and furthermore those households in reiept of all three programs are at least 30 percentage points better off than those that receive none. As suggested by Bah et al (2018), the innovation also represented good value for money since the cost of PPLS11 was about 11 percent of the value of additional benefits received by households from the poorest three deciles previously omitted from the registry. Our results also serve as a cautionary tale however, to the results of any policy evaluation that omits complimentary programs since such results might otherwise be upward biased.

Our results also serve as a warning to those countries that are currently rolling out unified targeting systems. While the tangible benefits in the Indonesian context were large, these results are relative to the low base from which the targeting initiatve began. In 2014, 17.5% of households that were eligible for all three social programs in fact received none. Further work is therefore needed to understand exactly why such households are falling through the social net.

## Appendices.

**Table A1**
Household Characteristics by Receiving Poverty Program

| | Non-Receiving Program | | Receiving Program | | Difference | |
|---|---|---|---|---|---|---|
| PMT Score | 13.616 | (0.43) | 13.492 | (0.352) | −0.100 | [0.013] |
| Percapita Expenditure ('000) | 913.84 | (1034) | 632.980 | (529.81) | −239,707 | [24,571] |
| *Head of Household Characteristics* | | | | | | |
| Male | 0.858 | (0.349) | 0.842 | (0.364) | −0.012 | [0.007] |
| Married | 0.818 | (0.386) | 0.813 | (0.390) | −0.005 | [0.007] |
| Age | 47.676 | (13.568) | 48.811 | (13.737) | 0.789 | [0.179] |
| Education | | | | | | |
| Elementary | 0.202 | (0.401) | 0.248 | (0.432) | 0.042 | [0.008] |
| Junior High | 0.206 | (0.405) | 0.247 | (0.431) | 0.037 | [0.005] |
| Senior High & University | 0.415 | (0.493) | 0.299 | (0.458) | −0.106 | [0.012] |
| Working Status: Employed | 0.879 | (0.326) | 0.893 | (0.310) | 0.015 | [0.005] |
| Employment Sector: | | | | | | |
| Agriculture | 0.362 | (0.481) | 0.457 | (0.498) | 0.098 | [0.010] |
| Mining & Quarrying | 0.020 | (0.139) | 0.015 | (0.122) | −0.000 | [0.002] |
| Processing Industry | 0.063 | (0.242) | 0.068 | (0.251) | −0.001 | [0.003] |
| Trading | 0.128 | (0.334) | 0.112 | (0.315) | −0.016 | [0.004] |
| Construction/building | 0.067 | (0.249) | 0.078 | (0.268) | 0.010 | [0.004] |
| Hotel & Restaurant | 0.013 | (0.115) | 0.009 | (0.097) | −0.004 | [0.001] |
| Transportation & ICT | 0.050 | (0.218) | 0.047 | (0.212) | −0.002 | [0.003] |

(continued on next column)

**Table A1** (*continued*)

| | Non-Receiving Program | | Receiving Program | | Difference | |
|---|---|---|---|---|---|---|
| *Household Characteristics* | | | | | | |
| Size (Person) | 3.878 | (1.725) | 3.787 | (1.687) | −0.056 | [0.021] |
| Dependency ratio | 0.654 | (0.649) | 0.650 | (0.651) | −0.004 | [0.010] |
| Number of Household Member: 0–4 yrs | 0.336 | (0.568) | 0.334 | (0.554) | 0.003 | [0.005] |
| Number of Household Member at School Age | | | | | | |
| Elementary | 0.527 | (0.737) | 0.471 | (0.696) | −0.043 | [0.010] |
| Junior High | 0.218 | (0.457) | 0.201 | (0.440) | −0.013 | [0.004] |
| Senior High | 0.160 | (0.405) | 0.138 | (0.371) | −0.019 | [0.003] |
| University | 0.076 | (0.308) | 0.039 | (0.217) | −0.035 | [0.004] |
| Assets | | | | | | |
| Bicycle | 0.327 | (0.469) | 0.321 | (0.467) | −0.030 | [0.008] |
| Gas ≥ 3 kg | 0.148 | (0.355) | 0.043 | (0.203) | −0.091 | [0.010] |
| Refrigerator | 0.445 | (0.497) | 0.298 | (0.458) | −0.128 | [0.014] |
| Motorcycle | 0.671 | (0.470) | 0.627 | (0.484) | −0.041 | [0.015] |
| Water Access | | | | | | |
| Branded/Recycled Bottle Water | 0.290 | (0.454) | 0.163 | (0.369) | −0.106 | [0.011] |
| Pipe with Meter | 0.121 | (0.326) | 0.094 | (0.292) | −0.025 | [0.008] |
| Terrestrial well/pump | 0.119 | (0.323) | 0.143 | (0.350) | 0.012 | [0.006] |
| Protected/Covered well | 0.197 | (0.398) | 0.254 | (0.435) | 0.038 | [0.008] |
| Unprotected/Uncovered well | 0.274 | (0.446) | 0.346 | (0.476) | 0.082 | [0.011] |
| From buying from other parties | 0.444 | (0.497) | 0.312 | (0.463) | −0.115 | [0.009] |
| Housing | | | | | | |
| Own | 0.799 | (0.401) | 0.864 | (0.342) | 0.049 | [0.006] |
| rent | 0.036 | (0.186) | 0.015 | (0.123) | −0.017 | [0.002] |
| Lease | 0.046 | (0.210) | 0.018 | (0.131) | −0.021 | [0.003] |
| Company House | 0.024 | (0.152) | 0.006 | (0.078) | −0.015 | [0.003] |
| Others | 0.096 | (0.294) | 0.096 | (0.295) | 0.004 | [0.005] |

| | Non-Receiving Program | | Receiving Program | | Difference | |
|---|---|---|---|---|---|---|
| Lighting Sources | | | | | | |
| PLN Electricity 450 W | 0.784 | (0.412) | 0.759 | (0.427) | −0.030 | [0.013] |
| PLN Electricity without Meter | 0.104 | (0.306) | 0.120 | (0.325) | 0.008 | [0.007] |
| Non-PLN Electricity | 0.050 | (0.218) | 0.047 | (0.212) | 0.004 | [0.005] |
| Non-Electricity | 0.062 | (0.241) | 0.073 | (0.261) | 0.019 | [0.006] |
| Final disposal | | | | | | |
| Septic Tank | 0.624 | (0.484) | 0.554 | (0.497) | −0.067 | [0.014] |
| Pit hole | 0.118 | (0.322) | 0.147 | (0.354) | 0.026 | [0.008] |
| River/Lake/Sea | 0.176 | (0.380) | 0.195 | (0.396) | 0.018 | [0.007] |
| Beach/open field/farm | 0.064 | (0.245) | 0.078 | (0.269) | 0.019 | [0.006] |
| Defecation facility use | | | | | | |
| Personal | 0.715 | (0.451) | 0.657 | (0.475) | −0.053 | [0.016] |
| Mutual | 0.285 | (0.451) | 0.343 | (0.475) | 0.053 | [0.016] |
| House Characteristics | | | | | | |
| Wall material: Concrete | 0.624 | (0.484) | 0.597 | (0.491) | −0.057 | [0.017] |
| Wall material: Wood | 0.376 | (0.484) | 0.403 | (0.491) | 0.057 | [0.017] |
| Roof Materials: Concrete | 0.025 | (0.156) | 0.017 | (0.127) | −0.008 | [0.002] |
| Roof Materials: Roof Tile | 0.370 | (0.483) | 0.477 | (0.500) | 0.007 | [0.007] |
| Roof Materials: Iron Sheet/Asbeston | 0.546 | (0.498) | 0.445 | (0.497) | −0.009 | [0.008] |
| Roof Materials: Shingle/Fiber/Palm | 0.059 | (0.235) | 0.061 | (0.240) | 0.011 | [0.006] |
| Number of Households | 49,949 | 17,075 | 66,972 | | | |

This table present the mean tests of the characteristics of households who received the poverty program and did not. Number inside the parentheses is the standard deviation, while inside the square brackets denote the standard error.

**Table A2**
Village Characteristics by Receiving Poverty Program

| | Non-Receiving Program | | Receiving Program | | Difference | |
|---|---|---|---|---|---|---|
| *Village Characteristics* | | | | | | |
| Rural area | 0.650 | (0.477) | 0.819 | (0.385) | 0.142 | [0.011] |
| Distance to the nearest | | | | | | |
| Market (Km) | 6.968 | (16.655) | 7.587 | (17.647) | 1.259 | [0.583] |
| Health Facility (Km) | 5.098 | (11.853) | 6.168 | (13.250) | 1.318 | [0.311] |
| Sub-district office (Km) | 6.261 | (25.432) | 6.803 | (20.573) | 0.699 | [0.438] |
| District office (Km) | 29.843 | (53.452) | 34.582 | (47.342) | 6.132 | [1.708] |
| *Village has:* | | | | | | |
| Shophouse | 0.340 | (0.474) | 0.223 | (0.416) | −0.117 | [0.011] |
| Hotel | 0.152 | (0.359) | 0.074 | (0.262) | −0.065 | [0.007] |
| Cooperation | 0.525 | (0.499) | 0.472 | (0.499) | −0.062 | [0.009] |
| Credit Finance | 0.502 | (0.500) | 0.496 | (0.500) | −0.025 | [0.008] |
| Access to the Bank | 0.297 | (0.457) | 0.180 | (0.384) | −0.105 | [0.010] |
| School building | | | | | | |

(*continued on next column*)

**Table A2** (*continued*)

| | Non-Receiving Program | | Receiving Program | | Difference | |
|---|---|---|---|---|---|---|
| Elementary | 0.947 | (0.224) | 0.947 | (0.223) | −0.002 | [0.003] |
| Junior High School | 0.609 | (0.488) | 0.552 | (0.497) | −0.054 | [0.008] |
| Senior High School | 0.435 | (0.496) | 0.332 | (0.471) | −0.095 | [0.008] |
| Village Health Facility (*Polindes*) | 0.460 | (0.498) | 0.519 | (0.500) | 0.034 | [0.009] |
| Sub-Vil. Health Facility (*Posyandu*) | 0.978 | (0.147) | 0.977 | (0.151) | −0.003 | [0.003] |
| | Non-Receiving Program | | Receiving Program | | Difference | |
| Asphalt Road | 0.782 | (0.413) | 0.730 | (0.444) | −0.060 | [0.010] |
| Road can be accessed 4-wheel car | 0.929 | (0.257) | 0.913 | (0.282) | −0.026 | [0.008] |
| *Head of Village Characteristics* | | | | | | |
| Gender: Male | 0.910 | (0.286) | 0.933 | (0.250) | 0.019 | [0.004] |
| Age (years old) | 44.067 | (10.150) | 44.321 | (9.507) | 0.019 | [0.176] |
| Education background | | | | | | |
| No Education | 0.014 | (0.116) | 0.019 | (0.135) | 0.005 | [0.002] |
| Elementary | 0.017 | (0.128) | 0.018 | (0.133) | 0.002 | [0.002] |
| Junior High School | 0.101 | (0.302) | 0.137 | (0.344) | 0.032 | [0.007] |
| Senior High School | 0.456 | (0.498) | 0.512 | (0.500) | 0.051 | [0.010] |
| University | 0.040 | (0.196) | 0.044 | (0.204) | 0.001 | [0.003] |
| Number of Households | 49,949 | | 17,075 | | 66,972 | |

This table present the mean tests of the village characteristics where the households who received the poverty program and did not. Number inside the parentheses is the standard deviation, while inside the square brackets denote the standard error.

**Table A3**
Joint Probabilities of the Poor Households Receiving Poverty Programs Between Different of Targeting Regimes

| | Joint Probabilities | | | Difference | | |
|---|---|---|---|---|---|---|
| | 2006 | 2009 | 2014 | 2006 vs. 2009 | 2006 vs. 2014 | 2009 vs. 2014 |
| BLT only | 0.079 | 0.053 | 0.039 | −0.026 | −0.040 | −0.014 |
| | (0.270) | (0.224) | (0.194) | [0.002] | [0.003] | [0.003] |
| Raskin only | 0.183 | 0.232 | 0.193 | 0.049 | 0.010 | −0.040 |
| | (0.387) | (0.422) | (0.394) | [0.003] | [0.005] | [0.006] |
| Jamkesmas only | 0.009 | 0.017 | 0.044 | 0.008 | 0.035 | 0.027 |
| | (0.096) | (0.131) | (0.206) | [0.001] | [0.002] | [0.002] |
| BLT and Raskin only | 0.310 | 0.248 | 0.096 | −0.062 | −0.214 | −0.152 |
| | (0.462) | (0.432) | (0.295) | [0.003] | [0.006] | [0.006] |
| BLT and Jamkesmas only | 0.017 | 0.017 | 0.084 | −0.001 | 0.066 | 0.067 |
| | (0.130) | (0.128) | (0.277) | [0.001] | [0.002] | [0.002] |
| Raskin and Jamkesmas only | 0.029 | 0.033 | 0.092 | 0.004 | 0.063 | 0.059 |
| | (0.169) | (0.178) | (0.289) | [0.001] | [0.003] | [0.003] |
| BLT, Raskin and Jamkesmas | 0.157 | 0.125 | 0.273 | −0.032 | 0.117 | 0.148 |
| | (0.363) | (0.331) | (0.446) | [0.003] | [0.005] | [0.005] |
| None | 0.216 | 0.275 | 0.179 | 0.059 | −0.037 | −0.096 |
| | (0.412) | (0.447) | (0.383) | [0.003] | [0.005] | [0.006] |
| Number of HHDs | 40280 | 34,680 | 6511 | | | |

This table present the mean test of the Joint Probabilities as in Column (1), (5), and (6) of Table 3. The number inside of the parentheses is the standard deviation, while inside the square brackets denote the standard test.

**Table A4**
Joint Probabilities of the Poor Households Receiving Poverty Programs Between KPS and Non-KPS Holders

| | Joint Probabilities | | Difference |
|---|---|---|---|
| | Non KPS | KPS | |
| BLT only | 0.019 | 0.064 | 0.044 |
| | (0.138) | (0.244) | [0.005] |
| Raskin only | 0.349 | 0.006 | −0.342 |
| | (0.477) | (0.078) | [0.009] |
| Jamkesmas only | 0.071 | 0.013 | −0.058 |
| | (0.257) | (0.112) | [0.005] |
| BLT and Raskin only | 0.039 | 0.167 | 0.127 |
| | (0.195) | (0.373) | [0.007] |
| BLT and Jamkesmas only | 0.018 | 0.166 | 0.148 |
| | (0.132) | (0.373) | [0.007] |
| Raskin and Jamkesmas only | 0.158 | 0.014 | −0.144 |
| | (0.364) | (0.118) | [0.007] |
| BLT, Raskin and Jamkesmas | 0.038 | 0.566 | 0.529 |
| | (0.191) | (0.496) | [0.009] |
| None | 0.308 | 0.004 | −0.304 |
| | (0.462) | (0.067) | [0.009] |
| Number of HHDs | 3545 | 2906 | |

This table present the mean test of the Joint Probabilities as in Column (4) and (7) of Table 5. The number inside of the parentheses is the standard deviation, while inside the square brackets denote the standard test.

**Table A5**
Underlying Variables of PMT Score

| | dy/dx | (S.E) | | dy/dx | (S.E) |
|---|---|---|---|---|---|
| Head of HHD: Male | −0.099 | (0.014) | *Primary income source (reference = other)* | | |
| Married Status Head of HHD | 0.042 | (0.012) | Head of HHD working | −0.017 | (0.014) |
| h_hhsize | 0.058 | (0.004) | Agriculture | 0.111 | (0.016) |
| Age of Head of HHD | 0.000 | (0.001) | Mining and Quarrying | 0.092 | (0.034) |
| # HHD member 0–4 years | −0.021 | (0.009) | Processing Industry | 0.110 | (0.023) |
| Dependency Ratio | 0.008 | (0.007) | Trading | 0.060 | (0.015) |
| | | | Construction/building | 0.189 | (0.016) |
| *Household head education level (reference = No education)* | | | Hotel and Restaurant | 0.011 | (0.028) |
| Elementary | −0.073 | (0.010) | Transportation and warehousing | 0.115 | (0.016) |
| Junior High | −0.126 | (0.017) | Public service | 0.054 | (0.012) |
| High School - S3 | −0.291 | (0.022) | | | |
| | | | Self-Owned business | 0.014 | (0.009) |
| *Highest Education Background in the Household (reference: No education)* | | | Self-Owned business with non-permanent worker | −0.013 | (0.011) |
| Elementary | 0.056 | (0.011) | Self-Owned business with permanent worker | −0.124 | (0.020) |
| Junior High | 0.056 | (0.009) | | | |
| Senior High - S3 | −0.059 | (0.010) | *Home ownership Status (reference = Other)* | | |
| | | | Own | −0.019 | (0.014) |
| *Number of Household members who are studying at:* | | | rent | −0.207 | (0.038) |
| Elementary | 0.000 | (0.005) | Lease | −0.279 | (0.033) |
| Junior High | 0.002 | (0.007) | Company House | −0.332 | (0.073) |
| Senior High | −0.024 | (0.009) | | | |
| University | −0.063 | (0.014) | *Source of Ligthing (Reference = No Electricity)* | | |
| | | | Source of Lighting: | 0.059 | (0.040) |
| | | | PLN Electricity without Meter | 0.124 | (0.042) |
| | | | Non-PLN Electricity | 0.002 | (0.030) |

| | dy/dx | (S.E) | | dy/dx | (S.E) |
|---|---|---|---|---|---|
| *Household Assets:* | | | Final Disposal Location (Reference = Other) | | |
| Bicycle | 0.004 | (0.008) | Septic Tank | −0.060 | (0.026) |
| gas $\geq$ 12 kg | −0.262 | (0.019) | River/Lake/Sea | −0.015 | (0.028) |
| Refrigerator | −0.164 | (0.014) | Pit hole | −0.032 | (0.024) |
| Motorcycle | −0.092 | (0.011) | Beach/open field/farm | −0.038 | (0.026) |
| | | | River/Lake/Sea | −0.015 | (0.028) |
| *Source of Drinking Water (reference = Unprotected well)* | | | Pit hole | −0.032 | (0.024) |
| Branded/Recycled Bottle Water | −0.124 | (0.016) | Beach/open field/farm | −0.038 | (0.026) |
| Pipe with Meter | −0.065 | (0.024) | | | |
| Terrestrial well/pump | −0.027 | (0.018) | *Defecation facility use (Reference = mutual)* | | |
| Protected/Covered well | 0.005 | (0.014) | Personal | −0.083 | (0.013) |
| Buying | 0.007 | (0.011) | | | |
| | | | *Type of wall material (reference = wood)* | | |
| *Roof Materials (Reference = Shingle/Fiber/Palm)* | | | Type of wall material: Concrete | −0.099 | (0.010) |
| Concrete | −0.073 | (0.037) | | | |
| Roof Tile | −0.013 | (0.043) | Type of flooring material: Not Soil | −0.076 | (0.056) |
| Iron Sheet/Asbeston | −0.027 | (0.032) | | | |
| | | | | | |
| Pseudo R2 | 0.2953 | | | | |
| Households | 66,972 | | | | |

This table presents the marginal effect of Probit estimation. The dependent variable is 1 if the household receive any poverty programs, 0 otherwise. Standard errors in parentheses.

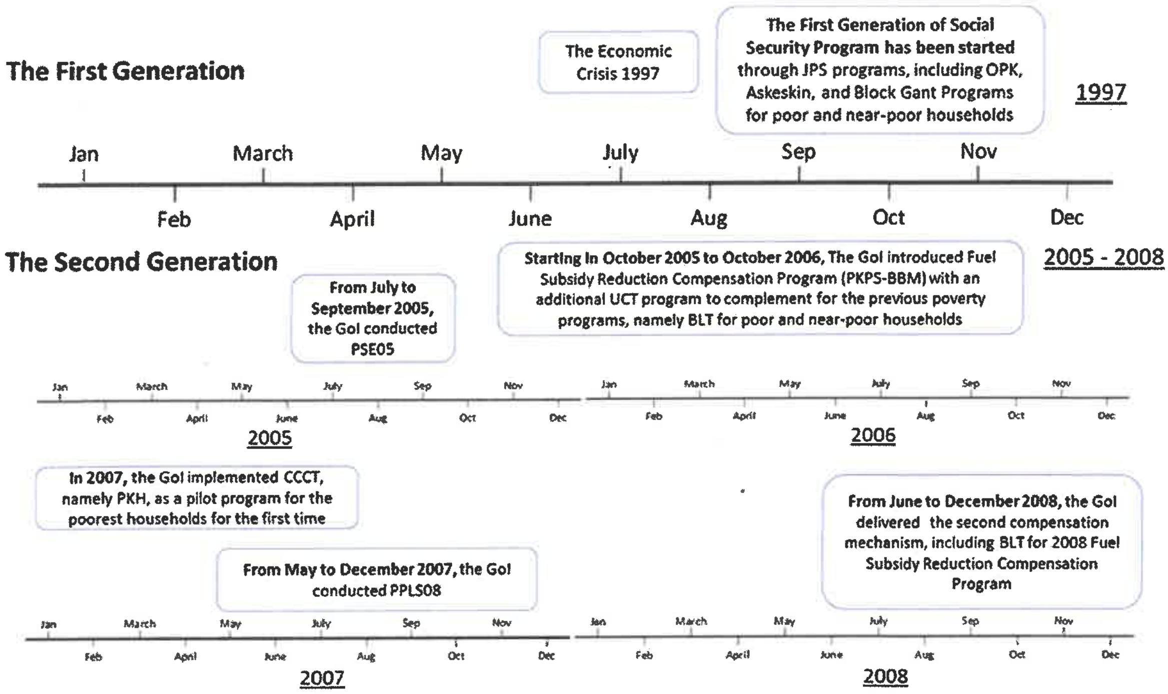



**Fig. A1.** The Evolution of the Social Protection Programs in Indonesia: The First and Second Generations

## References


Abadie, A., 2005. Semiparametric difference-in-differences estimators. Rev. Econ. Stud. 72 (1), 1–19.

Abadie, A., Imbens, G.W., 2011. Bias-corrected matching estimators for average treatment effects. J. Bus. Econ. Stat. 29 (1), 1–11.

Alatas, V., Banerjee, A., Hanna, R., Olken, B.A., Tobias, J., 2012. Targeting the poor: evidence from a field experiment in Indonesia. Am. Econ. Rev. 102 (4), 1206–1240.

Alatas, V., et al., 2016. Self-targeting: evidence from a field experiment in Indonesia. J. Political Econ. 124 (2), 371–427.

Angelucci, M., De Giorgi, G., 2009. Indirect effects of an aid program: how do cash transfers affect ineligibles' consumption? Am. Econ. Rev. 99 (1), 486–508.

Athey, Susan, Imbens, Guido W., 2017. The state of applied econometrics: causality and policy evaluation. J. Econ. Perspect. 31 (2), 3–32.

Banerjee, Abhijit, Hanna, Rema, Jordan, Kyle, Olken, Benjamin A., Sumarto, Sudarno, 2018. Tangible information and citizen empowerment: Identification cards and food subsidy programs in Indonesia. J. Political Econ. 126 (2), 451–491.

Bah, A., Bazzi, S., Sumarto, S., Tobias, J., 2018. (forthcoming). "Finding the poor vs. Measuring their poverty: exploring the drivers of targeting effectiveness in Indonesia. World Bank Econ. Rev.

Banerjee, A., et al., 2015. A multifaceted program causes lasting progress for the very poor: evidence from six countries. Science 348 (6236), 1260799.

Bazzi, S., et al., 2015. It's all in the timing: cash transfers and consumption smoothing in a developing country. J. Econ. Behav. Organ. 119, 267–288.

Brown, C., Ravallion, M., Van de Walle, D., 2018. A poor means test? Econometric targeting in Africa. J. Dev. Econ. 134, 109–124.

Busso, M., DiNardo, J., McCrary, J., 2014. New evidence on the finite sample properties of propensity score reweighting and matching estimators. Rev. Econ. Stat. 96 (5), 885–897.

Cameron, L., Shah, M., 2014. Can mistargeting destroy social capital and stimulate crime? Evidence from a cash transfer program in Indonesia. Econ. Dev. Cult. Change 62 (2), 381–415.

Cameron, Colin, Gelbach, Jonah, Miller, Douglas, August 2008. Bootstrap-based improvements for inference with clustered errors. Rev. Econ. Stat. 90, 414–427.

Castaneda, T., Fernandez, L., 2005. "Targeting Social Spending to the Poor with Proxy-Means Testing: Colombia's SISBEN System. " World Bank Human Development Network Social Protection Unit Discussion Paper 529.

Cattaneo, M.D., 2010. Efficient semiparametric estimation of multi-valued treatment effects under ignorability". J. Econom. 155 (2), 138–154.

Coady, D., Grosh, M.E., Hoddinott, J., 2004. Targeting of Transfers in Developing Countries: Review of Lessons and Experience, vol. 1. World Bank Publications.

Cornia, G.A., Stewart, F., 1995. Two errors of targeting. In: van de Walle, D., Nead, K. (Eds.), In Public Spending and the Poor: Theory and Evidence. Johns Hopkins University Press, Baltimore, MD, pp. 350–386.

Crump, R.K., Hotz, V.J., Imbens, G.W., Mitnik, O.A., 2009. Dealing with limited overlap in estimation of average treatment effects. Biometrika 96 (1), 187–199.

Currie, J., Gahvari, F., 2008. Transfers in cash and in-kind: theory meets the data. J. Econ. Lit. 46 (2), 333–383.

De Janvry, A., Finan, F., Sadoulet, E., 2012. Local electoral incentives and decentralized program performance. Rev. Econ. Stat. 94 (3), 672–685.

De la Brière, B., Lindert, K., 2005. "Reforming Brazil's Cadastro Único to Improve the Targeting of the Bolsa Família Program. " World Bank, Social Protection Unit and DFID.

Drake, C., 1993. Effects of misspecification of the propensity score on estimators of treatment effect. Biometrics 49 (4), 1231–1236.

Foster, J., Greer, J., Thorbecke, E., 1984. A class of decomposable poverty measures. Econometrica 761–766.

Galasso, E., Ravallion, M., 2005. Decentralized targeting of an antipoverty program. J. Public Econ. 89 (4), 705–727.

Godtland, E., Sadoulet, E., de Janvry, A., Murgai, R., Ortiz, O., 2004. The impact of farmer field schools on knowledge and productivity: a study of potato farmers in the Peruvian Andes. Econ. Dev. Cult. Change 53 (1), 63–92.

Grosh, M., et al., 2008. For Protection and Promotion: the Design and Implementation of Effective Safety Nets. World Bank Publications.

Hastuti, et al., 2006. A rapid appraisal of the implementation of the 2005 Direct cash transfer program in Indonesia: a case study of five kabupaten/kota. jakarta, SMERU research report.

Hidrobo, M., Hoddinott, J., Peterman, A., Margolies, A., Moreira, V., 2014. Cash, food, or vouchers? Evidence from a randomized experiment in northern Ecuador. J. Dev. Econ. 107, 144–156.

Hirano, K., Imbens, G.W., 2004. The propensity score with continuous treatment. In: Gelman, A., Meng, X.L. (Eds.), Applied Bayesian Modeling and Causal Inference from Incomplete-Data Perspectives. Wiley InterScience, West Sussex, pp. 73–84.

Hirano, K., Imbens, G.W., Ridder, G., 2003. Efficient estimation of average treatment effects using the estimated propensity score. Econometrica 71 (4), 1161–1189.

Hoddinott, J., Skoufias, E., 2004. The impact of PROGRESA on food consumption. Econ. Dev. Cult. Change 53 (1), 37–61.

Honorati, M., Gentilini, U., Yemtsov, R.G., 2015. The State of Social Safety Nets 2015. World Bank, Washington, DC. http://documents.worldbank.org/curated/en/2015/07/24741765/state-social-safety-nets-2015.

Imbens, Guido, W., 2000. "The role of the propensity score in estimating dose-response functions. Biometrika 87 (3), 706–710.

Imbens, G.W., Wooldridge, J.M., 2009. Recent developments in the econometrics of program evaluation. J. Econ. Lit. 47 (1), 5–86.

Jalan, J., Ravallion, M., 2003. Estimating the benefit incidence of an antipoverty program by propensity-score matching. J. Bus. Econ. Stat. 21 (1), 19–30.

Jayne, T.S., Strauss, J., Yamano, T., Molla, D., 2002. Targeting of food aid in rural Ethiopia: chronic need or inertia? J. Dev. Econ. 68 (2), 247–288.

Jellema, J.R., Noura, H., 2012. Main report. Public Expenditure Review (PER). World Bank, " Washington, DC.
Khera, R., 2014. Cash vs. in-kind transfers: Indian data meets theory. Food Policy 46, 116–128.
Lindert, K., Linder, A., Hobbs, J., De la Brière, B., 2007. The nuts and bolts of Brazil's Bolsa Família Program: implementing conditional cash transfers in a decentralized context, 709 (Social Protection Discussion Paper).
Lunceford, J.K., Davidian, M., 2004. Stratification and weighting via the propensity score in estimation of causal treatment effects: a comparative study. Stat. Med. 23 (19), 2937–2960.
Niehaus, P., Atanassova, A., Bertrand, M., Mullainathan, S., 2013. Targeting with agents. Am. Econ. J. Econ. Policy 5 (1), 206–238.
Olken, B.A., 2005. Revealed community equivalence scales. J. Public Econ. 89 (2–3), 545–566.
Pradhan, M., Saadah, F., Sparrow, R., 2007. Did the health card program ensure access to medical care for the poor during Indonesia's economic crisis? World Bank Econ. Rev. 21 (1), 125–150.
Pendataan Program Perlindungan Sosial (PPLS), 2011. Badan Pusat Statistik Republik Indonesia, Jakarta.
Pritchett, L., Suryahadi, A., Sumarto, S., 2000. Quantifying Vulnerability to Poverty: A Proposed Measure, Applied to Indonesia. World Bank Publications. No. 2437.
Ravallion, M., 1990. On the coverage of public employment schemes for poverty alleviation. J. Dev. Econ. 34 (1), 57–79.
Ravallion, M., 2007. Evaluating anti-poverty programs. Handb. Dev. Econ. 4, 3787–3846.
Ravallion, M., 2008. Miss-targeted or miss-measured? Econ. Lett. 100 (1), 9–12.
Ravallion, M., 2009. How relevant is targeting to the success of an antipoverty program? World Bank Res. Obs. 24 (2), 205–231.
Tim Sosialisasi Penyesuaian Subsidi Bahan Bakar Minyak, 2013. Buku Pegangan Sosialisasi Dan Implementasi Program-Program Kompensasi Kebijakan Penyesuaian Subsidi Bahan Bakar Minyak 2013. In: The Guidelines for the Implementation of the 2013 Compensation Program for Fuel Subsidy Reduction Compensation Program). Sekretariat Wakil Presiden, K. W. P. RI. Jakarta.
Rosenbaum, P.R., Rubin, D.B., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 41–55.
Rosenbaum, P.R., Rubin, D.B., 1984. Reducing bias in observational studies using subclassification on the propensity score. J. Am. Stat. Assoc. 79 (387), 516–524.
Rosfadhila, M., Toyamah, N., Sulaksono, B., Devina, S., Sodo, R.J., Syukri, M., 2011. A Rapid Appraisal of the Implementation of the 2008 Direct Cash Transfer Program and Beneficiary Assessment of the 2005 Direct Cash Transfer Program in Indonesia. " SMERU Research Institute.
Scharfstein, D.O., Rotnitzky, A., Robins, J.M., 1999. Adjusting for nonignorable drop-out using semiparametric nonresponse models. J. Am. Stat. Assoc. 94 (448), 1096–1120.
SUSENAS, 2011. Survei Sosial Ekonomi Nasional Badan Pusat Statistik Republik Indonesia, Jakarta.
Schultz, T.P., 2004. School subsidies for the poor: evaluating the Mexican Progresa poverty program. J. Dev. Econ. 74 (1), 199–250.
Smith, J.A., Todd, P.E., 2005. Does matching overcome LaLonde's critique of nonexperimental estimators? J. Econom. 125 (1), 305–353.
Sparrow, R., 2008. Targeting the poor in times of crisis: the Indonesian health card. Health Policy Plan. 23 (3), 188–199.
Sparrow, R., et al., 2013. Social health insurance for the poor: targeting and impact of Indonesia's Askeskin programme. Soc. Sci. Med. 96, 264–271.
Sumarto, S., Bazzi, S., 2011. Social Protection in Indonesia: Past Experiences and Lessons for the Future." Paper Presented at the 2011 Annual Bank Conference on Development Opportunities (ABCDE) Jointly Organized by the World Bank and OECD.
Sumarto, S., Suryahadi, A., Widyanti, W., 2002. Designs and implementation of the Indonesian social safety net programs. Develop. Econ. 40 (1), 3–31.
Sumarto, S., Suryahadi, A., Pritchett, L., 2003. Safety nets or safety ropes? Dynamic benefit incidence of two crisis programs in Indonesia. World Dev. 31 (7), 1257–1277.
Suryahadi, A., Widyanti, W., Sumarto, S., 2003. "Short-term poverty dynamics in rural Indonesia during the economic crisis. J. Int. Dev. 15 (2), 133–144.
TNP2K, 2015. Indonesia's unified database for social protection programmes - management standard. Jakarta, Secretariat of the Vice President of the Republic of Indonesia.
Tohari, A., Parsons, C., Rammohan, A., 2018. Does Information Empower the Poor? Evidence from Indonesia's Social Security Card. IZA Discussion Paper No, p. 11137.
Uysal, S.D., 2015. Doubly robust estimation of causal effects with multivalued treatments: an application to the returns to schooling. J. Appl. Econom. 30 (5), 763–786.
van de Walle, D., Mu, R., 2007. Fungibility and the flypaper effect of project aid: micro-evidence for Vietnam. J. Dev. Econ. 84 (2), 667–685.
Widianto, B., 2013. The political economy of social protection reforms in Indonesia. In: Social Protection in Developing Countries: Reforming Systems, vol. 2, p. 161.
Widjaja, M., 2009. An Economic and Social Review on Indonesian Direct Cash Transfer Program to Poor Families Year 2005." the Association for Public Policy Analysis and Management International Conference on Asian Social Protection in Comparative Perspective (Singapore).
World Bank, 2006. Making the New Indonesia Work for the Poor. Jakarta.
World Bank, 2012a. Targeting Poor and Vulnerable Households in Indonesia. Jakarta.
World Bank, 2012b. Protecting Poor and Vulnerable Households in Indonesia. Jakarta.
Yusuf, A.A., Resosudarmo, B.P., 2008. Mitigating distributional impact of fuel pricing reform: the Indonesian experience. ASEAN Econ. Bull. 25 (1), 32–47.

This page is intentionally left blank

# Chapter 3

## Does Information Empower the Poor? Evidence from the Indonesia's Social Security Card

**Abstract**

In 2013, the Government of Indonesia conducted one of the largest information interventions in history, in an attempt to further alleviate poverty and as a complement to the Social Protection Card (KPS). Drawing upon administrative data and nationally representative surveys, we evaluate the impact of the information campaign on the receipt of two of Indonesia's largest social programs, the Raskin (rice for the poor) and the BLSM (temporary unconditional cash transfers). Exploiting the design of the *Raskin* program, we implement a (normalised) fuzzy regression discontinuity methodology across 482 Indonesian districts, using program eligibility as an instrument for having received the information treatment. Further corroborating our results with semi-parametric and parametric techniques, we show that the information treatment increases the amount of rice received under the Raskin program by around 30 percentage points. In terms of the BLSM, we further show that the information treatment reduces the likelihood of elite capture by local leaders by around 25 percentage points. We also provide evidence that *understanding* the information treatment is crucial for poor household's outcomes, since fully informed households receive their full entitlement of rice.

**Keywords:** Poverty, Targeting, Indonesia, Information

**JEL Classifications: D04, D73, I32, I38, O12.**

## 3.1 Introduction

*"Knowledge is power. Information is liberating. Education is the premise of progress, in every society, in every family"*

Kofi Annan

Poor households in developing countries typically do not have access to complete information about their rights to social welfare programs. This constrains such households' ability to fully benefit from social programs aimed at poverty reduction. In addressing this challenge, the World Bank has championed greater dissemination of information on various poverty programs among social welfare recipients to empower the poor (World Bank 2004). In recent years, governments in several developing countries, including Indonesia, have implemented various strategies to inform potential recipients on their eligibility for programs as well as their level of benefit entitlements. Their aim is to improve both the transparency and accountability of service delivery from poverty programs using information-based interventions. In this paper, we evaluate the largest such information campaign in Indonesia using nationally representative administrative data.

The prominent role of access to information has been firmly established in seminal research by Stigler (1961) and Akerlof (1970). When governments represent monopoly providers of services, access to information allows the public to improve the accountability of those programs, thereby reducing the potential for local capture and mismanagement of public resources (World Bank 2004, Kosack and Fung 2014). A recent study by Banerjee et al. (2018) however, also warns that too much information can be counterproductive, since it may place local leaders under greater pressure thereby reducing their willingness to fully implement programs**.**

Despite the potentially crucial importance of information provision for successful targeting social programs to the poor, the existing literature focuses almost exclusively on analysing the provision of information in alternative contexts. Their results have largely been inconclusive. Studies by Reinikka and Svensson (2004) in Uganda, and Pandey, Goyal and Sundararaman (2009) in India for example, find that access to information on these programs contributed positively to education-related outcomes. Others however, such as Banerjee et al. (2010) in India, Pradhan et al. (2014) in Indonesia, and Lieberman and Posner and Tsai (2014) in Kenya, fail to uncover any statistically significant impact of information on the quality of children's schooling  Olken's (2007) study from Indonesia, finds that disseminating information locally reduced leakage from road project funds, although he also notes that increased public participation in monitoring had no discernible impact on the same outcome. It remains unclear why some information-based interventions succeed in improving service delivery, while others do not. One possible explanation relates to the extent to which information is understood by eligible households (Fox 2007). Previous research, with the exception of Ravallion et al. (2013), assumes that targeted households fully understand the information content provided to them. To the best of our knowledge, there are only two studies that evaluate information-based interventions in poverty programs, both of which use field experiments.

Ravallion et al. (2013) evaluate the impact of an information intervention consisting of a 25-minute long video on India's National Rural Employment Guarantee Act (NREGA). They conclude that the intervention to disseminate information about the NREGA had no discernible impact on individuals seeking and obtaining employment, although the intervention furthered citizens' knowledge about their rights and entitlements to employment opportunities under the NREGA. In a similar vein, Banerjee et al. (2018) implement field experiments across six Indonesian districts. They find that households treated with information received 26% more subsidy (under the auspices of the Raskin program).[3,4] The authors argue that the increased benefits were driven by an improvement in recipients' awareness and ability to bargain with village leaders, as opposed to leaders more assiduously complying with program rules.

In this paper we evaluate the impact of household's access to and understanding of information on the intensive margin of benefit received under two of Indonesia's largest social welfare programs, Raskin and BLSM.[5] The KPS program, one of the largest (information) interventions in the history of poverty reduction programs, seeks to provide eligible households with information about various social welfare programs in addition to detailing the amount of benefits households are entitled to

[3] *Raskin* (*Beras untuk Keluarga Miskin* or Rice for the Poor) is one of the poverty programs aimed at targeted households, which seeks to reduce household spending on food, especially on rice. Before 2002, this program was called OPK (for *Operasi Pasar Khusus* or Special Market Operation program).

[4] This study can be seen as a pilot project for the KPS. Together with the GoI, these authors implemented a field experiment in 378 villages (randomly selected from among 572 villages spread across three provinces). The GoI sent the "*Raskin* identification cards" to eligible households to inform them of their program eligibility in addition to information about the amount of benefit they should receive. Ravallion (2008), however, argues that partial equilibrium assumptions may hold for a pilot study, but that general equilibrium effects (sometimes called "feedback" or "macro" effects in the evaluation literature) may play more prominent roles when such interventions are scaled up nationally. This paper can therefore be considered a complement to Banerjee et al. (2018) in terms of providing the overall (general equilibrium) effects.

[5] BLSM (for *Bantuan Langsung Sementara Masyarakat* or Temporary Unconditional Cash Transfer program) is an unconditional cash transfer that was introduced for the first time in 2005 known as BLT (*Bantuan Langsung Tunai* - or Direct Cash Assistance). The program was implemented by the GoI as one of compensation schemes to subsidise for oil prices.

(see Tohari, Parsons, and Rammohan (2019) for further details). The KPS card was issued to approximately 25% of the poorest Indonesian households (equivalent to 15.5 million of beneficiaries) as identified by their rank in the Unified Database System (UDB). KPS card-holding households are entitled to *Raskin*, temporary unconditional cash transfers (BLSM) and financial assistance for student family members (TNP2K, 2015a). The KPS card therefore confirms eligibility status, while the KPS program additionally provided information about Indonesia's social programs to entitled households.

This information campaign was delivered through various media outlets including television, radio and internet, as well as by local government. We contribute to the literature by evaluating the KPS information treatment using nationally representative administrative data. Specifically we exploit the programs' designs to establish causal inference of the impacts of information provision as well as individuals' understanding of information on the intensive margins of benefit received from two of Indonesia's largest social welfare programs, namely Raskin and BLSM. These are the only two programs that can be examined in this context due to the design and specific questions asked in the Social Protection Survey (SPS).[6] Using all 482 official Proxy Mean Test (PMT) thresholds (i.e. PMT coefficients)[7] and cut-offs used by the Government of Indonesia (GoI) to identify households' eligibility, we subsequently exploit the resulting discontinuity using a range of parametric, semiparametric and non-parametric methods.

Importantly, as shown in Table 3-8 in the Appendix, not all eligible households received the information treatment, and some ineligible households also received information on the programs. Our initial information treatment therefore is whether a household is both eligible for the KPS and received information (we aggregate complete and incomplete information-treated households). The remainder of our sample in the initial estimation therefore comprises ineligible households that also received the information. Based on their eligibility (for KPS), 63.97% of households in the sample who received the information are eligible. Our study differs from Banerjee et al. (2018) in several ways: (1) we evaluate two programs nationwide as opposed to a single program using a smaller

[6] SPS (for *Survei Perlindungan Sosial* or Social Protection Survey) was conducted together by TNP2K and BPS in the period from first quarter of 2013 to first quarter of 2014 as a supplement for regular SUSENAS for Survei Sosial Ekonomi Nasional or National Socioeconomic Survey). This survey aimed to evaluate the performance of poverty targeting and the implementation poverty alleviation programs, especially for the implementation of UDB and the KPS).

[7] Proxy means testing is often used for targeting poverty programs in developing countries. The method assigns a score to all potential participants as a function of observed characteristics. When strictly applied, the program is assigned if and only if a unit's score is below some critical level, as determined by the budget allocation of the scheme (Ravallion, 2007).

sample (2) we provide evidence of an alternative causal mechanism via which information interventions affect poor household's outcomes and finally (3) we are able to gauge the impacts of both information provision and understanding the content of the information provided.

Our results show that households treated with information provision received 30 percentage points more rice under the Raskin program. Further, this study also shows that receiving information reduced the likelihood of elite capture of the BLSM fund being levied by local leaders by around 25 percentage points. Households that reported understanding the content of the information provided, received significantly higher benefits, receiving almost their full entitlement of rice. This finding is in accordance with studies by Reinikka and Svensson (2004, 2005), who argued that the provision of information succeeded in increasing household benefits by ensuring that local leaders did not divert the benefits of poverty programs away from their intended beneficiaries.

In the following section we outline the background to the introduction of the KPS as well as the delivery mechanism of the programs. In Section II we present our data and detail our estimation of households' PMT Score that in turn determines their eligibility. In Section III we discuss our estimation strategy and present our results, while in Section IV we conclude.

## 3.2 Institutional Background

### 3.2.1 Pre-Information Campaign Performance of Targeted Poverty Programs

Since 1997 the Government of Indonesia has implemented several strategies and programs to alleviate poverty (see Tohari et al. 2019). These programs are clustered according to their targeted beneficiaries. Programs targeted at the individual (e.g. Jamkesmas)[8] and household (e.g. Raskin, BLSM, and PKH)[9] levels are classified under the first cluster. Community targeted programs (e.g.

[8] Jamkesmas is health insurance for the poor (previously known as *Asuransi Kesehatan untuk Keluarga Miskin*, or Askeskin, later renamed Jamkesmas). In 2014, Jamkesmas covered some 24.7 million households or 96.4 million people.

[9] PKH is a Conditional Cash Transfer program managed by the Indonesian Ministry of Social Affairs that targets the bottom 5% of the population. PKH beneficiaries receive direct cash transfers ranging from IDR. 600,000 to IDR. 2.2 million or (about USD$67–$250) depending on their family composition, school attendance, pre-/postnatal check-ups and vaccination completions.

*PNPM Mandiri*)[10] fall under the second. A third cluster includes programs targeted at micro and small enterprises (e.g. *Kredit Usaha Rakyat* – KUR).[11]

Previous research has identified several program deficiencies. For Raskin these include: (1) Rice not reaching eligible households, i.e. leakage during the delivery process.[12] (2) Evidence of frequent Raskin purchases by poor and non-poor households alike (Banerjee et al. (2018), Olken 2005)[13] and (3) Local governments failing to judiciously allocate the Raskin budget thereby leading poor households having to pay higher prices for rice in addition to delays in rice distribution (Hastuti, Sulaksono and Mawardi 2012).

The BLT program in 2005 and 2008 suffered from similar problems. According to Sumarto et al. (2006) and World Bank (2012a), the problems associated with the BLT implementation include: (1) Significant targeting errors (2) Elite capture through deductions of BLT benefits that increased markedly between 2005 and 2008[14] and (3) Significant time and travel costs associated with the BLT disbursement process via district post offices, which are typically located in the capital district.

To address these shortcomings, the GoI, between 2011 and 2014, made significant changes to both the targeting mechanisms and service deliveries of poverty programs. The UDB was developed to identify the poorest 40% of the population for inclusion in social assistance programs through proxy means testing (see Tohari et al. 2017 for detail discussion on the targeting improvement). Following improvements in targeting, in the third quarter of 2013, the GoI also introduced the Social Security Card (*Kartu Perlindungan Social - KPS*).

---

[10] PNPM Mandiri (for *Program Nasional Pemberdayaan Masyarakat Mandiri* or the National Program for Community Empowerment) is Indonesia's largest community-driven development program to help alleviate poverty through empowering local communities. There are several components of the PNPM Mandiri, two of which are PNPM Rural, that began in 1998 as Kecamatan Development Program (KDP) and PNPM Urban, which begun in 1999 as the Urban Poverty Program (UPP). Interested readers are referred to TNP2K (2015b).

[11] KUR (for *Kredit Usaha Rakyat* or credit for micro and small enterprises) are credit/working capital and/or investment financing schemes for enterprises that are unable to meet certain banking requirements. The amount of credit provided to each enterprise is less than IDR. 5 million (about 500 USD).

[12] Existing administrative records are unable to indicate the point at which the “missing” rice exits the delivery chain since no single authority is responsible from the point of Raskin rice procurement to household purchase (World Bank (2012b).

[13] The amount of Raskin rice purchased by a household is roughly constant across the entire consumption distribution, meaning non-poor households buy as much Raskin as poor, near-poor, or vulnerable households (World Bank, 2012b). In 2010, the World Bank (2012b) estimates that the average amount of Raskin rice bought by poor households was approximately 3.8 kilograms per month.

[14] Deductions from BLT are most commonly made by village or sub-village level officials ostensibly so that BLT funds can be redistributed among non-beneficiaries (the most common reason for deductions) (World Bank, 2012a).

Targeting performance can be evaluated along (i) the extensive margin i.e. whether eligible households take receipt of program benefits and (ii) the intensive margin i.e. whether eligible households take reciept of all the benefits to which they are entitled. In this paper, we focus on the intensive margin. First in relation to the Raskin program, we examine the effects of information provision on the amount of rice received, using data on the number of kilograms of raskin rice purchased by households and the price that they paid. We proceed to evaluate the impact of information provision on BLSM deductions; in other words the impact of information provision on elite capture. Finally, we provide evidence of households' comprehension of the information provided in terms of Raskin and BLSM, on both rice reciept and elite capture.

### 3.2.2 The KPS and the Information Intervention

The KPS card was the first attempt by the GoI to confirm the eligibility status of households. Where possible it was sent directly to households using the postal service. As shown in Appendix Figure 3-5, the card contains information on the household head, their spouse and address as well as barcodes representing the family card number, in an effort to protect the card from fraud. Accompanying the KPS card was additional information about how to use the card for accessing the benefits of poverty programs (see Appendix Figure 3-6). Among KPS card recipients, around 16% reported that they did not receive any information whatsoever. 77% reported receiving a complete information package, while 7% stated they had received an information package but that it was incomplete.

### 3.2.3 Delivery Mechanism for Raskin and BLSM Programs

Our outcomes of interest include the benefits received from the Raskin program, which is measured by the number of kilograms of rice purchased through Raskin and the probability of the BLSM fund being levied by local leaders. It is critical to understand the delivery mechanisms for these two programs in 2014, which we address below.

*Raskin Program*

The Raskin program aims to reduce household expenditure on food, and particularly on rice, the staple food in Indonesia. In 2013 and 2014, the program covered around 15.5 million of the poorest

Indonesian households based on UDB and PPLS11. According to the 2014 Raskin Guidelines,[15] the implementation of the program has not changed since its inception. Panel A of Figure 3-7 in the Appendix describes the delivery mechanism for the Raskin program. Since 2011 several agents have been involved in the procurement and delivery of Raskin rice. They include: (i) the Coordinating Minister of Social Affairs (for *Kementerian Koordinator Bidang Kesejahteraan Rakyat* or Coordinating Minister of Social Affairs), later called Kemmenko PMK (for *Menteri Koordinator Bidang Pembangunan Manusia and Kebudayaan* or Coordinating Minister of Human Resources and Culture), and the Vice President's National Team for the Acceleration of the Poverty Reduction (TNP2K), which together determine yearly allocation and price of rice,[16] (ii) the Bulog (the National Logistics Agency) responsible for procuring rice from producers and delivering the rice to over 50,000 distribution points across Indonesia. Raskin beneficiaries are expected to make monthly Raskin purchases from these distribution centres[17] and (iii) the District government that is responsible for the logistics of transporting Raskin rice to recipient households.

We measure the effectiveness of the information intervention using the average amount of Raskin rice bought by the beneficiary household in the last three months. Summary statistics of this outcome variable and characteristics of Raskin beneficiaries are presented in Table 3-10 of the Appendix. Although all three programs, Raskin, BLSM, and the KPS should potentially be targetted at the same households (those in the bottom quartile of the population), the number of households that actually received Raskin benefits is almost double the number of BLSM recipients (26,212 for Raskin as opposed to 13,423 for BLSM respectively). Further, among those who bought rice under the Raskin program, only 33.2% held the KPS card, while 27.4% also received the information treatment. The average amount of rice bought by households that received the information is only six kilograms however, which is less than half the intended allocated benefit. Even though this means that the rice received by these targeted households is higher when compared to the average rice bought in 2010, which was only 3.8 kilograms.

---

[15] Kemenkokesra. (2014). *"Pedoman Umum Raskin 2014"* (General Guideline: Rice Subsidy for Poor People 2014). Jakarta: Kemenkokesra.

[16] According to the general guidelines of Raskin 2014, the total number and the list of Raskin beneficiaries were obtained from the Unified Database of TNP2K. In terms of benefit, each targeted household should receive 15 kg/month per month of rice. The price of Raskin rice is IDR 1600 /kg at the Sharing Point (*Titik Bagi*).

[17] The distribution centres (or *Titik Distribusi*) of Raskin are mostly located in village offices or other places that are decided upon between Local Government and Bulog. The local government and village administrative apparatuses are then responsible for notifying eligible beneficiaries and arranging the transport of rice from distribution points to households (*Titik Bagi* or sharing points).

*BLSM*

The BLSM program aims to maintain the purchasing power of targeted households that would otherwise be affected by oil price increases. Similarly to Raskin, the BLSM covers around 15.5 million of the poorest households who received cash benefits of about IDR 150 thousand per month for a four-month period.[18] In 2013, BLSM payments were made in June/July and September/October via PT POS Indonesia, the State-owned postal company. In contrast to Raskin that is disbursed monthly. Since the SPS was conducted in the first quarter of 2014, we examine the effect of the information treatment on benefits received under both the BLSM and Raskin programs.

The payment process of the BLSM in 2013 began by delivering the KPS directly to targeted households by PT POS Indonesia. Hastuti et al. (2013), based on a rapid assessment in four municipalities, argue that there was some evidence that PT POS Indonesia used local leaders to deliver the KPS. To access cash payments, beneficiary households are expected to have a KPS card, an authorisation letter and additional supporting documents (e.g. family card or identity card or domicile card).[19] The fund can be accessed by other household members only under special circumstances with evidence of official supporting documents, typically issued by the local leader. This makes it almost impossible for households that did not receive the KPS to access BLSM, except if they received the fund 'unofficially'; for example if local leaders levied the BLSM fund and redistributed benefits to non KPS holder households (World Bank, 2012a).

The BLSM payment processing facilities are located in District Post Offices. In remote areas and those without access to a post office, PT POS Indonesia was expected to visit and open special payment counters. These special counters were based in local leaders' offices. The BLSM program rules are more stringent than those of Raskin and accordingly, households that did not receive the KPS card could not access the BLSM.

We examine the effect of information provision on households' access to the BLSM by comparing the probabilities of levies being imposed by local leaders on the household's allocated BLSM funds, between treated and non-treated households. Summary statistics on BLSM beneficiaries and their

[18] Tim Sosialisasi Penyesuaian Subsidi Bahan Bakar Minyak (2013). *"Buku Pegangan Sosialisasi dan Implementasi Program-Program Kompensasi Kebijakan Penyesuaian Subsidi Bahan Bakar Minyak 2013"* (The guidelines for the implementation of the 2013 compensation program for Fuel Subsidy Reduction Compensation Program). K. W. P. RI. Jakarta: Sekretariat Wakil Presiden.

[19] Domicile Card is issued by local leaders (sub village or village heads) to prove that the individual/household live in the same village.

characteristics are presented in Table 3-11 in the Appendix. Of the total BLSM beneficiaries, around 70% received the information treatment, while the remaining households received the KPS although without the information intervention. The summary statistics further highlight that treated households are less likely to have their BLSM funds levied by local leaders (16% for those that received the information, as opposed to 20% for those who did not).

## 3.3 Data, PMT Score and Eligibility

To evaluate the effect of the information campaign on the benefits received from poverty programs, this study uses several sources of nationally representative data in conjunction with administrative data from the GoI; specifically the PMT coefficients and the official district quotas used by the GoI to select the beneficiary households from the UDB. Below we describe these datasets in addition to the challenges faced and the steps used to merge them.

### 3.3.1 Data

The data for this study come from the National Socioeconomic Survey (SUSENAS), the Social Protection Survey (SPS) and the Village Potential Census (PODES), and are described in detail below.

*The SUSENAS Survey*

The National Socioeconomic Survey (SUSENAS) is an annual cross-sectional, nationally representative dataset, initiated in 1963-1964 and fielded once every year or two since then. In 2011, the Central Bureau of Statistics of Indonesia (BPS) changed the survey frequency to quarterly, and for each quarter, the SUSENAS covers some 300,000 individuals and 75,000 households. In this paper, we utilize data from the 2014 wave of the SUSENAS survey to: (i) generate variables that are required to estimate the PMT Score for each household using the official PMT coefficients (ii) obtain control variables that are not included in the PMT score estimation and (iii) construct poverty indicators as outcome variables.

*Social Protection Survey (SPS)*

The second dataset used in our analysis is the 2014 Social Protection Survey (SPS), which was conducted jointly by the BPS and TNP2K, as a supplement to the SUSENAS. This survey was implemented from the first quarter of 2013 to the first quarter of 2014, and was specifically aimed at examining the performance of poverty targeting under the implementation of the UDB. A question pertaining to the KPS was only asked in the last two rounds of the survey however. We therefore use data from the first quarter of 2014 since it was the period just after the implementation of the KPS in order to construct our outcome and treatment variables.

*Village Census (PODES)*

The last source of data are from the 2011 and 2014 waves of the PODES, which provide information on all villages/*desa* in Indonesia. The variables produced using this census include the characteristics of the village, some of which were used in estimating the PMT scores.

### 3.3.2 Merging the datasets

The greatest challenge in merging the datasets is the fact that since 2011 the BPS has not published the village and subdistrict codes for their household-based surveys. To address this, we proceed in the following way:

i) First, we merge data from Quarter 1 2014 SPS with Quarter 1 2014 SUSENAS. Using the actual household ID that is available in these two datasets, the selected variables from these two datasets are combined. Overall, around 70,336 households of the SPS sample can be identified from the total of 71,051 households in the SUSENAS survey.
ii) These combined data are then merged with the 2014 pooled SUSENAS to obtain village and sub-district IDs using a 'bridging code' shared privately with us by the BPS.[20]
iii) Finally, we merge the resulting dataset with selected variables from the PODES data using a village identifier in order to obtain village-level variables. After merging with the PODES data, we are able to identify 67,118 households including details of their expenditure, social protection and village information that can be combined with the official PMT coefficients in order to obtain individual household PMT scores, discussed in detail below.

### 3.3.3 Estimating the Household's PMT Score and their eligibility

Measuring PMT scores, thereby defining the eligibility criterion of each household for the KPS, are important steps in providing social protection in Indonesia. Estimating the PMT score involves:

[20] We are grateful to a staff member of the TNP2K targeting team who provided us with this bridging code.

1. Selecting 15.5 million beneficiaries (or 25% of the poorest households) for the KPS using data from the UDB. The UDB contains information on the bottom 40% of the Indonesian population collected through PPLS11 (*Program Pendataan Perlindungan Sosial 2011*) together with their estimated PMT scores. To estimate the PMT score and rank of each household in the UDB, the GoI used coefficients that are measured using SUSENAS and PODES 2011. These coefficients are unique to the 482 districts from the total of Indonesia's 497 districts in 2011.[21] The PMT score for each household is then measured using each household's observable information, which in turn is plugged into the corresponding district coefficient and subsequently ranked. Using household's PMT scores and ranks, the government then selects a list of intended beneficiary households.
2. Using these official PMT coefficients, this study recovers households' PMT scores in 2014: (1) using data from SPS, SUSENAS and PODES in 2014, to construct variables that are comparable to those variables used in PPLS11 (2) following the same steps as conducted by the GoI in which the 2014 variables are plugged into the official PMT coefficients and (3) ranking each household based on their PMT score. As our study uses nationally representative data, the household rank represents their rank relative to the total population. Each household's eligibility for social welfare programs depends upon whether their PMT scores lies above or below their district's cut-off. The cut-off for each district is measured using the official quota used by the GoI to select the list of KPS program beneficiaries that are unique to each district.

We plot the result of PMT score estimation against the probability of receiving KPS using a nonparametric Fan (1992) regression estimation in Figure 3-1.

[21] For other 15 districts, the GoI implement universal targeting system. For these specific areas, such as several districts which have high incidence of poverty, the GoI selects intended beneficiaries using a 'negative lists' method, which means all households are eligible for poverty programs, except those that contain a public servant, local leaders, high ranking military officials etc.

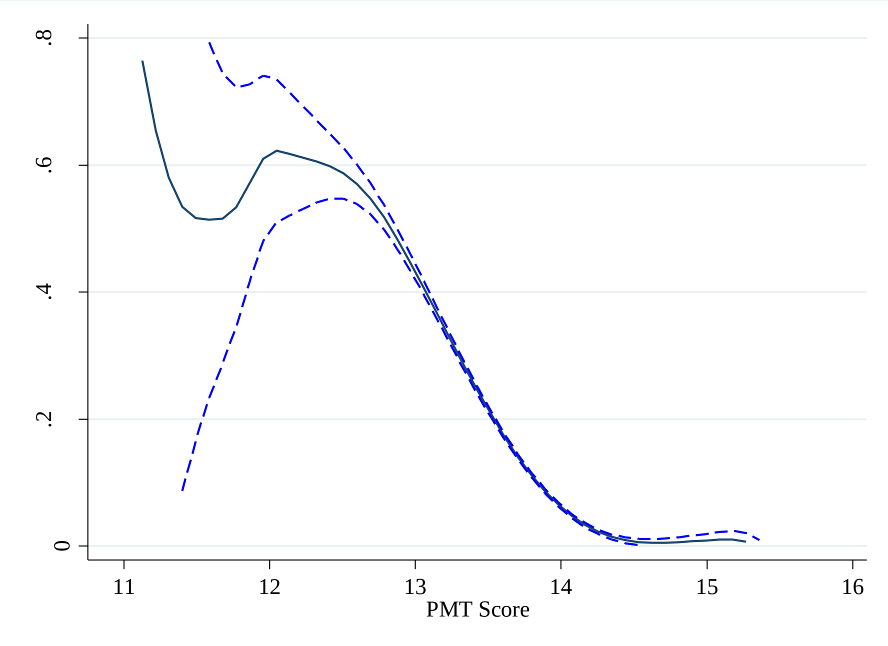



**Figure 3-1. KPS recipient versus PMT Score**

*Notes:* This figure shows a nonparametric Fan regression of the estimated PMT Score against the probability of receiving KPS. Bootstrapped pointwise 95 percent confidence intervals, clustered at the village level, are shown in dashes.

## 3.4 Empirical Estimation

Household's eligibility for social welfare programs is based upon their PMT score relative to their district's cut-off. We investigate the impact of receiving information on the intensive margin of receiving rice under the Raskin program as well as the likelihood of receiving full benefits under the BLSM initiative. Let $pmt_i$ be the PMT score for each household and $\overline{pmt}$ be the PMT cutoff for each district. Then, I, defines the eligibility of each household to receive the information intervention, (TNP2K, 2015a):

(1) $I = 1$ if $pmt_i \leq \overline{pmt}$, and

$I = 0$ if $pmt_i > \overline{pmt}$.

For each eligible household, we can define their potential outcome, $B$, with $(B_1)$ if they received the treatment and $(B_0)$ otherwise. Following Rubin (1974), the difference between the average benefit of recipient households relative to non-treated households becomes:

$$(2) \qquad E(B|I=1) - E(B|I=0) = \underbrace{E(B_1 - B_0|I=1)}_{\theta} + \underbrace{E(B_0|I=1) - E(B_0|I=0)}_{\varepsilon}$$

Our estimate of interest is the average treatment-on-the-treated, i.e, the effect of receiving the information treatment, $\theta$, for subgroup of compliers. The main challenge faced in this study is the prospect of omitted variable bias, $\varepsilon$; unobserved determinants that are potentially correlated with the probability of receiving the information and with the level of benefits received.

### 3.5 The Impact of Information on the Benefit Received

First we implement a regression discontinuity methodology by exploiting the discontinuity of program eligibility in Equation (1). Our outcome variable is the average amount of Raskin rice bought per month in kilograms following the intervention ($R$). The average treatment effect in Equation (2) can then be written as:

$$(3) \qquad \theta_R \equiv E(R_1 - R_0|I=1)$$

Where $\theta_R$ denotes the causal effect of receiving the information treatment. $R_1$ is the average amount of rice bought by households that received the information, $I$. $R_0$ rather refers to the average amount of rice bought by non-treated households.

The empirical challenge in obtaining a consistent estimate of $\theta_R$ in Equation (3) is that selection into treatment is endogenous. As shown in Appendix Table 3-10 and Table 3-11, households that receive information have different characteristics compared to those households that did not receive the information. For example, on average, they have lower PMT scores, are more likely to also receive the BLSM, are less likely to be living in close proximity to the district office, have access to national TV channels and live in a village with a male leader. Such differences tend to zero however, when we restrict our sample to households close to the cutoff, while the amount of rice bought still changes (discontinuously) at the cutoff.[22] Therefore, comparing households within a sufficiently narrow bandwidth of the cutoff, but on opposite sides of it, identifies the [local average] treatment effect of the information treatment. Figure 3-10 in the Appendix depicts the discontinuity of the outcome variable around the cut-off and this is consistent when implementing higher order polynomials.

As previously discussed, the Indonesian Government implemented 482 unique PMT models and cut-offs for each district in Indonesia, of which 471 are used in our analysis. Eleven districts were dropped when we merged our datasets. Since the sample for each district is not representative however, we pool our data and conduct our analysis at the national as opposed to the district level. In order to implement a single cut-off, i.e. discontinuity, we normalize each district's cut-off by subtracting the district's PMT cut-off from the PMT score for each household. Our running variable, $S_i$, then equals the district cut-off minus the PMT score $s_i \equiv \overline{pmt} - pmt_i$, with cut-off at zero. If $s_i$ is positive, this means that the household should receive the information treatment. If $s_i$ is negative, households should not be receiving the treatment. More formally, let $S$ denote our running variable which represents the district cut-off minus the PMT Score with $S = 0$ at the cut-off. Then, $Z \equiv 1(S \geq 0)$ is a treatment assignment dummy that equals 1 for those households whose PMT score is lower than or equal to the district cut-off. The causal effect of the information on benefits received from the Raskin program can be estimated for those households around $S = 0$ by considering the ratio between the discontinuity of the outcome and the discontinuity of the probability to be treated at the threshold. Moreover, the ATT in Equation (3) can be shown as:

$$(4) \qquad \theta_R = \frac{\lim_{S \to 0} E(R \mid S = 0^+) - E(R \mid S = 0^-)}{\lim_{S \to 0} E(I \mid S = 0^+)}$$

Where $S = 0^+$ and $S = 0^-$ denote households that are marginally above and marginally below the cut-off, and the conditional expectation refers to the benefits received under Raskin and the proportion of the households who received the information treatment, $I$, in these two groups. The fundamental identifying assumption is that Z is as good as randomly assigned within an arbitrarily narrow bandwidth of $S = 0$. This assumption is particularly plausible in this study since the total number of households for each district are selected on the basis of district quotas (TNP2K, 2015a).

[22] Since we only have the PMT score for each household as pre-intervention indicators at the household level, we assume that household-specific variables are represented by their differences in the PMT scores, since households around the cut-off are similar.

It implies that there must be a significant number of households just to the right of the cut-off that have PMT scores very close to eligible households that did not receive the treatment. Figure 3-2 shows the distribution of the running variable and the discontinuity test based on Cattaneo, Jansson, and Ma (2019). Similarly, we also conduct a standard McCrary and the result is reported in Figure 3-9 in the Appendix.

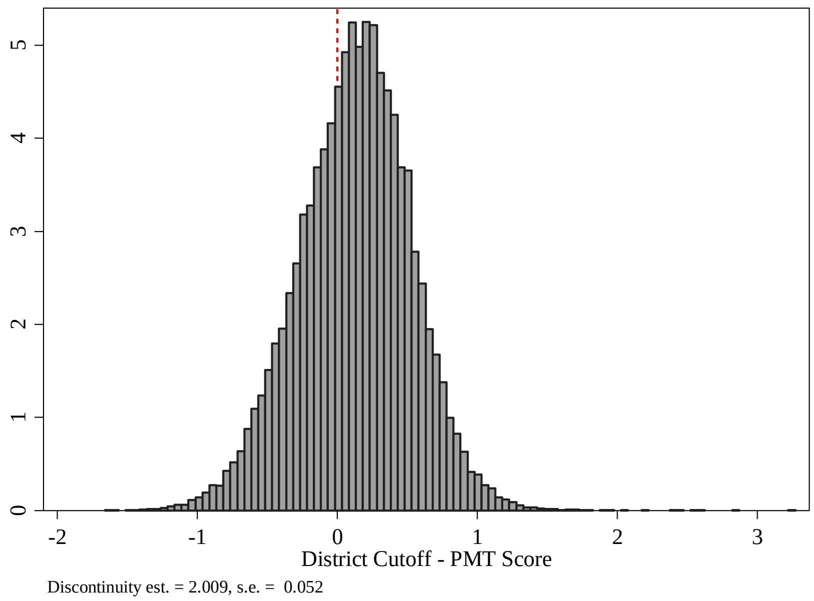



**Figure 3-2. Distribution of Household's Running Variable with Cut-off = 0**

Notes: This figure shows the distribution of the household's running variable, $s_i$, which is calculated by subtracting the district cut-off with the household's PMT Score. Due to this normalization and the eligibility rule of the program design, households would receive the information treatment if their running variables are positive or equal to zero, $s_i \geq \bar{s} = 0$ and they would not receive the treatment if their running variables are negative or less than the threshold, $s_i < \bar{s} = 0$. Discontinuity test is conducted using Cattaneo, Jansson, and Ma (2019)

As a result of the programs' eligibility rules, the probability of receiving the information treatment for households below the threshold, $S = 0$, is zero by definition since they are not eligible for treatment. The targeting of this intervention contains both exclusion and inclusion errors however (Tohari et al., 2019).[23] For example, Table 3-8 in the Appendix shows that only 63.97% of total households who received the treatment were eligible households. As such, there is a degree of fuzziness in the application of the eligibility test.

[23] It is well established that the targeting of poverty programs often suffer from errors of inclusion and exclusion. The inclusion error refers to non-eligible households being erroneously included, while exclusion errors occur when some eligible households are erroneously excluded from receiving the program benefits (for further details please refer to Ravallion (2007).

In the presence of measurement errors, the sample analog of (4) is inconsistent for the parameter of interest. Rescaling we can write:

$$(5) \qquad (\theta_R | \, compliers) = \frac{\lim_{S \to 0} E(R \mid S = 0^+) - E(R \mid S = 0^-)}{\lim_{S \to 0} E(I \mid S = 0^+) - E(I \mid S = 0^-)}$$

Assuming monotonicity and conditional on $S^*$, the process generating measurement error is orthogonal to the process of interest. The ratio in (5) is then the Local Average Treatment Effect (LATE) of receiving information on the benefit received from Raskin on the subset of compliers near the cut-off (Imbens and Angrist, 1994, Hahn, Todd and Van der Klaauw, 2001). The causal effect can then be estimated using a simple instrumental variable strategy, where the eligibility status is utilized as an instrument for treatment.

Table 3-1 presents the results of the 2SLS kernel local linear regressions of the effects of receiving information on the benefits received from the Raskin program. To select the optimal bandwidth, we follow the criteria proposed by Imbens and Kalyanaraman (2012) henceforth, IK2012 in the first three Columns and Calonico, Cattaneo and Titiunik (2014), henceforth, CCT2014, in Columns four to six. The polynomial order, the size of the bandwidth and the observations inside the bandwidth are presented in Table 3-1.

The 2SLS coefficients using nonparametric estimates without adjusting for covariates, in Columns (1) and (4) in Panel A of Table 3-1, show that in general, receiving information increases the benefit received from Raskin by about 30.6 percentage points according to IK2012, and 39.2 percentage points according to CCT2014. We also test whether the treatments differed between Java and Non-Java, by splitting the sample. Java is the most populous island in Indonesia and previous studies (e.g., Ravallion and Dearden (1988)) have shown that Java tends to be more egalitarian whereby benefits are more often shared. Given this, the distribution of the benefits received from poverty programs could differ between Java and other areas of the country. The results using linear order polynomials in Panel A of Table 3-1, as presented in Columns (2) and (3) based on IK2012 and Columns (5) and (6) based on CCT2014, show that there is significant difference in the impact of information between Java and other provinces, even though the effects are not statistically significant using lower order of polynomials. When we implement cubic order polynomials, the results in both Java and Non-Java become statistically significant. Under this specification, the effect of information on the Java subsample is about 61.1 percentage points higher and statistically significant, while the effects in the Non-Javan provinces are about 32.8 percentage points under IK bandwidths. Our estimates using higher order polynomials, except cubic order polynomials under the CCT bandwidth selection, are likely generating higher estimates because higher order polynomials assign far greater weights to observations further away from the discontinuity (Gelman and Imbens, 2017).

**Table 3-1. The Effect Of Receiving Information on Log (Raskin Bought) Using RD Estimation**

| | Bandwidth: IK (2012) | | | Bandwidth: CCT (2014b) | | |
|---|---|---|---|---|---|---|
| | All | Java | Non Java | All | Java | Non Java |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *E* (*R* \| Information = *0*) (Kg) | 4.738 | 4.178 | 5.263 | 4.738 | 4.178 | 5.263 |
| | ***Panel A: Without Covariates-Adjusted*** | | | | | |
| Linear | 0.306 | 0.542 | 0.170 | 0.392 | 0.522 | 0.266 |
| | (0.146) | (0.445) | (0.156) | (0.131) | (0.386) | (0.144) |
| Quadratic | 0.416 | 0.539 | 0.290 | 0.447 | 0.595 | 0.315 |
| | (0.130) | (0.385) | (0.142) | (0.126) | (0.341) | (0.134) |
| Cubic | 0.457 | 0.611 | 0.328 | 0.402 | 0.759 | 0.243 |
| | (0.128) | (0.334) | (0.137) | (0.133) | (0.356) | (0.140) |
| Size of bandwidth [L: R] | [0.178 : 198] | [0.168 : 0.341] | [0.196 : 0.198] | [0.115 : 0.128] | [0.125 : 0.229] | [0.129 : 0.131] |
| Observations inside bandwidth | 8,483 | 6,219 | 4,731 | 5,573 | 4,111 | 3,229 |
| Observations | 26,083 | 12,302 | 13,781 | 26,083 | 12,302 | 13,781 |
| | ***Panel B: With Covariates-Adjusted*** | | | | | |
| Linear | 0.259 | 0.568 | 0.140 | 0.350 | 0.503 | 0.225 |
| | (0.148) | (0.489) | (0.156) | (0.132) | (0.455) | (0.145) |
| Quadratic | 0.381 | 0.513 | 0.255 | 0.410 | 0.495 | 0.270 |
| | (0.132) | (0.437) | (0.142) | (0.127) | (0.388) | (0.136) |
| Cubic | 0.428 | 0.521 | 0.294 | 0.371 | 0.689 | 0.204 |
| | (0.129) | (0.404) | (0.139) | (0.135) | (0.394)* | (0.143) |
| Size of bandwidth [L: R] | [0.180 : 0.193] | [0.192 : 0.419] | [0.202 : 0.193] | [0.116 : 0.124] | [0.129 : 0.281] | [0.131 : 0.127] |
| Observations inside bandwidth | 8,322 | 7,435 | 4,676 | 5,496 | 4,971 | 3,174 |
| Observations | 26,083 | 12,302 | 13,781 | 26,083 | 12,302 | 13,781 |

Notes: This table displays nonparametric estimates of the effect of receiving information on the benefit received from the Raskin Program. The outcome variable is the log average Raskin rice bought in the last three months. All coefficients are estimated using a kernel local linear regression in an asymmetric bandwidth around the cutoff. *E (R | Z = 0)* denotes the average monthly of Raskin Rice bought in the last three month by households who are not eligible for the KPS program (*Z=0*). The table reports the bandwidth selection rule, IK2012 or CCT2014, the size of the bandwidth (distance from zero) and the number of observations included in the bandwidth. The standard errors (presented in parentheses) are clustered by the village.

We also include pre-intervention covariates related to village and head of village characteristics following Frolich (2007) and Calonico et. al. (2016).[24] Imbens and Kalyanaraman (2012) however, note that the inclusion of additional covariates should not affect such analyses significantly. The

[24] Pre-intervention covariates related to village and head of village are derived from 2011 PODES data.

results are presented in panel B of Table 3-1, which shows that in general the inclusion of covariates produces slightly lower estimates. For example, using linear order polynomials and the IK bandwidth selection, the covariates-adjusted estimates of providing information on Raskin are about 25.9 percentage points higher, while under non-adjusted covariates estimation it is about 30.9 percentage points.

Interestingly the covariates-adjusted RDD estimation under IK2012 bandwidth selection and linear order polynomial produces the closest estimate when compared to the results of Banerjee et al. (2018). Those authors find that providing information through the Raskin card increases the rice subsidy received by about 26% when compared to the control group. It can be argued that our research provides external validity of Banerjee et al. results therefore.

## 3.6 Robustness Checks and Extensions

### 3.6.1 Sensitivity Tests

First, we choose a range of placebo cut-offs to ensure that the discontinuity of the outcome of interest only occurs at the true cut-off. Table 3-2 summarizes the estimate of the effect of information for selected cut-offs ranging from -0.1 to 0.1 in increments of 0.05. Figure 3-3 plots the estimates. The cut-off at 0 is included as a benchmark. As expected, with the exception of 0 i.e the true cut-off, the information treatment did not change at any other placebo cut-offs. In terms of magnitude, the effect of information is smaller compared to the true effects at all other cut-offs. This implies that the outcome of interest does not jump discontinuously at any other cut-off other than at 0.

**Table 3-2. Kernel Local Linear Estimation at Selected Cut-Offs**

| Alternative Cutoff | Optimal Bandwidth: IK2012 | Effect of Information | Robust Inference | | | | Observation | |
|---|---|---|---|---|---|---|---|---|
| | | | *P-value* | *CI* | | | Left | Right |
| (1) | (2) | (3) | (4) | (5) | | | (6) | |
| -0.1 | 0.035 | -0.010 | 0.947 | [-0.200 | : | 0.187] | 485 | 513 |
| -0.05 | 0.026 | -0.126 | 0.152 | [-0.346 | : | 0.054] | 444 | 460 |
| 0 | 0.177 | 0.071 | 0.013 | [0.018 | : | 0.148] | 2,670 | 5,106 |
| 0.05 | 0.037 | 0.024 | 0.470 | [-0.095 | : | 0.260] | 940 | 962 |
| 0.1 | 0.035 | -0.050 | 0.335 | [-0.218 | : | 0.074] | 956 | 1,009 |

This table displays nonparametric estimates of the effect of receiving information on the benefit received from the Raskin Program at several different cut-offs. All coefficients are estimated using a kernel local linear regression in an asymmetric bandwidth around the cutoff. Optimal bandwidths are selected using IK2012. Robust *P-value* and *Confidence Interval* are reported in Column 4 and 5, respectively.

In choosing a bandwidth, it is critical to consider an optimal balance between estimation precision and estimation bias (Lee and Lemieux 2010). Larger bandwidths, on the one hand, yield more precise estimates since more observations can be relied upon in estimation (i.e. greater efficiency). On the other hand, when a larger bandwidth is used, resulting estimates are less likely to be accurate as increasingly observations are considered that are located further from the threshold (i.e. greater bias). Figure 3-4 plots the estimated 2SLS coefficients of the effect of information and the associated confidence intervals for different bandwidth selections or window lengths using IK2012. The area within the vertical dashed lines represents the location of the true optimal bandwidths that are selected based on both IK2012 and CCT2014. Evidentally, as the bandwidth increases, the bias of the estimator increases as its variance decreases. Therefore, it is natural in such a set-up that the larger the bandwidth, the smaller the confidence intervals, but due to bias, the effects will also be displaced.

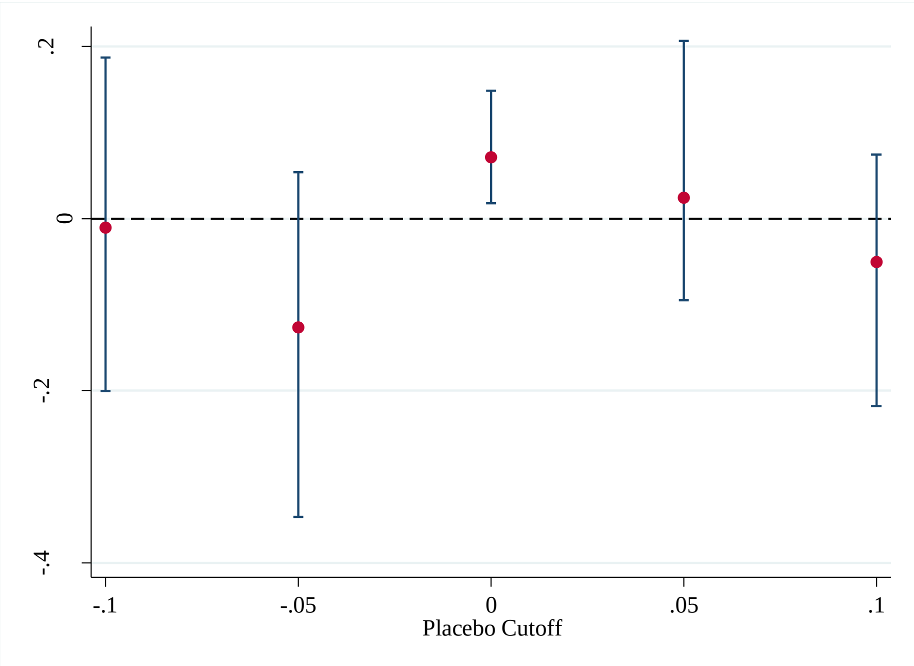



**Figure 3-3. Sensitivity Analysis on Selected Cut-offs – All sample**

*Notes*: This figure presents the sensitivity tests of the effect of information using different placebo cut-offs. The true cut-off, 0, is used as a benchmark for other artificial cut-offs. All coefficients are estimated using a kernel local linear regression in an asymmetric bandwidth around the cut-off. Optimal bandwidths are selected using IK2012.

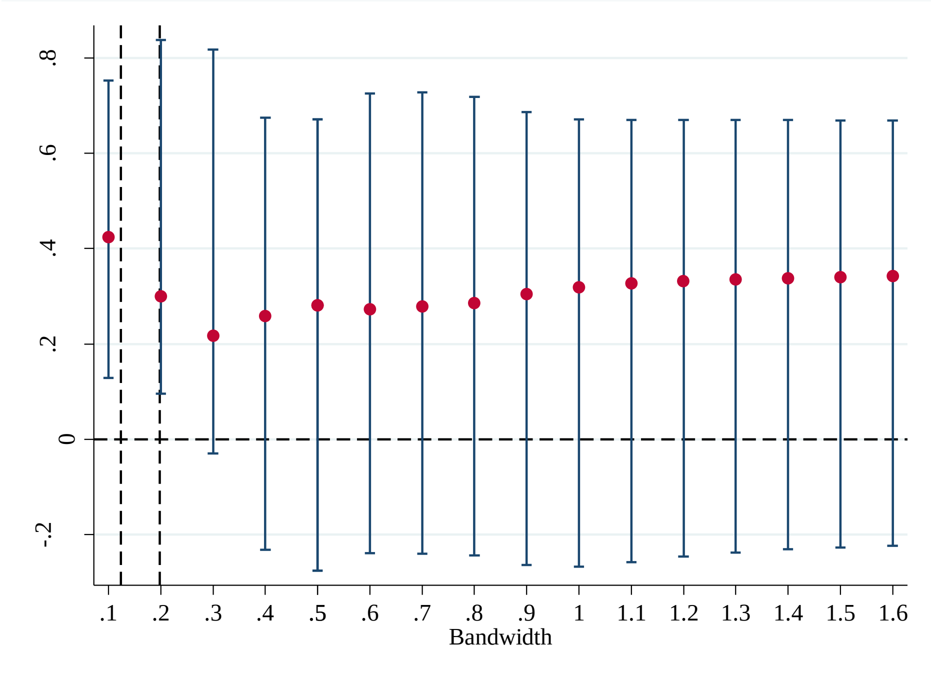



**Figure 3-4. Sensitivity Analysis on Selected Bandwidths – All sample**

*Notes*: This figure presents the sensitivity tests of the effect of information using different placebo bandwidth. Within the vertical dashed denotes the area in which optimal bandwidths are selected using IK2012 and CCT2014. All coefficients are estimated using a kernel local linear regression and blue lines represent the confidence intervals.

### 3.6.2 Comparing RD, LATE and LARF

The results from the local kernel regression results confirm that receiving information significantly increases the benefits received from the Raskin program. Below we examine whether the effects are also consistent if they are estimated following Angrist, Imbens and Rubin's (1996) parametric estimate and Abadie (2003) semiparametric approach.[25] Our parametric approach, the estimation of the LATE, implements an instrumental variable technique with eligibility status of the household used as our instrument for treatment. Our semiparametric approach as detailed in Abadie (2003), instead proposes to use a Local Average Response Function (LARF) that allows one to compare the characteristics of treated and non-treated individuals within the compliers' subset, in the absence of knowledge as to who is and is not a complier. The estimation of the LARF is conducted in two steps which are: (1) to measure the weights, $w$, by estimating parametrically (or non-parametrically) $p(Z = 1 \,|X)$ and (2) estimating the effects using Weighted Least Square (WLS) with weights equal to $w$.

[25] Lee and Lemieux (2010) note a number of alternative estimation strategies and suggest that no single method be relied upon. Our parametric and semiparametric estimations are therefore included to complement our non-parametric approach.

With regards to national level effects, Columns (2) and (5) in Table 3-3, show the results from both our parametric and semiparametric estimators, which are slightly different and statistically significant. The magnitude of the effects and their signs show that the provision of information increases the benefits received from the Raskin program by about 37.1 percentage points in parametric and 48.5 in semiparametric estimations, respectively. The result of parametric estimation is in the range of the estimated effects from our nonparametric approach in Table 3-1, while the result of semiparametric estimation is slightly higher in all nonparametric alternative estimations.

**Table 3-3. The Effect of Receiving Information on RASKIN Intensive Margins Using LATE and LARF Estimations**

| | OLS | LATE | | | LARF | | |
|---|---|---|---|---|---|---|---|
| | | All Sample | Java | Non-Java | All Sample | Java | Non-Java |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Reduced form | | 0.184 | 0.192 | 0.181 | | | |
| | | (0.003) | (0.006) | (0.004) | | | |
| Effect of Information | 0.215 | 0.371 | 0.426 | 0.368 | 0.485 | 0.465 | 0.426 |
| | (0.012) | (0.043) | (0.066) | (0.057) | (0.068) | (0.142) | (0.080) |
| First Stage Coef. of Z | | 0.226 | 0.217 | 0.238 | | | |
| | | (0.006) | (0.009) | (0.009) | | | |
| First Stage *F-Stat* of Z | | 1239.46 | 598.1 | 687.95 | | | |
| Control Village | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Control Vill. Head | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 26,212 | 26,212 | 12,302 | 13,910 | 8,011 | 3,285 | 4,726 |

This table shows the estimates of the effect of receiving information on the benefit received from the Raskin Program. Dependent variables are the log average Raskin rice bought in the last three months. Column (1) is the estimation result using OLS estimation, ignoring the endogeneity on selection. The first stage instrument denotes a dummy $Z = 1$ if households are eligible, the first stage coefficient of $Z$ and the F-statistic (for the excluded instrument which is adjusted for heteroskedastic and clustered standard errors) are also reported in Column (2) – (4). Column (2)-(4) is the LATE estimation result following Angrist, Imbens, and Rubin (1996). Column (5)-(7) is the LARF result following Abadie (2003). All standard errors are clustered at the village level and computed over the entire two-step using a block bootstrap with 500 repetitions following (Cameron, Gelbach and Miller, 2008).

The difference in the effect of the information treatment between Java and Non-Java is noteworthy. In general, our parametric and semiparametric estimates produce consistent results with the nonparametric estimation in which the effect of information on social benefits away from Java is lower than in Java itself and all the results are statistically significant. In terms of the magnitude however, using our parametric results in Columns (3) and (4) of Table 3-3, we observe that the provision of information increases the benefits received from the Raskin program by about 42.6 percentage points in Java households and by 36.8 percentage points in Non-Java households, respectively. Moreover, our semiparametric results for Java and Non-Java households, produce the same results with small difference between Java and Non-Java compared to our parametric results.

Finally, it is also important to note that the OLS estimate in Column (1) of Table 3-3 is downwardly biased. According to the OLS result, the increase in the benefits received from Raskin is about 21.5 percentage points conditional on covariates. The estimated effect of information increases when we instrument this variable with the household's eligibility to receive treatment however. Overall therefore, we can conclude that the provision of information to eligible households increases the level of benefits received by between 30-40 percentage points on average.

## 3.7 How did Information Affect the Benefit Received?

Next we examine the mechanism through which information interventions may influence program recipients. Kosack and Fung (2014) drawing upon evidence from 16 experimental evaluations explain the manner in which the provision of information could improve public services. They hypothesise that information can be useful for improving program governance via: (1) the action cycle (2) the short and long routes of accountability and (3) the willingness of providers, policymakers, and politicians to make improvements.

Two possible arguments can be used to explain the effect of information when the government is a monopoly service provider. The first is that the provision of information could improve the awareness of individual's rights among potential beneficiaries, which in turn could lead to more proactive participation by the public in monitoring program delivery. This is shown by Pandey et al. (2009) in India. Secondly, additional information could increase the bargaining position of the beneficiaries in their dealings with the local leader, as shown by Banerjee et al. (2018) for Indonesia. Fox (2007) however argues that information can only improve public participation and increase benefits if the information is understandable and actionable.

Another possible argument is that information could reduce the probability of local leaders capturing program benefits, i.e. elite capture. This argument has been supported by (Reinikka and Svensson, 2004, 2005) using evidence from Uganda. They show that the provision of information to both schools and parents helped to monitor local officials handling education funds and was highly successful in reducing elite capture, while also having a positive impact on education outcomes. Local capture and corruption in the Indonesian context has been studied by Suryadarma and

Yamauchi (2013) who investigated missing funds in *Inpres Desa Tertinggal* (IDT) program.[26] Olken (2007) found that increasing top-down monitoring or central government audits reduced missing funds from the Indonesian village project.

In this study, while corroborating the external validity of Banerjee et. al. (2018), we are unable to test their proposed mechanism through which information empowers poor households; since suitable questions were not posed in the SPS. Rather, following Reinikka and Svensson (2004, 2006), Olken (2006) and Suryadarma and Yamauchi (2013), we investigate an alternative channel, that of reducing elite capture. We hypothesise that information provision influences the benefits received via reducing the likelihood of local elites capturing poverty program benefits. In order to test this hypothesis, our proxy measure of local capture is an indicator variable, which takes the value 1 if the recipient household had a levy imposed by local leaders or not, (L).[27] The average treatment on the treated from Equation 2 can be rewritten as:

$$(6) \qquad \theta_L \equiv E(L_1 - L_0 | I = 1)$$

Where $\theta_L$ denotes the causal effect of receiving the information, $L_1$ refers to the probability of a levy being imposed on the BLSM fund by the local leader given the household received the information and $L_0$ the probability of the fund being levied for those households who did not receive the information treatment.

In estimating (6), it is important to take into account the following considerations. The first is that households need to bring the KPS card with supporting documents to access benefits from BLSM. It is unlikely (if not impossible) for households without KPS to receive any benefits directly from the Post Office. Taking this into account, the usage of eligibility rules as an instrument for information treatment is no longer valid. The most plausible explanation for why households do not receive the package completely include: (1) geographical difficulties (such as the distance between

---

[26] *Inpres Desa Tertinggal* (IDT, Presidential aid for poor villages) was a village targeted poverty program implemented by the GoI in the period of 1990s. Under this program, selected villages were assigned to choose poor households that would be eligible for IDT loans based on village-level meetings that were facilitated by the village head and a local government agency called *Lembaga Ketahanan Masyarakat Desa* (LKMD, Village Community Resilience Board). The selected households were formed into community groups (*pokmas*,or kelompok masyarakat). These *pokmas* leaders were also responsible for managing loan activities within their groups (Suryadarma and Yamauchi 2013).

[27] Our proxy follows the logic behind the definition of local capture used by Reinikka and Svensson (2005). They used the proportions of intended and actual funds received as a proxy for local capture. It is also consistent with Alatas et al. (2013) whom argue that capture by formal elites occurs during the distribution of benefits and not during the processes when the beneficiary lists are determined by central government.

the village and the post office), such that the postman is unable to send the package directly or (2) as a consequence of the first condition, the postman usually uses the help of local village leader to deliver the package. At this stage, local leaders potentially have the opportunity to take the package or information, such that households fail to receive the entire package. To reduce the selection bias into treatment therefore we use whether the household received the package from a postman as an instrument.

Given that the dependent variable in Equation (6) is binary, Angrist (2001) suggests that simple IV models such as those based on Abadie (2003) can be implemented to estimate average effects in a non-linear model with covariates. In addition to Abadie (2003), this study also corrects the selection bias for a non-linear model using a Heckman selection model as well as a simple bivariate probit model (Heckman, 1978). Columns (1) and (2) in Table 3-4 report the results from using simple OLS and probit ignoring the endogeneity problem of receiving the information.[28] The estimates show that receiving information is associated with a statistically significant decrease of 5 percentage points in the probability of a levy being imposed by local leaders on the BLSM. The estimated effect of receiving information decreases significantly when we correct for selection bias by instrumenting this variable with a dummy variable that equals 1 if households receive the package directly from the postman and 0 otherwise. Column (4) uses the methodology proposed by Abadie (2003). The effect of receiving information on the probability of local capture is further reduced (by 26.7 percentage points), while remaining statistically significant. Similarly in Columns (5) and (6), which implement the Bivariate probit and Heckman two-stage estimators respectively, the effect of receiving information is approximately the same and statistically significant.

Despite receiving information, households' understanding of the content of information campaigns proves crucial in reducing elite capture. This finding complements Banerjee et al. (2018) whom find that information campaigns increase community awareness and empower citizens to more effectively demand their rights. According to the SPS, about 18% of households that receive information understand the content. [29] We further hypothesise that the status quo, one characterised

[28] The endogeneity in receiving treatment among the KPS beneficiaries could be caused, for example, by the local leader sorting the information materials with the objective of preventing households knowing their rights. As shown in Table 3-10 and Table 3-11 in the Appendix, the percentage of households that receive information is higher when they receive the package directly from postmen.

[29]Appendix Table 3-9 reports the percentage of households whether they understood about the content of information or did not. The understanding of the household is measured based on a question in SPS which clarify how many of the program should be received by the KPS holders. Based on the KPS guideline, number of the programs should be at least 4.

by incomplete information, is potentially due to local leaders wanting to maintain control of the delivery of poverty programs. Alatas et al. (2013) similarly find that formal elites are more likely to be beneficiaries from the Jamkesmas and Raskin programs, which could be an indication of rent-seeking behaviour.

**Table 3-4. The Effect of Receiving Information on Local Capture of BLSM Fund**

| | OLS | Probit | Endogenous treatment | | | |
|---|---|---|---|---|---|---|
| | | | | LARF | Biprobit | Heckman |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Effect of Information | -0.053 | -0.051 | | -0.267 | -0.258 | -0.253 |
| | (0.017) | (0.017) | | (0.037) | (0.059) | (0.087) |
| First Stage Coef. of Z | | | 0.075 | | | |
| | | | (0.013) | | | |
| First Stage *F-Stat* of Z | | | 35.94 | | | |
| Control distance to Post | Yes | Yes | Yes | Yes | Yes | Yes |
| Control Village | Yes | Yes | Yes | Yes | Yes | Yes |
| Control Vill. Head | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 11,324 | 11,324 | 11,324 | 9,536 | 11,324 | 11,324 |

This table shows the estimates of the effect of receiving information on the probability of households receiving BLSM funds without levied. The independent variable is 1 if the BLSM fund was levied by local leaders and 0 otherwise. Columns (1) – (2) display the estimation results using simple OLS and Probit estimations thereby ignoring the endogeneity problem. The first stage coefficient denotes a dummy $Z = 1$ if households received the package directly from Postman and the F-statistic for the excluded instrument (adjusted for heteroskedastic and clustered standard errors) are also reported in Column (3). Columns (4)-(6) present the estimation results that include endogeneity treatment using Abadie (2003), bivariate probit and Heckman two-stage respectively. The standard errors (presented in parentheses) are clustered at the village and in Columns (4) – (6) computed over the entire two-step using a block bootstrap with 500 repetitions following (Cameron, Gelbach and Miller, 2008).

## 3.8 Implications of households understanding the content of information campaign

To test if understanding the contents of information campaign affects the intensive margin of programs, we estimate a simple Heckman selection model. The outcome variables are similar to Equations (4) and (6) in understanding whether households understood the content of the campaign.

Table 3-5 presents the results of estimating Heckman selection models, where Panel A presents estimates using the log of kgs of Raskin rice purchased as the dependent variable, while in Panel B we present estimates as to whether a levy was imposed on the BLSM fund. The estimated equations used to generate the results in Columns (2) and (4) include the same variables as the selection equation, except for a dummy variable that takes the value of 1 if the household received the information, and a dummy equal to 1 if the household lives in a village with access to TV stations. The use of these variables is similar to an approach that uses those two variables as instruments. The results from our selection models show that those households that receive information are more likely to have a better understanding of the program benefits compared to non-treated households. Those households that understood the content of the information campaign received on average a 278 percentage point increase in the amount of Raskin rice, equivalent to almost the full amount of the intended benefit (13.9 of total benefit 15 kg/month/household). Similarly, in the case of the BLSM, as presented in Column (4), those who understood the information content are more likely to receive the full amount of the BLSM fund.

**Table 3-5. The Effect of Understanding on RASKIN Benefit and BLSM Fund Deduction**

| | Panel A: Raskin | | Panel B: BLSM | |
|---|---|---|---|---|
| | Selection | Outcome | Selection | Outcome |
| | (1) | (2) | (3) | (4) |
| Information | 0.283 | | 0.128 | |
| | (0.021) | | (0.031) | |
| Village has access to TV Station | 0.151 | | 0.331 | |
| | (0.068) | | (0.095) | |
| Effect of Understanding | | 2.780 | | -0.864 |
| | | (0.222) | | (0.241) |
| *E (Y* \| Understanding = *0)* | | [5.003] | | [0.178] |
| Province Dummy | No | Yes | No | No |
| Control Village | Yes | Yes | Yes | Yes |
| Control Vill. Head | Yes | Yes | Yes | Yes |
| Control Eligibility | Yes | Yes | Yes | Yes |
| Observations | | 26,212 | | 13,242 |
| Wald $X^2$ | | 1,325.36 | | 416.21 |
| Prob > $X^2$ | | 0.000 | | 0.000 |

This table shows the estimates of the effect of understanding information using Heckman selection models. The dependent variable in the selection models, in Column (1) and (3), is a dummy variable that equals 1 if households understood the content of the information campaign. The dependent variable in the outcome equation is the log average Raskin rice bought in the last three months in Panel A, while in the panel B is a dummy variable that equals 1 if the BLSM fund was levied by local leaders and 0 otherwise. The outcome equation includes the same variables as the selection equation, except for a dummy variable that equals 1 if households received the information and 0 otherwise and a dummy variable equal to 1 if a village has an access to TV stations or 0 otherwise; and with province dummy variables in Raskin outcome. Estimations are conducted using two-step consistent estimators. The standard errors (presented in parentheses) are computed over the entire two-step using a block bootstrap with 500 repetitions following (Cameron et al., 2008).

## 3.9 Conclusion

Information campaigns have been proffered as low cost interventions to improve take-up rates of poverty programs' in developing countries. We contribute to the limited evidence base on the effectiveness of information interventions. In 2013, the Indonesian Government implemented one of the largest targeted information interventions in history, covering about 15.5 million households. To our knowledge, the effectiveness of this campaign on take up of benefits by eligible households has not been rigorously investigated at the national level.

In this paper we contribute to the literature by (i) investigating the extent to which households receive an information campaign and (ii) whether this in turn led to an improvement in the level of benefits. Our results show that the information campaign contributed positively to the benefits received from the Raskin program. However, it should be noted that eligible beneficiaries still received less than their allocated amount. One possible explanation is that local implementers, village leaders, still have authority to distribute the Raskin rice and they may allocate it to both poor and non-poor households.

Further, we investigate a potential mechanism through which information influences the level of benefits received. Our analysis shows that when eligible beneficiaries understand the content of the information campaign, it significantly reduces the possibility of local leaders imposing a levy on the BLSM fund. We speculate that this is because the campaign material included information on the grievance mechanism, advising households to report directly to the central government in case village heads captured the benefit. The complaint resolution puts pressure on local leaders to comply with program rules. Another important finding from our study is that understanding the content of the information campaign improves the likelihood of a household receiving their allocated amount of rice in full. This suggests that the information based intervention should be mindful as to whether their message is understandable and accessible to their beneficiaries. This is clearly challenging for policy makers in developing countries, particularly in Indonesia.

## 3.10 References


Abadie, A. (2003). Semiparametric instrumental variable estimation of treatment response models. *Journal of econometrics, 113*(2), 231-263.

Akerlof, G. A. (1970). The market for" lemons": Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, 488-500.

Alatas, V., Banerjee, A., Hanna, R., Olken, B. A., Purnamasari, R., & Wai-Poi, M. (2013). *Does elite capture matter? Local elites and targeted welfare programs in Indonesia*. Retrieved from

Angrist, J. D. (2001). Estimation of limited dependent variable models with dummy endogenous regressors: simple strategies for empirical practice. *Journal of Business & Economic Statistics, 19*(1), 2-28.

Angrist, J. D., Imbens, G. W., & Rubin, D. B. (1996). Identification of causal effects using instrumental variables. *Journal of the American statistical Association, 91*(434), 444-455.

Banerjee, A., Banerji, R., Duflo, E., Glennerster, R., & Khemani, S. (2010). Pitfalls of participatory programs: Evidence from a randomized evaluation in education in India. *American Economic Journal: Economic Policy, 2*(1), 1-30.

Banerjee, A., Hanna, R., Kyle, J., Olken, B.A. and Sumarto, S., 2018. Tangible information and citizen empowerment: Identification cards and food subsidy programs in Indonesia. *Journal of Political Economy*, 126(2), pp.451-491.

Calonico, S., Cattaneo, M. D., & Titiunik, R. (2014). Robust nonparametric confidence intervals for regression-discontinuity designs. *Econometrica, 82*(6), 2295-2326.

Calonico, S., M. D. Cattaneo, M. H. Farrell, and R. Titiunik. 2016. Regression discontinuity designs using covariates. *Working Paper, University of Michigan.*

Cattaneo, M.D., Jansson, M. and Ma, X., 2019. Simple local polynomial density estimators. *Journal of the American Statistical Association*, pp.1-11.

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2008). Bootstrap-based improvements for inference with clustered errors. *The Review of Economics and Statistics, 90*(3), 414-427.

Cameron, L., & Shah, M. (2013). Can mistargeting destroy social capital and stimulate crime? Evidence from a cash transfer program in Indonesia. *Economic Development and Cultural Change, 62*(2), 381-415.

Fox, J. (2007). The uncertain relationship between transparency and accountability. *Development in practice, 17*(4-5), 663-671.

Frolich, M. (2007). Regression Discontinuity Design with Covariates. *IZA Discussion Paper No. 3024, Bonn.*

Gelman, A., & Imbens, G. (2017a). Why high-order polynomials should not be used in regression discontinuity designs. *Journal of Business & Economic Statistics*, 0-0. doi:10.1080/07350015.2017.1366909

Hahn, J., Todd, P., & Van der Klaauw, W. (2001). Identification and estimation of treatment effects with a regression-discontinuity design. *Econometrica, 69*(1), 201-209.

Hastuti, Sulaksono, B., & Mawardi, S. (2012). Tinjauan Efektivitas Pelaksanaan Raskin dalam Mencapai Enam Tepat. *Smeru Working Paper*.

Hastuti, S. U., Sulaksono, B., Mawardi, S., & Syukri, M. (2013). *Pemantauan Cepat Pelaksanaan Penyaluran Bantuan Langsung Sementara Masyarakat (BLSM)*. Retrieved from

Heckman, J. J. (1978). Dummy Endogenous Variables in a Simultaneous Equation System. *Econometrica, 46*(4), 931-959. doi:10.2307/1909757

Imbens, G., & Kalyanaraman, K. (2012). Optimal bandwidth choice for the regression discontinuity estimator. *The Review of Economic Studies, 79*(3), 933-959.

Imbens, G. W., & Angrist, J. D. (1994). Identification and Estimation of Local Average Treatment Effects. *Econometrica, 62*(2), 467-475. doi:10.2307/2951620

Kosack, S., & Fung, A. (2014). Does transparency improve governance? *Annual Review of Political Science, 17*, 65-87.

Lee, D., & Lemieux, T. (2010). Regression Discontinuity Designs in Economics. Journal of Economic Literature, 48(2), 281-355.

Lieberman, E. S., Posner, D. N., & Tsai, L. L. (2014). Does information lead to more active citizenship? Evidence from an education intervention in rural Kenya. *World Development, 60*, 69-83.

McCrary, J., 2008. Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of econometrics*, 142(2), pp.698-714.

Olken, B. A. (2005). Revealed community equivalence scales. *Journal of Public Economics, 89*(2), 545-566.

Olken, B. A. (2007). Monitoring corruption: evidence from a field experiment in Indonesia. *Journal of Political Economy, 115*(2), 200-249.

Pandey, P., Goyal, S., & Sundararaman, V. (2009). Community participation in public schools: impact of information campaigns in three Indian states. *Education Economics, 17*(3), 355-375.

Pradhan, M., Suryadarma, D., Beatty, A., Wong, M., Gaduh, A., Alisjahbana, A., & Artha, R. P. (2014). Improving educational quality through enhancing community participation: Results from a randomized field experiment in Indonesia. *American Economic Journal: Applied Economics*, 105-126.

Ravallion, M. (2007). Evaluating anti-poverty programs. *Handbook of development economics, 4*, 3787-3846.

Ravallion, M., & Dearden, L. (1988). Social security in a" moral economy": An empirical analysis for Java. *The Review of Economics and Statistics*, 36-44.

Ravallion, M., Van de Walle, D. P., Dutta, P., & Murgai, R. (2013). Testing information constraints on India's largest antipoverty program. *World Bank policy research working paper*(6598).

Reinikka, R., & Svensson, J. (2004). Local Capture: Evidence from a Central Government Transfer Program in Uganda. *The Quarterly Journal of Economics, 119*(2), 679-705.

Reinikka, R., & Svensson, J. (2005). Fighting Corruption to Improve Schooling: Evidence from a Newspaper Campaign in Uganda. *Journal of the European Economic Association, 3*(2/3), 259-267.

Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of educational Psychology, 66*(5), 688.

Stigler, G. J. (1961). The economics of information. *Journal of Political Economy, 69*(3), 213-225.

Sumarto, S., Toyamah, N., Usman, S., Sulaksono, B., Budiyati, S., Widyanti, W. D., . . . Sodo, R. J. (2006). *A rapid appraisal of the implementation of the 2005 direct cash transfer program in indonesia: A case study in five kabupaten/kota*. Retrieved from

Suryadarma, D., & Yamauchi, C. (2013). Missing public funds and targeting performance: Evidence from an anti-poverty transfer program in Indonesia. *Journal of Development Economics, 103*, 62-76. doi:http://dx.doi.org/10.1016/j.jdeveco.2013.01.007.

TNP2K. (2015a). *Indonesia's Unified Database for Social Protection Programmes - Management Standard*. Jakarta: The Office of the Vice President of the Republic of Indonesia.

TNP2K. (2015b). *Integrating Community-Driven Development Principles into Policy: From PNPM Mandiri to the Village Law*. Jakarta: The Office of the Vice President of the Republic of Indonesia.

Tohari, A., Parsons, C., & Rammohan, A. (2019). Targeting poverty under complementarities: Evidence from Indonesia’s unified targeting system. *Journal of Development Economics*, (140), 127–144.

World Bank. (2004). *World Development Report 2004: Making Services Work for Poor People*. Washington, DC.

World Bank. (2012a). *BLT Temporary Unconditional Cash Transfer. Social assistance program and public expenditure review 2*. Washington, DC: World Bank.

World Bank. (2012b). *Raskin subsidized rice delivery. Social assistance program and public expenditure review 3*. Washington, DC: World Bank.

## 3.11 Appendices

**Table 3-6. Proportion of the Sample Based on Whether They Received the KPS**

| Did you receive KPS card? | Freq. | Percent | Cum. |
|---|---|---|---|
| No | 53,167 | 80.23 | 80.23 |
| Yes | 13,100 | 19.77 | 100 |
| Total | 66,267 | 100 | |

**Table 3-7. Proportion of KPS Holders According to Whether They Received Information**

| Did you receive information in the KPS package? | Freq. | Percent | Cum. |
|---|---|---|---|
| Yes, complete | 10,065 | 76.83 | 76.83 |
| Yes, but not complete | 941 | 7.18 | 84.02 |
| No | 2,094 | 15.98 | 100 |
| Total | 13,100 | 100 | |

**Table 3-8. Proportion of the Sample Based on Their Treatment and Eligibility**

| | | | Eligible | | Households |
|---|---|---|---|---|---|
| | | | Yes | No | |
| Information | Yes | *n* | 9,929 | 1,077 | 11,006 |
| | | % | 90.21 | 9.79 | 100 |
| | No | *n* | 32,911 | 23,055 | 55,966 |
| | | % | 58.81 | 41.19 | 100 |
| Households | | | 42,840 | 24,132 | 66,972 |
| | | % | 63.97 | 36.03 | 100 |

*Notes*: This table presents the numbers and proportions of households that received information conditional on their eligibility. The eligibility rule is based upon whether households' PMT score is above or below its district cut-off. Eligibility rule equals 1 if the PMT Score is less than its district cut-off and 0 otherwise.

**Table 3-9. The Characteristics of KPS Beneficiaries on Responding to the Information Delivered**

| Whether HHDs receive Information in the envelope | Does HHD understand the benefit of the KPS? | | | | |
|---|---|---|---|---|---|
| | No | % | Yes | % | Total |
| Yes, and Complete | 8,271 | 0.822 | 1,794 | 0.178 | 10,065 |
| Yes, but not complete | 801 | 0.851 | 140 | 0.149 | 941 |
| No | 1,763 | 0.842 | 331 | 0.158 | 2,094 |
| Total | 10,835 | 0.827 | 2,265 | 0.173 | 13,100 |

Source: Social Protection Survey, Author's calculation.

**Table 3-10. Outcome Variable and Household's Characteristics Between Treatment and Control Groups of RASKIN Beneficiaries**

| | Did Households receive information? | | | | Difference | |
|---|---|---|---|---|---|---|
| | No | | Yes | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 |
| Monthly Raskin Bought (Kg) | 4.738 | (3.215) | 6.012 | (3.799) | 1.274 | [0.079] |
| Receive BLSM | 0.145 | (0.352) | 0.969 | (0.174) | 0.824 | [0.005] |
| | | | | | | |
| PMT Score | 13.462 | (0.343) | 13.298 | (0.317) | -0.164 | [0.006] |
| *Village Characteristics* | | | | | | |
| Ln Distance to Nearest District office | 2.914 | (1.159) | 2.818 | (1.187) | -0.089 | [0.026] |
| Ln Distance to Post office | 1.651 | (1.235) | 1.642 | (1.209) | -0.010 | [0.029] |
| Availability of Asphalt Road in the village | 0.752 | (0.432) | 0.760 | (0.427) | 0.008 | [0.010] |
| Road can be accessed for a car | 0.928 | (0.258) | 0.931 | (0.254) | 0.002 | [0.007] |
| Cultural Mono | 0.774 | (0.418) | 0.773 | (0.419) | -0.001 | [0.009] |
| Availability Access to the National TV Station | 0.642 | (0.479) | 0.614 | (0.487) | -0.028 | [0.011] |
| Local Leader Directly Elected | 0.840 | (0.367) | 0.810 | (0.393) | -0.030 | [0.008] |
| Sea Transport | 0.037 | (0.188) | 0.034 | (0.182) | -0.003 | [0.004] |
| Padi as main Agriculture Product | 0.490 | (0.500) | 0.500 | (0.500) | 0.009 | [0.011] |
| Slum Area | 0.094 | (0.292) | 0.093 | (0.291) | -0.001 | [0.006] |
| *Head of Village Characteristics* | | | | | | |
| Male | 0.933 | (0.250) | 0.922 | (0.268) | -0.011 | [0.006] |
| Age | 44.437 | (9.334) | 44.173 | (9.430) | -0.264 | [0.204] |
| Education: | | | | | | |
| No Education | 0.013 | (0.114) | 0.010 | (0.098) | -0.003 | [0.003] |
| Primary | 0.017 | (0.131) | 0.013 | (0.111) | -0.005 | [0.003] |
| Junior High | 0.137 | (0.344) | 0.131 | (0.338) | -0.006 | [0.008] |
| Senior High | 0.526 | (0.499) | 0.522 | (0.500) | -0.004 | [0.011] |
| University | 0.045 | (0.206) | 0.048 | (0.214) | 0.004 | [0.004] |
| *Head of Household Characteristics* | | | | | | |
| Widow | 0.151 | (0.358) | 0.151 | (0.358) | -0.000 | [0.005] |
| Age | 49.389 | (13.892) | 49.796 | (13.547) | 0.407 | [0.209] |
| Years of schooling | 6.319 | (3.711) | 5.519 | (3.359) | -0.801 | [0.055] |
| Position/Status of the main job: | | | | | | |
| Self-Owned Business (SOB) | 0.244 | (0.430) | 0.234 | (0.423) | -0.010 | [0.007] |
| SOB with non-permanent worker | 0.262 | (0.440) | 0.259 | (0.438) | -0.003 | [0.008] |
| SOB with permanent worker | 0.033 | (0.179) | 0.022 | (0.148) | -0.011 | [0.003] |
| Worker | 0.347 | (0.476) | 0.373 | (0.484) | 0.026 | [0.008] |
| Non Paid Worker | 0.010 | (0.099) | 0.010 | (0.101) | 0.000 | [0.001] |
| *Household Characteristics* | | | | | | |
| Max years of schooling | 8.974 | (3.719) | 8.381 | (3.398) | -0.593 | [0.056] |
| Dependency ratio | 0.648 | (0.643) | 0.792 | (0.692) | 0.145 | [0.010] |
| Urban area | 0.338 | (0.473) | 0.334 | (0.472) | -0.004 | [0.010] |
| Receive the KPS from Postman | 0.160 | (0.367) | 0.227 | (0.419) | 0.067 | [0.021] |
| | | | | | | |
| Number of households | 19,032 | | 7,180 | | 26,212 | |

*Notes*: This table presents the averages of various outcome variables and household characteristics for treated and non-treated households and provides t-test of households who received the information but were no among Raskin beneficiaries. The numbers inside brackets represent standard deviations, while inside square brackets are standard errors.

**Table 3-11. Outcome Variable and Household's Characteristics between Treatment and Control Groups of BLSM beneficiaries**

| | Did Households receive information? | | | | Difference | |
|---|---|---|---|---|---|---|
| | No | | Yes | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 |
| Monthly Raskin Bought (Kg) | 6.007 | (4.331) | 5.993 | (3.783) | -0.014 | [0.203] |
| BLSM fund was levied (%) | 0.199 | (0.399) | 0.160 | (0.367) | -0.039 | [0.014] |
| | | | | | | |
| PMT Score | 13.290 | (0.384) | 13.302 | (0.329) | 0.012 | [0.013] |
| *Village Characteristics* | | | | | | |
| Ln Distance to Nearest District office | 3.130 | (1.207) | 2.884 | (1.214) | -0.246 | [0.047] |
| Ln Distance to Post office | 2.213 | (1.535) | 1.781 | (1.274) | -0.432 | [0.063] |
| Availability of Asphalt Road in the village | 0.571 | (0.495) | 0.735 | (0.442) | 0.164 | [0.020] |
| Road can be accessed for a car | 0.763 | (0.425) | 0.912 | (0.284) | 0.149 | [0.019] |
| Cultural Mono | 0.706 | (0.456) | 0.786 | (0.410) | 0.080 | [0.018] |
| Availability Access to the National TV Station | 0.502 | (0.500) | 0.527 | (0.499) | 0.025 | [0.020] |
| Local Leader Directly Elected | 0.884 | (0.320) | 0.809 | (0.393) | -0.075 | [0.010] |
| Sea Transport | 0.045 | (0.208) | 0.055 | (0.229) | 0.010 | [0.009] |
| Padi as main Agriculture Product | 0.395 | (0.489) | 0.453 | (0.498) | 0.058 | [0.018] |
| Slum Area | 0.063 | (0.243) | 0.085 | (0.278) | 0.022 | [0.009] |
| *Head of Village Characteristics* | | | | | | |
| Male | 0.926 | (0.262) | 0.919 | (0.272) | -0.007 | [0.009] |
| Age | 43.967 | (9.836) | 44.107 | (9.642) | 0.139 | [0.360] |
| Education: | | | | | | |
| No Education | 0.050 | (0.217) | 0.013 | (0.113) | -0.037 | [0.010] |
| Primary | 0.078 | (0.268) | 0.014 | (0.116) | -0.064 | [0.013] |
| Junior High | 0.183 | (0.387) | 0.136 | (0.342) | -0.048 | [0.016] |
| Senior High | 0.465 | (0.499) | 0.523 | (0.500) | 0.057 | [0.019] |
| University | 0.036 | (0.188) | 0.047 | (0.211) | 0.010 | [0.006] |
| *Head of Household Characteristics* | | | | | | |
| Widow | 0.141 | (0.348) | 0.138 | (0.345) | -0.004 | [0.007] |
| Age | 48.531 | (14.121) | 49.203 | (13.465) | 0.672 | [0.340] |
| Years of schooling | 4.854 | (3.725) | 5.682 | (3.392) | 0.829 | [0.099] |
| Position/Status of the main job: | | | | | | |
| Self-Owned Business (SOB) | 0.213 | (0.410) | 0.241 | (0.427) | 0.027 | [0.011] |
| SOB with non-permanent worker | 0.390 | (0.488) | 0.285 | (0.452) | -0.105 | [0.016] |
| SOB with permanent worker | 0.019 | (0.137) | 0.024 | (0.153) | 0.005 | [0.003] |
| Worker | 0.281 | (0.449) | 0.350 | (0.477) | 0.069 | [0.012] |
| Non Paid Worker | 0.013 | (0.115) | 0.010 | (0.100) | -0.003 | [0.002] |
| *Household Characteristics* | | | | | | |
| Max years of schooling | 7.412 | (4.055) | 8.533 | (3.357) | 1.122 | [0.118] |
| Dependency ratio | 0.742 | (0.702) | 0.818 | (0.708) | 0.075 | [0.015] |
| Urban area | 0.224 | (0.417) | 0.305 | (0.460) | 0.080 | [0.014] |
| Receive the KPS from Postman | 0.148 | (0.355) | 0.237 | (0.425) | 0.089 | [0.017] |
| | | | | | | |
| Number of households | 3,810 | | 9,432 | | 13,423 | |

*Notes*: This table presents the averages of various outcome variables and household characteristics for treated and non-treated households and provides t-test of households who received the information but were no among BLSM beneficiaries. The numbers inside brackets represent standard deviations, while inside square brackets are standard errors.

## Figures


**The front side of the KPS**


**The backside of the KPS**

**Figure 3-5. The KPS Card**


Panel A: Complaint mechanism of the KPS Card


Panel B: How to access BLSM program


Panel C: How to access Raskin program


Panel D: How to access Scholarship program

**Figure 3-6. . Information included in the KPS package**

*Notes:* The figures present the information included in the KPS package. Panel A is about complaint mechanism of the KPS in case the household has a problem with their eligibility. Panels B, C, and D show the mechanism as to how KPS holders can access the benefit from BLSM, Raskin, and Scholarship programs respectively.

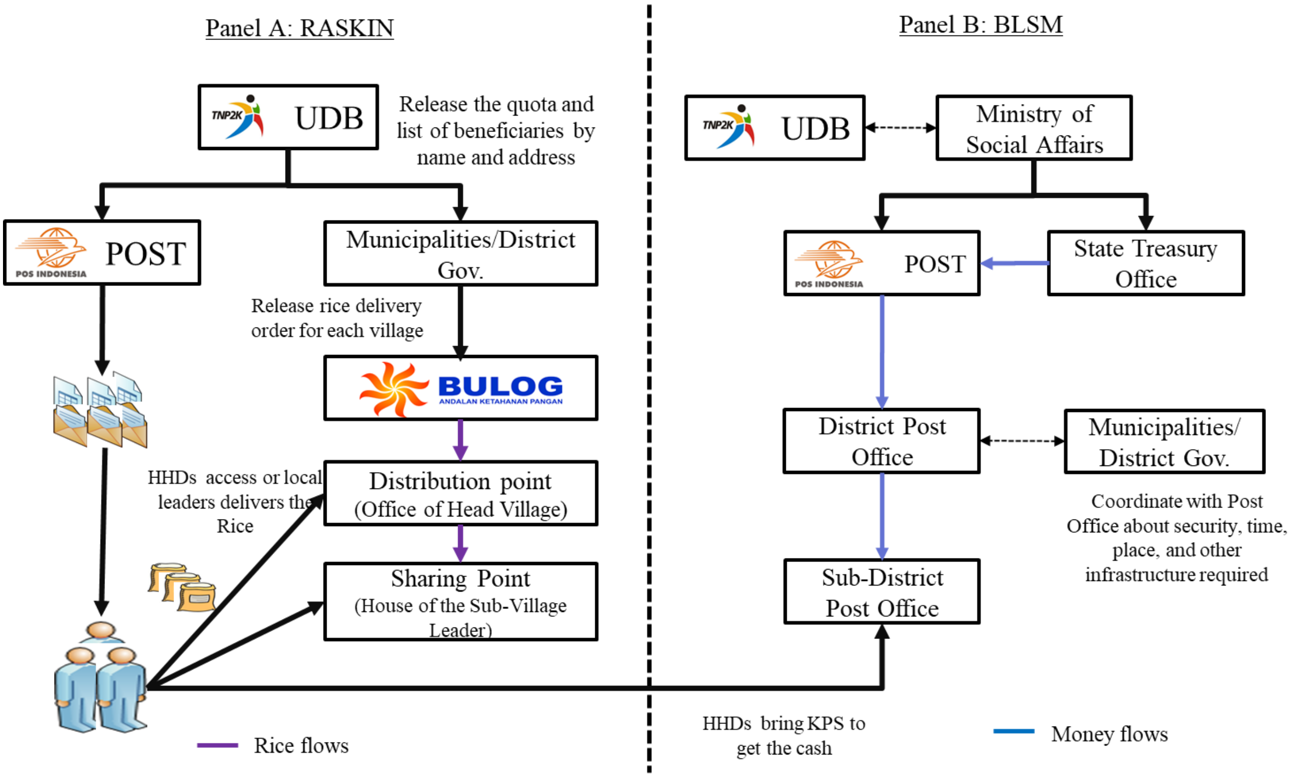



**Figure 3-7. The Delivery Mechanism of Raskin and BLSM Programs**

*Notes*: This figure shows the differences in delivery mechanism between the Raskin and BLSM programs. The distribution of the Raskin rice relies on the authority of village leaders, while the BLSM beneficiaries are extracted directly from the TNP2K's UDB database such that they should use their KPS to access the BLSM fund.

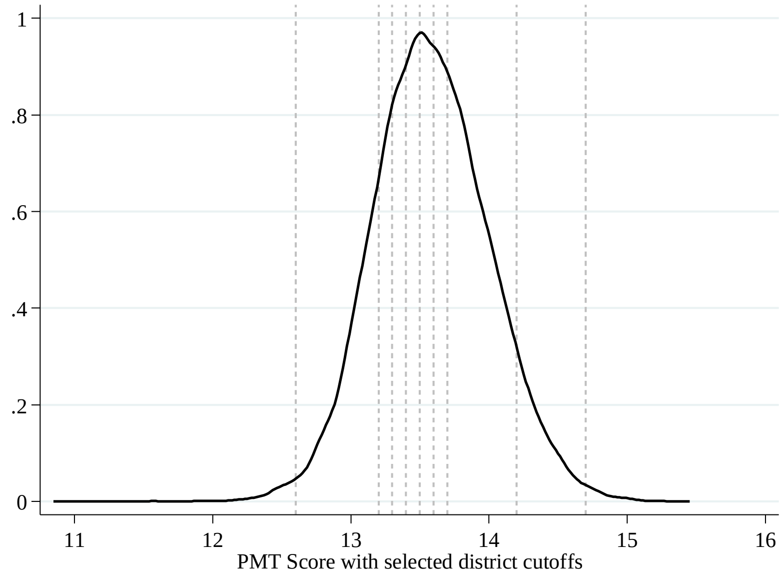



**Figure 3-8. The Distribution of Household's PMT Score and Selected District Cut-offs**

*Notes:* This figure presents the distribution of the household's PMT score, which is produced by applying the official PMT coefficients that are unique to all 482 districts of Indonesia in order to estimate each household's PMT score, thereby ensuring as close a comparison as possible with the official PMT used in developing the UDB, while the vertical lines represent the selected district's official cut-offs. The eligibility rule of the program is that households whose PMT score are below their district cut-offs would receive the information treatment.

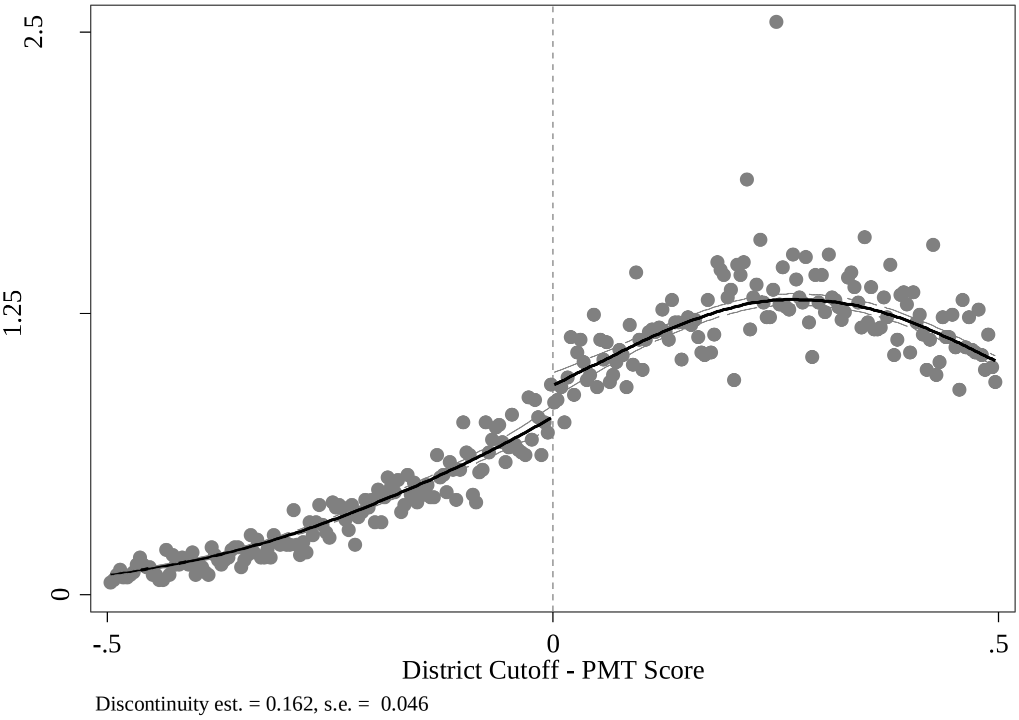
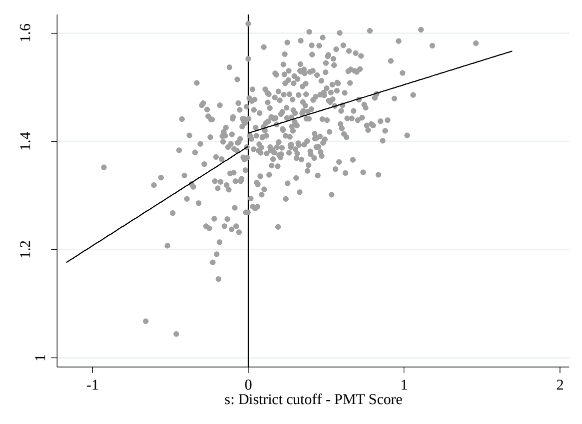


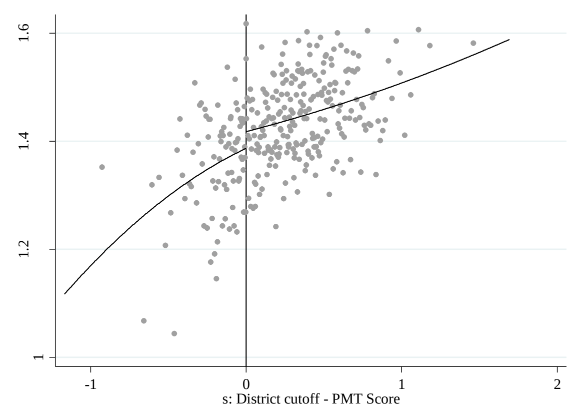

**Figure 3-9. McCrary test**

*Notes:* This figure shows the result of McCrary test (McCrary, 2008).

Panel A: Linear Order Polynomial




Panel B: Quadratic Order Polynomial




Panel C: Cubic Order Polynomial

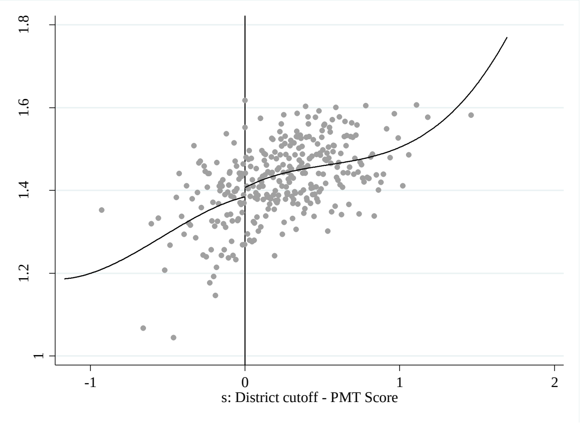
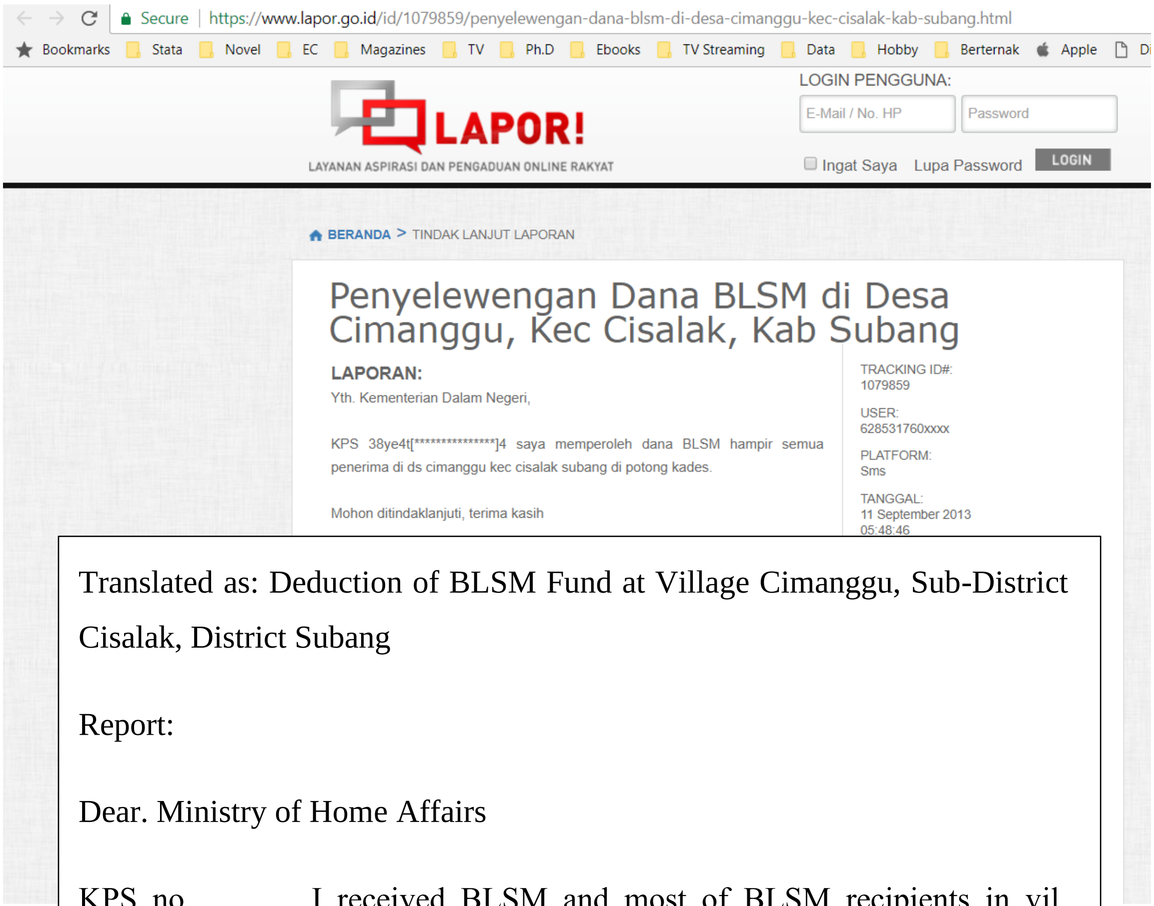



**Figure 3-10. Discontinuity of Outcome variable at Cut-off (s=0)**

*Notes:* These figures represent graphical illustration of our RD design of Log(Raskin Bought). The scatterplots are the average number within bins that are selected under IMSE-optimal quantile-spaced method using spacing estimators and the solid lines are the predicted outcomes, respectively, based on linear polynomial regression in Panel (A), quadratic polynomial regression in Panel (B), and Cubic polynomial regression in Panel (C).




Translated as: Deduction of BLSM Fund at Village Cimanggu, Sub-District Cisalak, District Subang

Report:

Dear. Ministry of Home Affairs

KPS no………., I received BLSM and most of BLSM recipients in vil.

**Figure 3-11. Report of Deduction of BLSM Fund**

*Notes:* This figure presents one of examples of household's complaints about BLSM fund levied by village local leaders. This complaint was reported directly by the household to the President's Delivery Unit for Development Monitoring and Oversight Unit (*Unit Kerja Presiden Bidang Pengawasan dan Pengendalian Pembangunan* - UKP4).

# Chapter 4

## Capital Fundamentalism and Structural Transformation


### Abstract

We conduct the first judicious evaluation of Capital Fundamentalism, in the context of the Government of Indonesia's *Inpres Desa Tertinggal* (IDT or *Left Behind Village*) Program. Originally scheduled between 1994 and 1997, the IDT program aimed to inject capital into the economies of poor households in selected villages. Drawing upon several publically available and administrative village censuses in tandem with satellite-based datasets, we evaluate: (1) the impact of capital injection into rural economies on household welfare, (2) how capital investments expedite the process of structural transformation and (3) the extent to which the processes of structural transformation depend upon existing infrastructure. We adopt a (fuzzy) regression discontinuity design, by exploiting the official village 'scores' of the IDT program along with their provincial thresholds. The IDT program significantly increased household welfare (as measured by night time luminosity, enrolment rates, infant mortality rates, numbers of livestock, numbers of poor households and numbers of small and micro enterprises) in Java, Sumatra and Bali and Nusa Tenggara as households exited agriculture in favour of more productive activities. We find no evidence of the program affecting structural transformation in Kalimantan, Sulawesi or Papua. The effects of the program were larger for villages with access to better quality infrastructure. Our evidence suggests that structural transformation was a necessary condition for injections of capital to foster regional development.



**Keywords:** Capital Fundamentalism, Structural Transformation, Infrastructure, Government Intervention, Welfare

**JEL Classifications: L16, H53, H54, E22, O10, O18, I38.**

## 4.1 Introduction

*High Development Theory* was a term coined by Krugman (1993) to describe an era of thought in development economics, spanning from Rosenstein-Rodan (1943) to Hirschman (1958). Summarising in Krugman's own words, "*the view that development is a virtuous circle driven by external economies – that is, that modernization breeds modernization*."[30] This was the era of 'Big Ideas' the models from which laid the foundations for modern development theory by emphasizing the roles of spillovers, co-ordination failures, multiple equilibria and poverty traps. According to this view, Government intervention is advocated to ensure economies break free from vicious cycles of under-development and Rosenstein-Rodan himself advocated simultaneous investments across many industries, which would only be profitable in tandem, i.e. strategic complementarities.

Central to the models of the period (Harrod (1939), Domar (1946), Lewis (1954), Rostow (1960)), was Capital Fundamentalism, "*the notion that increasing investment is the best way to raise further output, either for an individual or a nation*" (King and Levine 1994a). With the advent of growth accounting in later years however (Solow (1957), Denison (1962, 1967)), Capital Fundamentalism fell out of academic favour, with technology being preferred as the primary explanation for observed differences in living standards. While capital no doubt can explain *how* countries with varying living standards differ (see for example Mankiw, Romer and Weil (1992)) and indeed may be intrinsically linked to the process of technological change (Romer 1990, Grossman and Helpman 1991, Aghion and Hewitt 1992), King and Levine in their classic (1994b) article nevertheless conclude that capital fundamentalism should not be resuscitated since capital "*seems to be part of the process…not the igniting source…indeed, economic growth tends to precede capital accumulation, not the other way round*" [Pg. 282].[31]

[30] Krugman regards Rosenstein-Rodan's Big Push theory, later formalised and enshrined by Murphy et al (1989) as the 'Essential high development model'.

[31] As popularity in development economics waned, those remaining in the profession "were most often consulted or given positions of influence in connection with the disbursements of foreign aid" (Krugman 1997, pg. 23). Easterly (2001) famously lamented the extent to which capital fundamentalism influenced the thinking of 'experts' in international organisations that deemed capital accumulation as a pre-requisite for economic development. Nevertheless, Adelman and Chenery (1968) and more rercently Arndt, Jones, and Trap (2016) confirm that foreign aid has over the past 40 years stimulated growth, promoted structural change, improved social indicators and reduced poverty.

This view, while contrasting with Krugman's counter-counterrevolution in development theory (1993), is also at odds with Young's (1992, 1994, 1995) 'contrarian view' of the East Asian newly industrialised countries, which highlights the fact that the Tiger economies' standout feature as their factor (including capital) accumulation, which played a pivotal role in their development (see also Collins, Bosworth and Rodrik 1996). This version of events, first told in relation to the Soviet economic growth and then as a means of debunking the "Myth of Asia's Miracle", was perhaps most famously detailed in Krugman's 1994 *Foreign Affairs* article of the same name. More recently, Dani Rodrik (2016) mused that public-driven-investment is making a resurgence, citing the examples of Bolivia and Ethiopia, which both have enjoyed remarkable success as a result of large public investments. Indeed, most if not all countries that have grown rapidly in recent years did so, at least in (large) part, by mobilizing domestic savings for public investment. Despite the strength of opinions on both sides of the debate, the underlying ethos of Capital Fundamentalist has yet to be tested.

In this paper, and filling this noticeable gap in the literature, we conduct the first judicious evaluation of Capital Fundamentalism. In other words, we seek to assess whether an initial injection of capital, across all sectors - with the notable exception of infrastructure - can catalyse subsequent economic development, *through the mechanism of structural transformation*. While not written in the classic tradition, nor making the classic assumption therefore, in this paper, we introduce for the first time a policy evaluation of what Lewis (1954) termed the 'classical question'. Testing these propositions proves difficult since capital is necessarily endogenous in the growth process and capital-intensive projects are not located randomly. The validity of cross-country studies may also be challenged since nations across the globe are all at different stages of development and countries industrialising today face different conditions to those that industrialised earlier.

The setting for our analysis is the Government of Indonesia's *Inpres Desa Tertinggal* (IDT or Left Behind Village) Program, which was originally planned to be implemented between 1994 and 1997. The overarching aim of the IDT program was to inject capital into the economies of poor households in selected villages. The program was abruptly curtailed however due to the Asian Financial Crisis, meaning that the last year of implementation was 1996. Our evaluation however, focuses on the implementation of the IDT in 1995 (IDT95), but as explained below, the overwhelming majority of villages that received IDT95, also received IDT funds in the previous year (please see below for further details).

The IDT program proves to be an ideal setting for our analysis for a number of reasons. First, the IDT program was Indonesia's first targeted poverty alleviation program, such that we need not worry that the effects of other programs might otherwise bias the results in any observed outcomes (see Tohari et al 2019). So too was the program large, with no fewer than one-third of the poorest villages in Indonesia receiving US$8,932 per annum. Indonesia in particular is an ideal setting for this study since during the period of our study, Indonesia underwent rapid industrialisation and concurrently a (further) fall in the share of agriculture in GDP (please refer to Figure 4-4 in the Appendix 4.8.1). Perhaps above all, we are able to exploit the specificities of the selection mechanism of the 1995 IDT in order to provide causal estimates of the program. Specifically, we are able to exploit the official village 'scores' of the IDT program (henceforth IDT scores) in tandem with their provincial (IDT score) thresholds, to implement a (fuzzy) regression discontinuity design.

Exploiting this set-up, this paper poses the following questions: (1) Does the injection of additional capital in the rural economy contribute to an improvement in household welfare? (2) Does increased capital investment in a village expedite the process of structural transformation? and (3) How does this process of structural transformation vary across space and in particular vary according to the available infrastructure?

Despite the scale of the IDT Program, insufficient evidence exists with which to determine the overall success of the program, not least in regard to the extent that results from existing studies are causal. Molyneaux and Gertler (1999) for example, examine the impact of the IDT on labour supply and household expenditure, by implementing a matching estimator in combination with village fixed effects. Those authors conclude that the IDT Program had no significant effect on either of those outcomes, although the spectre of omitted unobservables loom large. In contrast, in an unpublished manuscript, Alatas (2000), exploits the design of the IDT Program by implementing a Regression Discontinuity Design using *provincial* thresholds in the running variable to establish causality. Although the results showed that the program increased per capita expenditure by around 13 percentage points in rural areas, while decreasing per capita expenditure by about one percentage point in urban areas, the paucity of sufficient numbers of observations around the cut-off in the running variable evokes fears with regards the precision of those findings. Akita and Szeto (2000) also using provincial-level data, rather highlight the correlation between the receipt of larger IDT per capita grants and a decrease in inequality of consumption within provinces.[32] Significantly, no existing IDT studies leverage the administrative data on the IDT program that we have privileged access to, which necessarily stymies any attempt to establish causal estimates.

This paper nestles at the intersection of several branches of the economic literature, above all, the literature that examines the determinants of structural transformation as part of the process of economic development. This literature is essentially founded on the notion of 'dualism' first introduced by Lewis (1954), according to which, areas of differential productivity exist within countries, which provide opportunities for improvements in efficiency. Productivity wedges, between, for example, agricultural and non-agricultural areas, mean that the reallocation of labour between sectors can yield (aggregate) productivity gains (Gollin et al 2002; Au and Henderson 2006, Lagakos and Waugh, 2013; Bryan et al 2014, Gollin et al 2014, Munshi and Rosenzweig 2016).

An expansive literature explores factors that both expedite and impede the process of structural transformation and thus economic development. These include: labour regulation (Fallon and Lucas 1993, Besley and Burgess 2004, Manning, 2014), labour mobility costs (Nickell et al 2002, Lee and Wolpin, 2006, Messina, 2006 and Hayashi and Prescott 2008) and goods mobility (Herrendorf et al, 2012, Adamopolous, 2011 and Gollin and Regerson, 2010). We contribute to these literatures by examining the role of Capital Fundamentalism, the role of a pure injection of capital, in catalysing structural transformation, as captured by households exiting the agricultural sector.

Our paper also speaks directly to the literature that examines the role of *rural* infrastructure in facilitating structural transformation (Gollin and Rogerson, 2010, Adamapoulos, 2011, Herrendorf et al. 2012, Asher and Novosad, 2019). Crucially, since infrastructure is the only form of capital that recipient villages are *unable* to spend IDT funds on, and since those villages located within our RDD cut-off envelope have access to varying transport links, we are able to additionally provide causal estimates of the role of rural infrastructure for those

[32] In the parallel targeting literature that pertains to the IDT Program, Yamauchi (2010), using administrative data combined with SUSENAS and PODES data evaluates whether the IDT targeting mechanisms were pro-poor, finding that in wealthier and more unequal villages more resources tend to be provided to households that are relatively poor within a village. Similarly, Suryadarma and Yamauchi (2013) investigate the relationship between targeting performance and missing IDT Program funds, thereby demonstrating that the targeting effort of the IDT was less pro-poor.

villages that receive IDT funds. In doing so, we provide causal evidence on the role of initial conditions in infrastructure on the degree of structural transformation.

Finally, this paper also contributes to the literature that examines the relationship between structural transformation and welfare. The role of structural change in reallocating factors of production to in turn explaining countries' growth performance is already well known (Chenery et al, 1986 and Syrquin, 1995). Most studies (e.g. Nelson and Pack, 1999, and Ngai and Pissarides 2007) find a positive effect of structural change on economic performance, although Caselli (2005) argues such effects are negligible. Our measures of welfare include productivity (as captured through nightlight data), enrollment rates, infant mortality, livestock numbers, the number of poor households and the number of small and micro enterprises.

First we provide causal estimates of the IDT program on our various measures of village welfare. Our focus is on villages in rural areas, since we find no statistically significant evidence that the IDT program affected villages located in urban environs. The program had a revolutionary effect in Java where: productivity increased by 44 percentage points, enrolment rates increased by 5 percentage points, infant mortality reduced by nearly 15 percentage points, livestock numbers increased by approximately 90 percentage points, the number of poor households reduced by eight percentage points and the number of small and micro enterprises increased by over 78 percentage points. Sumatra and Bali and Nusa Tenggara also significantly benefited from the IDT program, although far fewer impacts of the IDT program are identified in the case of the two most remote parts of the country in Kalimantan and Sulawesi and Papua. The former did experience the largest increases in livestock numbers however, while the latter witnessed a ten-percentage point increase in enrolment rates. These results are robust to alternative specifications, including placebo bandwidths and various order of polynomial.

We continue by highlighting the mechanism of structural transformation - as captured by the numbers of households in agriculture - in leading to these welfare gains. Notably, we uncover no statistical evidence that the IDT program exerted any effect whatsoever on structural transformation in the case of Kalimantan and Sulawesi and Papua. Rather, in those islands in which we are able to identify causal effects of the IDT program on household welfare, we first show that villages that comprised more households exiting agriculture fared better in terms of their welfare indicators and secondly provide causal estimates of the *IDT95* program on the percentage of agricultural households in recipient villages. The *IDT95* program significantly reduced the percentage of households working in agriculture, most starkly in the case of Java (16 percentage points) and Sumatra (15 percentage points) and to a lesser extent in Bali and Nusa Tenggara (6 percentage points). These results suggest that structural transformation was a necessary condition for a region to benefit from the injections of capital from the IDT program. In other words, if a region was able to use funds from IDT to shift their factors of production away from agriculture and into higher productivity sectors, that region also experienced parallel improvements in their welfare.

Finally, motivated by the existing literature, we provide evidence that the impact of the IDT program on structural change (and thus welfare) was larger and statistically significant for rural villages that had access to better quality infrastructure. In particular in Sumatra and Java, our results suggest that villages closer to the district office experience a faster rate of structural transformation, thereby lending additional support for the main finding of Asher and Novosad (2019).

The rest of the paper proceeds in six sections. Section 2 provides relevant details on the IDT program, while Section 3 describes our main data sources. Section 4 presents our identification strategy and discusses the reason why our regressions are conducted at the *island* (as opposed to the provincial) level of observation. Section 5 presents our estimates of the impact of the IDT program on household welfare and structural transformation, while also examining to what extent available infrastructure expedites the processes of structural. Finally, we conclude.

## 4.2 Institutional Framework: IDT program

### 4.2.1 IDT Program

The IDT (*Inpres Desa Tertinggal* or Left-behind village) program, Indonesia's first anti-poverty program, was implemented by the Government of Indonesia (GoI) between 1994 and 1996, since the onset of the Asian Financial Crisis led to the curtailment of the program before any disbursements were made in 1997. The overarching objective of the program was to accelerate poverty reduction in so-called 'left-behind villages' through increasing economic activity in targeted villages (BAPPENAS, 1994). Under the auspices of the IDT Program, the government provided selected poor villages with lump-sum grants designated for small business loans.

Targeted villages each received 20 million Rupiah (approximately US$8,932) per annum, which was to be used as a small-scale rotating credit fund for poor households.[33] The wording of the policy allowed recipient households to spend funds from the IDT program on any form of capital expenditure, *with the exception of infrastructure projects.* This exception was made so as to expedite the process of poverty reduction in rural areas, since it was believed that any outcome from infrastructure projects would take too long to realise (BAPPENAS, 1994). Ultimately, the fund was disbursed across several activities including: husbandry (36%), trade (26%), agriculture (13%), industry (12%), fisheries (5%) and miscellaneous (8%).

### 4.2.2 Targeting of IDT Program

Initially, during the first year of the implementation in 1994, the IDT(94) program targeted about one-third (i.e. 20,633) of all Indonesian villages. At this time, the IDT village and province scores were constructed using 25 variables in urban areas and 27 for rural areas, all of which were collected from the 1990 and 1993 PODES, or village census (please refer to Appendix 4.8.2).[34] At first, the IDT implemented a two-step targeting method. The first step involved selecting eligible villages and the second to select poor households within those selected villages. The GoI initially selected ‘left behind villages’ by comparing village IDT scores with the standard deviation and range of the provincial IDT scores to which the village belonged. Concurrently, the government additionally conducted a field survey (based on the perceptions of the sub-district head and the Statistical Officer) to evaluate whether indeed selected villages were indeed poor (BPS, 1994), under *IDT94*. Ultimately, villages were deemed eligible for the IDT program should they be deemed poor by two of the three (standard deviation, range, field survey) methods.

The second step subsequently involved electing relatively poor households within selected villages that would be eligible for IDT loans based on local village-level meetings, which were

[33] This conversion is based on the 1995 average exchange rate of IDR 2,239 per 1995 US$ (Yamauchi, 2010). During fiscal years 1994-1996, the IDT fund disbursed approximately US$564 million.

[34] Fewer variables were used to construct the village and province IDT95 scores (see Appendix 1).

facilitated by the village head and a local government agency called LKMD (for *Lembaga Ketahanan Masyarakat Desa* or Village Community Resilience Board). The selected households were formed into POKMAS (for *kelompok masyarakat* or community groups) and each POKMAS comprised some twenty selected households. Each POKMAS submitted a brief proposal, called the DUK (*Daftar Usulan Kegiatan* or List of Proposed Activities), which detailed how their members would use the proposed monies from the IDT fund. These proposals were subsequently reviewed by the LKMD (for *Lembaga Ketahanan Masyarakat Desa* or the village council). According to its guidelines, the IDT program left the POKMAS member to select any possible investment activities, with the *exception* of physical infrastructure for the village.

Given the ad-hoc and arbitrary nature of the field survey conducted as part of *IDT94* however, the focus of our study is on evaluating the impact of *IDT95*, for which we have administrative data on recipient villages and perfect knowledge as to which village *should* have received the program, a setting that naturally lends itself to a (fuzzy) regression discontinuity design. According to the *IDT95* criteria (i.e. the range and standard deviation criteria alone), *all* villages based on *IDT94* methodology were retained, with the *exception* of those comprising fewer than 50 households. As such, 82.28 percent of *IDT95* recipient villages were also *IDT94* recipients (please refer to Appendix 4.8.3). A further 3,915 new villages were also added during *IDT95*, 126 of which were not on the *IDT94* recipient list and a further 3,789 village that previously were but whose IDT had since fallen below their provincial cut offs. Importantly therefore, whereas our evaluation focuses on *IDT95*, most of our recipient villages also received funds under *IDT94*, such that our results would be most fairly assigned to both years of the IDT program as opposed to *IDT95* alone.

## 4.3 Data

In order to conduct a judicious assessment of the role of capital fundamentalism in fostering structural transformation, it proves necessary to combine administrative data on the IDT Program with granular village level information.

### 4.3.1 Administrative IDT Program Data

Our first dataset comprises administrative data from the GoI, which details the actual village and provincial IDT scores, those used to select villages into the IDT program from 1994 to

1996, although our specific focus is on IDT95.[35,36] To facilitate the exploration of the effect of the IDT program on village productivity, we also digitised the official BPS map, which details the precise location and area (i.e. polygon) of each village (please refer to Appendices 4.8.4 and 4.8.5 for further details).

### 4.3.2 Triennial village administrative census or PODES

Our second source of data is the administrative triennial village census or PODES (for *Potensi Desa* or Village Potential Censuses), which comprises the universe of villages in Indonesia. PODES collects a panoply of data including physical and administrative characteristics, infrastructure and social organizations and amenities. We employ data from the 1990, 1993 and 1996 PODES for a variety of purposes: i) we reconstruct the IDT village and province scores from *IDT94* as a robustness check to test the fidelity of the aforementioned administrative data on the IDT program ii) we use data from PODES 1993 for the construction of some of our pre-treatment baseline measures such as percentage agriculture households (please refer to Appendix 4.8.6 for an exhaustive list of the available variables from PODES 1993 and the IDT Village Census 1994) and iii) conversely exploit data from 1996 PODES, to construct some of our post-treatment outcomes, a full list of which is provided in Appendix 4.8.7.

### 4.3.3 Administrative IDT village census

Due to the importance of the IDT program, the GoI, through the BPS, conducted an additional two village censuses in 1994 and 1995. In 1994, the GoI collected additional information on village characteristics, including details about the POKMAS (community groups) within villages. These data were used to construct both the village and province scores for *IDT95* and given our privileged access to these data, they were first employed to double-check the construction of the official *IDT95* scores. We further employ administrative data from 1994 and 1995 village censuses to construct a number of our baseline and outcome measures, which includes: rich data on school enrolments and infant mortality rates - neither of which were

---

[35] We would like to thank to Chikako Yamauchi and Jack Molyneaux for providing the administrative data.

[36] These data comprise the value of each constituent variable used to construct both the village and provincial scores.

features of the PODES prior to the implementation of the IDT and livestock numbers – information usually only captured in the agricultural census. Our study is the first to leverage these administrative data, the absence of which would otherwise hamstring attempts to causally identify the impact of the IDT program.

### 4.3.4 Night light intensity

Finally, we incorporate night light intensity data from the National Oceanic and Atmospheric Administration (NOAA) into our analysis. Luminosity was first used as a proxy for productivity by Henderson et al. (2012); but has subsequently been used in a similar vein by others including: Hodler and Raschky, (2014), Michalopoulos and Papaioannou (2014), Gibson and Olivia (2015) and Bazzi et al. (2016). Olivia and Gibson (2015) in particular, demonstrate that night light luminosity represents a good proxy for capturing subnational variation in productivity in Indonesia. We use the night light intensity both 1993 and 1996 to represent the periods before and after the implementation of IDT.

### 4.3.5 Merging the datasets

Since our datasets derive from different sources, the merging of the data proved challenging, not least since over the period 1990-1996, the GoI issued no fewer than 42 separate regulations, which aimed to redefine the administrative boundaries of several municipalities and sub-municipalities (please refer to Appendix 4.8.8). During this time, no fewer than 3,426 villages changed their village identifier during their realignment to the new administrative boundaries. For each of these villages, we manually tracked their name as stated in the regulations and subsequently painstakingly matched them to their original village identifier. Having combined all the datasets, our methodology yields a consistent and balanced panel dataset spanning 1993 to 1996, comprising some 56,480 villages, equivalent to 86.6 percent of the total number of villages in Indonesia (65,060 in 1993).

## 4.4 Estimation Strategy

We exploit the design of the IDT program in order to provide causal estimates of its effects on our outcomes of interest. Once the field survey criteria was dropped, the selection of the poor villages under *IDT95* solely relied upon a comparison of village IDT scores and provincial IDT thresholds. Under this mechanism, the selection of poor villages was formally:

$$\text{(1)} \qquad \Pr(IDT = 1) \quad \begin{aligned} &= 1 \quad \text{if} \quad villscore_{v,p} \le P \\ &= 0 \quad \text{if} \quad villscore_{v,p} > P \end{aligned}$$

Where $villscore_{v,p}$ is the village score of the village $v$ in province $p$, while $P$ is the provincial threshold.

In comparison with Alatas' (2000) study therefore, which estimates the impact of the IDT program on household expenditure and child labour at the provincial level, we instead conduct our estimation at the *island* level[37], in order to significantly increase our sample size, most specifically to better populate the envelope around the threshold of our running variable. One consequence of our doing so however, is that the distinction between our treatment and control villages is no longer sharp around the cut-off (please refer to Figure 4-1), which in turn lends itself to a fuzzy design.

Initially therefore, we pool all villages according to each major island grouping, together with their provincial thresholds, such that our running variable is then equal to the provincial threshold minus the village score (i.e. the *normalized village score*). Panel A of Figure 4-2 presents the original distribution of the village score, while Panel B instead depicts the normalised village score i.e. our running variable. We subsequently conduct the manipulation test of Cattaneo et al. (2019) to ensure no discontinuity of the running variable exists around the threshold.[38] The result for each island is presented below the distribution of each figure in Panel B. In all cases we reject the hypothesis, meaning here is no statistical evidence of systematic manipulation of the running variable.

[37] During the implementation of the IDT program the BPS defined six areas of Indonesia based on island groups, which is commonly known as Administrative Area Coding System. Under this system, islands are easily identified by the first number of the Administrative Area Code. For example, all provinces in Sumatra had their code starting with the first number equal to one. We adhere to this classification, one a single exception in which we pool Sulawesi (with island code equal 7) together with Maluku and Papua (with island code equal to 8) in order to increase our sample size.

[38] Cattaneo et al. (2019) develop a set of manipulation tests based on a novel local polynomial density estimator, which does not require pre-binning of the data. This test is relatively more flexible than the previous variant of the manipulation test, such as McCrary (2008) who introduced a test based on the nonparametric local polynomial density estimator of Cheng, Fan, and Marron (1997). This requires pre-binning of the data, which therefore introduces additional tuning parameters. Otsu, Xu, and Matsushita (2014) propose an empirical likelihood method employing boundary corrected kernels.

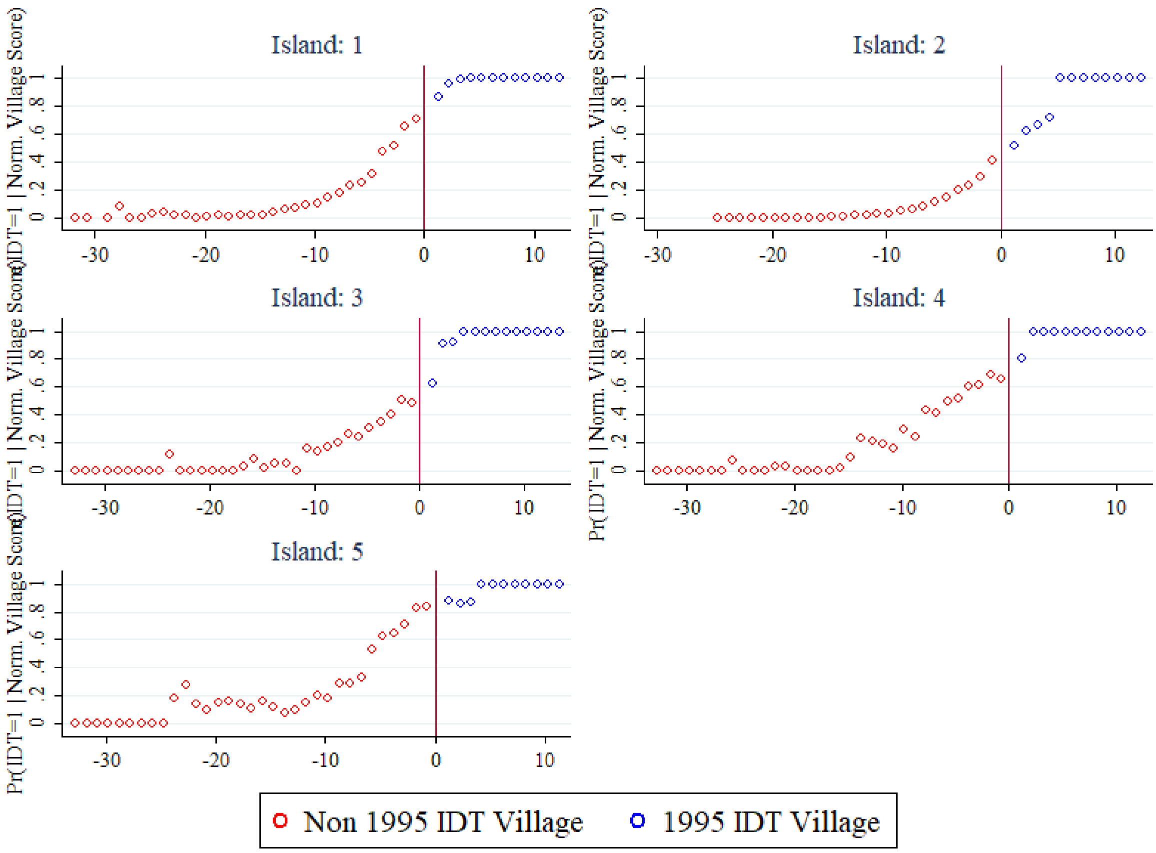



**Figure 4-1. Probability of Village receiving IDT given their normalized village score on each island**

*Notes:* These figures present the probability of the village to receive the IDT program given their normalized village score. Island 1 is the Sumatra island, and Island 2, 3, 4, and 5 are Java, Bali and Nusa Tenggara, Kalimantan, and Sulawesi and Papua, respectively.

**Panel A: Original Village Score** **Panel B: Normalized Village Score**

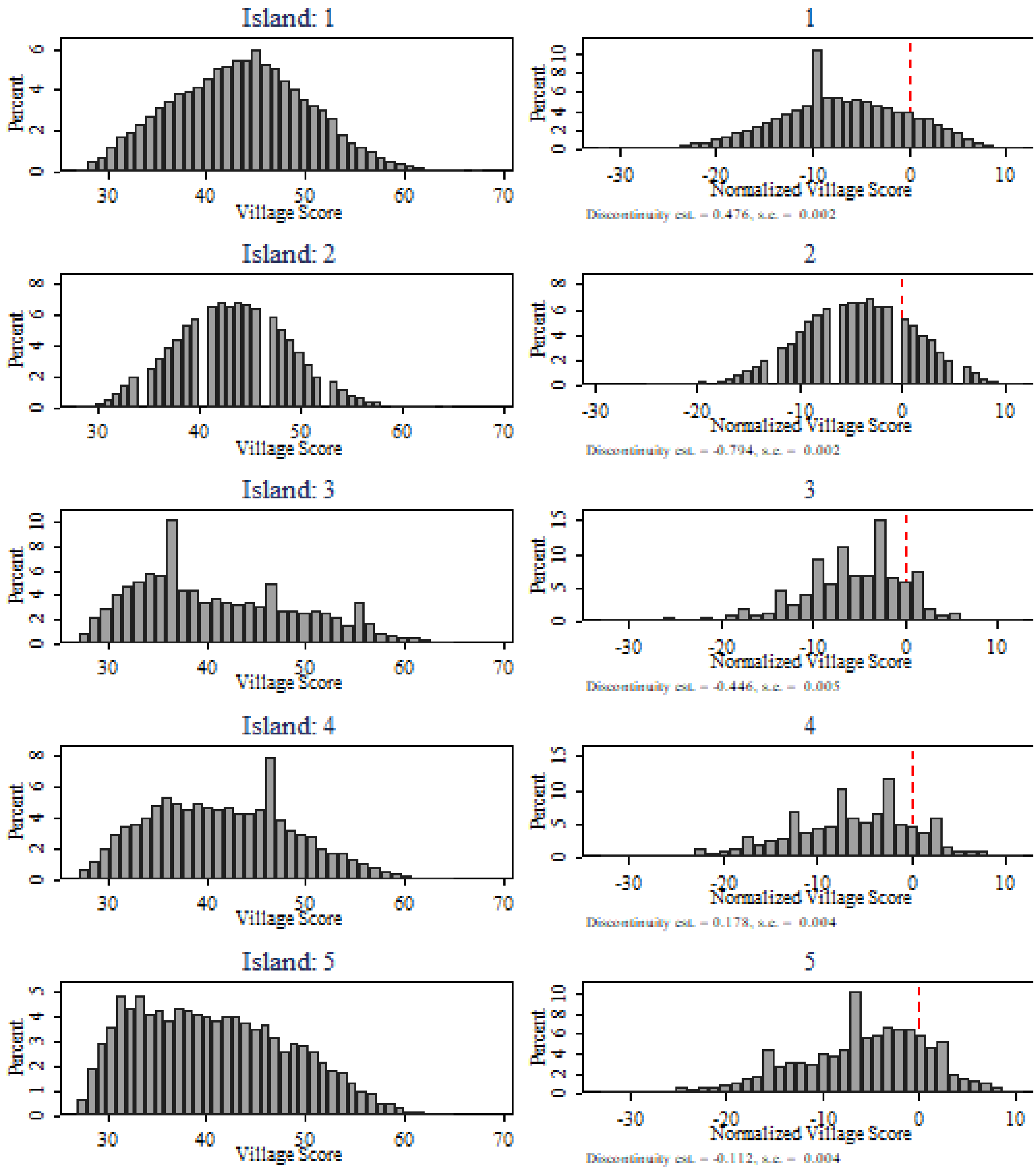



**Figure 4-2. Village Score and the Normalized Village Score**

*Notes*: Panel A show the distribution of the original village score, and Panel B is the normalized village score around the cut-off. Island 1 is the Sumatra island, and Island 2, 3, 4, and 5 are Java, Bali and Nusa Tenggara, Kalimantan, and Sulawesi and Papua, respectively. The numbers inside each figure in Panel B are the point estimate for the discontinuity and its standard error.

Prior to presenting our estimates, we first investigate whether any other village characteristics, *other* than the IDT program treatment vary around the threshold. As shown in Table 4-1, while many significant differences exist between the means of the various variables, we do not find any significant differences between these variables around the threshold of our running variable, with the notable exception of the number of cattle in Sumatra which subsequently become statistically insignificant after we combine with the other animals in our sample that results in our measure of livestock. In other words, our outcomes are continuous around the IDT thresholds for all islands. The results of both manipulation tests of the running variable and the balance of baseline covariates confirm the validity of our RD design. This also implies that we need not necessarily include our baseline covariates in our RD estimation (Lee and Lemieux 2010).

We subsequently implement a fuzzy RDD estimation to causally estimate the Local Average Treatment Effect (LATE) of receiving the IDT program. Following Imbens and Lemieux (2008) and Gelman and Imbens (2018) our estimation is conducted using local linear regressions within a given bandwidth, around the threshold, implementing the normalized village score as our running variable. Our first- and second-stage regressions are therefore modelled as follows:

$$\widehat{IDT}_{v,p} = \delta_0 + \delta_1 1\{villscore_{v,p} \leq P\} + \delta_2(P - villscore_{v,p}) + \delta_3(P - villscore_{v,p}) * 1\{villscore_{v,p} \leq P\} + \mu_p + v_{v,p} \tag{2}$$

$$Out_{v,p} = \beta_0 + \beta_1 \widehat{IDT_{v,p}} + \beta_2(P - villscore_{v,p}) + \beta_3(P - villscore_{v,p}) * \widehat{IDT}_{v,p} + \vartheta_p + \varepsilon_{v,p}. \tag{3}$$

Where $Out_{v,p}$ is the outcome of the interest in the village $v$ and the province-group threshold $p$. Our outcome variables to investigate the impact of IDT program on welfare include: the log of mean luminosity (NL)[39], school enrolment rates of the population aged between 7-15 years (ER), infant mortality rates per 1000 live birth (IMR), the log of the total number of

[39] To deal with zeros values, we follow Michalopoulos and Papaioannou (2014) by using Log (0.01 + Average Luminosity) in the regressions

livestock (LS) which is the sum of all animals in the survey (including: dairy cow, cattle, buffalo, horse, goat/sheep, pig, and broiler chicken), the percentage of poor people living in a village (POOR), and log number of Small and *Micro* Enterprises (SMEs). $\mu_p$ and $\vartheta_p$ are provincial-threshold fixed effects.

**Table 4-1. Summary Statistics – Pre-Treatment in the Island:**

**Panel A: Island 1 - Sumatra**

| Variable | NON - IDT | | IDT | | Difference of | | RD Estimation | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | S.E | Mean | S.E |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Pre -93- Percentage Agriculture Households in (1993) | 0.793 | 0.182 | 0.893 | 0.100 | 0.101*** | [0.003] | 0.004 | [0.006] |
| Pre -94- Percentage Agriculture Households | 0.763 | 0.199 | 0.895 | 0.100 | 0.132*** | [0.004] | -0.006 | [0.007] |
| Pre -94- Percentage Trade Households | 0.049 | 0.058 | 0.022 | 0.027 | -0.026*** | [0.001] | 0.000 | [0.002] |
| Pre -94- Percentage daily/manual Households | 0.078 | 0.126 | 0.091 | 0.168 | 0.013*** | [0.003] | 0.009 | [0.008] |
| Pre -94- School Enrol rate population aged 7-15 years | 0.880 | 0.152 | 0.793 | 0.192 | -0.087*** | [0.003] | -0.016 | [0.011] |
| Pre -94- Infant Mortality Rate per 1000 live birth | 71.657 | 84.204 | 94.534 | 92.333 | 22.877*** | [1.688] | 1.937 | [5.417] |
| Pre -94- Number of Livestock: 1. Dairy cow | 0.188 | 5.218 | 0.126 | 4.329 | -0.062 | [0.099] | 0.275 | [0.216] |
| Pre -94- Number of Livestock: 2. Cattle | 66.756 | 157.520 | 33.981 | 85.813 | -32.775*** | [2.877] | -15.674** | [7.807] |
| Pre -94- Number of Livestock: 3. Buffalo | 24.967 | 66.045 | 25.412 | 73.519 | 0.446 | [1.329] | -8.240 | [6.574] |
| Pre -94- Number of Livestock: 4. Horse | 0.603 | 6.133 | 0.889 | 5.654 | 0.285** | [0.119] | -0.371 | [0.333] |
| Pre -94- Number of Livestock: 5. Goat/sheep | 85.698 | 196.155 | 56.547 | 109.232 | -29.151*** | [3.588] | 2.273 | [6.326] |
| Pre -94- Number of Livestock: 6. Pig | 39.350 | 205.938 | 52.524 | 208.725 | 13.174*** | [4.061] | 7.975 | [8.178] |
| Pre -94- Number of Livestock: 7. Broiler Chicken | 1595.397 | 3902.121 | 814.692 | 1377.933 | -780.705*** | [69.859] | -125.730 | [139.477] |
| Pre -93- Night-Light indicators in 1993 | 1.635 | 4.585 | 0.371 | 2.327 | -1.264*** | [0.084] | -0.005 | [0.184] |
| Number of villages | 13195 | | 3219 | | | | | |

**Panel B: Island 2 - Java**

| Variable | NON - IDT | | IDT | | Difference of | | RD Estimation | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | S.E | Mean | S.E |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Pre -93- Percentage Agriculture Households in (1993) | 0.686 | 0.171 | 0.808 | 0.127 | 0.121*** | [0.003] | 0.002 | [0.006] |
| Pre -94- Percentage Agriculture Households | 0.657 | 0.179 | 0.809 | 0.130 | 0.152*** | [0.003] | 0.012* | [0.006] |
| Pre -94- Percentage Trade Households | 0.084 | 0.077 | 0.043 | 0.043 | -0.042*** | [0.001] | -0.002 | [0.002] |
| Pre -94- Percentage daily/manual Households | 0.099 | 0.114 | 0.099 | 0.126 | 0.000 | [0.002] | 0.002 | [0.005] |
| Pre -94- School Enrol rate population aged 7-15 years | 0.870 | 0.138 | 0.809 | 0.150 | -0.061*** | [0.002] | 0.002 | [0.007] |
| Pre -94- Infant Mortality Rate per 1000 live birth | 45.287 | 61.713 | 58.151 | 72.551 | 12.864*** | [1.051] | 2.105 | [3.011] |
| Pre -94- Number of Livestock: 1. Dairy cow | 9.518 | 93.896 | 4.485 | 45.283 | -5.033*** | [1.367] | -2.168 | [2.764] |
| Pre -94- Number of Livestock: 2. Cattle | 158.401 | 263.159 | 246.575 | 333.854 | 88.174*** | [4.602] | 0.793 | [14.367] |
| Pre -94- Number of Livestock: 3. Buffalo | 22.338 | 70.886 | 26.055 | 64.538 | 3.716*** | [1.127] | -0.361 | [2.368] |
| Pre -94- Number of Livestock: 4. Horse | 2.703 | 27.552 | 1.511 | 17.580 | -1.192*** | [0.412] | 0.311 | [1.002] |
| Pre -94- Number of Livestock: 5. Goat/sheep | 346.703 | 494.488 | 467.927 | 583.801 | 121.224*** | [8.438] | -19.275 | [25.868] |
| Pre -94- Number of Livestock: 6. Pig | 7.230 | 117.298 | 6.011 | 146.191 | -1.219 | [2.039] | -1.631 | [4.823] |
| Pre -94- Number of Livestock: 7. Broiler Chicken | 4481.246 | 7590.127 | 2792.072 | 3546.724 | -1,689.174*** | [110.283] | -297.657 | [234.143] |
| Pre -93- Night-Light indicators in 1993 | 6.080 | 5.539 | 1.992 | 2.723 | -4.088*** | [0.081] | 0.024 | [0.144] |
| Number of villages | 14684 | | 5100 | | | | | |

**Panel C: Island 3 - Bali and Nusa Tenggara**

| Variable | NON - IDT | | IDT | | Difference of | | RD Estimation | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | S.E | Mean | S.E |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Pre -93- Percentage Agriculture Households in (1993) | 0.792 | 0.177 | 0.882 | 0.120 | 0.091*** | [0.008] | 0.027* | [0.014] |
| Pre -94- Percentage Agriculture Households | 0.802 | 0.190 | 0.905 | 0.085 | 0.103*** | [0.008] | 0.008 | [0.012] |
| Pre -94- Percentage Trade Households | 0.031 | 0.055 | 0.012 | 0.024 | -0.018*** | [0.002] | -0.001 | [0.003] |
| Pre -94- Percentage daily/manual Households | 0.034 | 0.091 | 0.022 | 0.062 | -0.012*** | [0.004] | -0.017* | [0.009] |
| Pre -94- School Enrol rate population aged 7-15 years | 0.821 | 0.178 | 0.802 | 0.186 | -0.019** | [0.008] | -0.006 | [0.021] |
| Pre -94- Infant Mortality Rate per 1000 live birth | 90.172 | 86.074 | 94.117 | 85.268 | 3.946 | [3.987] | -3.234 | [9.766] |
| Pre -94- Number of Livestock: 1. Dairy cow | 0.209 | 6.681 | 0.019 | 0.460 | -0.190 | [0.279] | 0.176 | [0.183] |
| Pre -94- Number of Livestock: 2. Cattle | 426.196 | 682.322 | 467.873 | 802.006 | 41.677 | [32.815] | 35.403 | [71.118] |
| Pre -94- Number of Livestock: 3. Buffalo | 128.847 | 300.849 | 120.771 | 257.641 | -8.076 | [13.611] | 8.705 | [27.561] |
| Pre -94- Number of Livestock: 4. Horse | 72.944 | 142.349 | 78.319 | 145.350 | 5.375 | [6.637] | -2.213 | [14.004] |
| Pre -94- Number of Livestock: 5. Goat/sheep | 334.741 | 601.420 | 278.773 | 573.968 | -55.968** | [27.689] | 50.621 | [50.274] |
| Pre -94- Number of Livestock: 6. Pig | 745.496 | 1016.953 | 518.550 | 694.394 | -226.946*** | [44.758] | 73.539 | [73.357] |
| Pre -94- Number of Livestock: 7. Broiler Chicken | 4546.323 | 7932.085 | 3152.896 | 5472.746 | -1,393.427*** | [349.470] | -407.991 | [660.563] |
| Pre -93- Night-Light indicators in 1993 | 1.626 | 3.551 | 0.434 | 1.128 | -1.191*** | [0.151] | 0.168 | [0.147] |
| Number of villages | 2434 | | 574 | | | | | |

**Panel D: Island 4 - Kalimantan**

| Variable | NON - IDT | | IDT | | Difference of | | RD Estimation | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | S.E | Mean | S.E |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Pre -93- Percentage Agriculture Households in (1993) | 0.769 | 0.179 | 0.869 | 0.116 | 0.100*** | [0.006] | -0.012 | [0.012] |
| Pre -94- Percentage Agriculture Households | 0.752 | 0.192 | 0.880 | 0.111 | 0.129*** | [0.007] | 0.004 | [0.012] |
| Pre -94- Percentage Trade Households | 0.048 | 0.049 | 0.024 | 0.023 | -0.024*** | [0.002] | 0.000 | [0.002] |
| Pre -94- Percentage daily/manual Households | 0.050 | 0.105 | 0.039 | 0.100 | -0.011*** | [0.004] | -0.003 | [0.013] |
| Pre -94- School Enrol rate population aged 7-15 years | 0.852 | 0.149 | 0.765 | 0.195 | -0.087*** | [0.006] | -0.014 | [0.017] |
| Pre -94- Infant Mortality Rate per 1000 live birth | 60.779 | 85.467 | 70.278 | 90.886 | 9.499*** | [3.234] | 0.966 | [9.041] |
| Pre -94- Number of Livestock: 1. Dairy cow | 0.135 | 2.966 | 0.105 | 2.863 | -0.030 | [0.110] | 0.225 | [0.138] |
| Pre -94- Number of Livestock: 2. Cattle | 46.634 | 137.175 | 20.442 | 57.641 | -26.192*** | [4.698] | 8.830 | [5.596] |
| Pre -94- Number of Livestock: 3. Buffalo | 5.927 | 40.619 | 12.588 | 85.830 | 6.661*** | [1.963] | -1.210 | [5.642] |
| Pre -94- Number of Livestock: 4. Horse | 0.195 | 3.050 | 0.361 | 4.843 | 0.166 | [0.130] | -0.317 | [0.397] |
| Pre -94- Number of Livestock: 5. Goat/sheep | 24.093 | 56.690 | 11.436 | 38.701 | -12.657*** | [2.005] | 3.409 | [3.140] |
| Pre -94- Number of Livestock: 6. Pig | 71.774 | 227.780 | 107.735 | 280.494 | 35.961*** | [8.928] | 21.928 | [23.238] |
| Pre -94- Number of Livestock: 7. Broiler Chicken | 1417.724 | 3321.796 | 706.398 | 1064.012 | -711.326*** | [112.788] | 87.027 | [99.750] |
| Pre -93- Night-Light indicators in 1993 | 0.744 | 2.860 | 0.149 | 1.081 | -0.594*** | [0.098] | 0.139 | [0.115] |
| Number of villages | 3687 | | 889 | | | | | |

**Panel E: Island 5 - Sulawesi and Papua**

| Variable | NON - IDT | | IDT | | Difference of | | RD Estimation | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | S.E | Mean | S.E |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Pre -93- Percentage Agriculture Households in (1993) | 0.810 | 0.158 | 0.886 | 0.099 | 0.076*** | [0.005] | 0.000 | [0.008] |
| Pre -94- Percentage Agriculture Households | 0.779 | 0.181 | 0.891 | 0.101 | 0.112*** | [0.005] | 0.008 | [0.009] |
| Pre -94- Percentage Trade Households | 0.036 | 0.053 | 0.014 | 0.022 | -0.021*** | [0.001] | -0.001 | [0.002] |
| Pre -94- Percentage daily/manual Households | 0.055 | 0.125 | 0.060 | 0.153 | 0.005 | [0.004] | -0.004 | [0.016] |
| Pre -94- School Enrol rate population aged 7-15 years | 0.841 | 0.174 | 0.791 | 0.192 | -0.050*** | [0.005] | 0.007 | [0.017] |
| Pre -94- Infant Mortality Rate per 1000 live birth | 85.734 | 89.167 | 86.560 | 89.382 | 0.826 | [2.732] | -0.458 | [7.632] |
| Pre -94- Number of Livestock: 1. Dairy cow | 0.559 | 11.811 | 0.176 | 4.320 | -0.383 | [0.327] | 0.295 | [0.370] |
| Pre -94- Number of Livestock: 2. Cattle | 143.009 | 263.500 | 97.960 | 249.458 | -45.049*** | [7.980] | 7.322 | [16.332] |
| Pre -94- Number of Livestock: 3. Buffalo | 26.207 | 106.011 | 23.253 | 122.511 | -2.954 | [3.360] | -0.655 | [7.932] |
| Pre -94- Number of Livestock: 4. Horse | 15.420 | 51.069 | 14.092 | 57.032 | -1.328 | [1.604] | -4.879 | [4.328] |
| Pre -94- Number of Livestock: 5. Goat/sheep | 71.921 | 180.337 | 50.445 | 117.218 | -21.476*** | [5.174] | 5.973 | [8.583] |
| Pre -94- Number of Livestock: 6. Pig | 96.583 | 343.877 | 94.501 | 267.709 | -2.081 | [10.082] | -47.410 | [30.583] |
| Pre -94- Number of Livestock: 7. Broiler Chicken | 1826.357 | 3269.810 | 1064.701 | 2164.947 | -761.656*** | [93.987] | 157.958 | [155.395] |
| Pre -93- Night-Light indicators in 1993 | 0.593 | 1.881 | 0.054 | 0.482 | -0.539*** | [0.052] | 0.054 | [0.044] |
| Number of villages | 5036 | | 1353 | | | | | |

*Notes:* This table presents the mean value of village characteristics before the implementation of the 1995 IDT Program. Panel A presents the result from Sumatra island. Panel B, C, D, and E present the results of Java, Bali and Nusa Tenggara, Kalimantan and Sulawesi and Papua, respectively. In column 1-4, show unconditional means for Non-IDT and IDT Villages. Column 3 and 4 show the difference in means and standard errors. Column 7 and 8 present the result of the RDD estimation using linear RD polynomial and bandwidth equal to 2. *** significant at 1%, ** significant at 5%, * significant at 10%.

## 4.5 Results

### 4.5.1 The IDT program and Welfare

We proceed in the following way. First, we provide causal estimates of the IDT program on various measures of village welfare, including: productivity (luminosity), education (enrolment rates), health (infant mortality rate), agriculture (number of livestock), poverty (number of poor households) and industry (number of small and micro enterprises - SMEs). Next, focusing on the mechanism at play, we highlight the role of structural transformation, as captured by the number of households leaving agriculture; first by demonstrating that the greater the number of households leaving agriculture the greater are the increases in welfare, as broadly defined by our six measures; and then by providing causal results from our fuzzy RD design of the impact of the IDT program on structural transformation, as captured by the numbers of households engaged in agricultural activities. Finally, given that our results pertain to villages in rural areas, we delve deeper into the role of rural infrastructure in expediting capital injections on structural transformation.

We begin with graphical illustrations of our RD design (please refer to Appendix 4.8.9), in which the local averages of our outcome variables on each island are plotted against the corresponding normalized village scores. Panel A shows the results for Sumatra island. Panel B, C, D, and E present the results of Java, Bali and Nusa Tenggara, Kalimantan and Sulawesi and Papua, respectively. Each point represents the average value of the outcome in every bin. The solid line plots predicted values, while the outcome trends estimated on either side of the threshold. The dashed lines show 95 percent confident interval. The vertical dashed red line marks the cutoff at zero.

Table 4-2 and Table 4-3 report the causal estimates of the effect of the IDT program on productivity as proxied by night time luminosity (col. 1), enrolment rates: ages 7-15 years (col. 2), livestock numbers (col. 3) infant mortality rates (col. 4) the number of poor households (col. 5) and the number of small and micro enterprises (col. 6) for rural and urban villages respectively. Strikingly, in the case of urban villages we find almost no statistically significant results whatsoever, which while perhaps indicative of a real life phenomenon wherein urban villages do not benefit from injections of capital, so too are these results, at least for all island groups with the exception of Java, driven by the absence of sufficient numbers of observations, such that our estimated standard errors are large relative to our point estimates. We focus therefore, for the remainder of the paper, on the impacts of the IDT program on rural villages.

Panel B of Table 4-2 shows that rural villages in Java benefited from the *IDT95* program as measured by all of our six measures of welfare. Specifically, our causal estimates suggest that the program increased productivity (average luminosity) by 44 percentage points, enrolment rates by 5 percentage points, reduced infant mortality by nearly 15 percentage points, increased livestock numbers by approximately 90 percentage points, reduced the number of poor households by eight percentage points and increased the number of small and micro enterprises by over 78 percentage points.

Our estimates from the outer islands however, vary considerably from those we obtained for the most densely populated and interconnected island, Java. Our results highlight that Sumatra and Bali and Nusa Tenggara benefited the most from the IDT program after Java. Notably, Sumatra experienced a comparable increase in productivity in comparison with Java, while Bali and Nusa Tenggara experienced none. Both Sumatra and Bali and Nusa Tenggara witnessed significant decreases in their infant mortality rate, with Bali and Nusa Tenggara recording more than 32 percentage point fall; while both Sumatra and Bali and Nusa Tenggara experienced significant increases in livestock numbers. While smaller in magnitude, the IDT program nevertheless also played a significant role in bolstering the numbers of small and micro enterprises in both Sumatra and Bali and Nusa Tenggara. Far fewer impacts of the IDT program are identified in the case of the two most remote parts of the country in Kalimantan and Sulawesi and Papua. The former did experience the largest increases in livestock numbers however, while the latter witnessed a ten percentage point increase in enrolment rates.

In summary, the IDT95 program exerted a positive and significant effect on targeted rural villages in Java, Sumatra and Bali and Nusa Tenggara. Evidence on the impacts on other islands is mixed. These results are robust to alternative specifications, including placebo bandwidths and various order of polynomial (please refer to Appendices 4.8.10).

**Table 4-2. RDD Estimation Results of RURAL Village**

| | Dependent Variables: | | | | | |
|---|---|---|---|---|---|---|
| | NL<br>(1) | ER<br>(2) | IMR<br>(3) | LS<br>(4) | POOR<br>(5) | SME<br>(6) |
| *Panel A: Sumatra* | | | | | | |
| *IDT* | 0.619*<br>[0.346] | 0.012<br>[0.018] | -16.670**<br>[7.728] | 1.228***<br>[0.182] | -0.106*<br>[0.062] | 0.624***<br>[0.194] |
| $R^2$ | 0.014 | 0.006 | 0.027 | 0.210 | 0.048 | 0.035 |
| Clusters | 52 | 52 | 52 | 52 | 51 | 47 |
| Observations | 1,787 | 1,787 | 1,787 | 1,778 | 997 | 755 |
| *Panel B: Java* | | | | | | |
| *IDT* | 0.440***<br>[0.126] | 0.053***<br>[0.010] | -14.893***<br>[4.820] | 0.892***<br>[0.062] | -0.092***<br>[0.027] | 0.781***<br>[0.144] |
| $R^2$ | 0.033 | 0.041 | 0.011 | 0.204 | 0.025 | 0.055 |
| Clusters | 81 | 81 | 81 | 81 | 81 | 81 |
| Observations | 3,264 | 3,264 | 3,264 | 3,262 | 3,032 | 2,691 |
| *Panel C: Bali and Nusa Tenggara* | | | | | | |
| *IDT* | 0.012<br>[0.436] | 0.018<br>[0.031] | -32.875***<br>[10.637] | 0.692***<br>[0.147] | 0.068<br>[0.076] | 0.614*<br>[0.360] |
| $R^2$ | 0.014 | 0.008 | 0.035 | 0.129 | 0.018 | 0.055 |
| Clusters | 37 | 37 | 37 | 37 | 37 | 30 |
| Observations | 511 | 511 | 511 | 511 | 473 | 261 |
| *Panel D: Kalimantan* | | | | | | |
| *IDT* | -0.695<br>[0.464] | 0.055*<br>[0.030] | 3.045<br>[12.178] | 1.564***<br>[0.445] | 0.081*<br>[0.040] | -0.363<br>[0.402] |
| $R^2$ | 0.051 | 0.060 | 0.043 | 0.166 | 0.053 | 0.026 |
| Clusters | 24 | 24 | 24 | 24 | 24 | 21 |
| Observations | 596 | 596 | 596 | 548 | 342 | 237 |
| *Panel E: Sulawesi and Papua* | | | | | | |
| *IDT* | -0.252<br>[0.253] | 0.100***<br>[0.036] | -22.964<br>[17.513] | -0.254<br>[0.392] | 0.069<br>[0.063] | -0.119<br>[0.313] |
| $R^2$ | 0.013 | 0.035 | 0.005 | 0.006 | 0.021 | 0.017 |
| Clusters | 47 | 47 | 47 | 47 | 45 | 38 |
| Observations | 938 | 938 | 938 | 932 | 699 | 419 |

*Notes:* Panel A examines the impact of IDT program on dependent variables in Sumatra island. Panel B, C, D, and E present the results of Java, Bali and Nusa Tenggara, Kalimantan and Sulawesi and Papua, respectively. In column 1, the dependent variable is the log (0.01 + average luminosity) of the village. Dependent variables in column 2, 3, 4, 5, and 6 are school enrolment rate population aged between 7-15 years, infant mortality rate per 1000 live birth, the log total number of livestock in the village, percentage of poor household per total household in the village, and log number of small and micro enterprises, respectively. Quadratic RD polynomial and bandwidth equal to 2 are used in the estimation. Standard errors are clustered at the district level.

*** significant at 1%, ** significant at 5%, * significant at 10%.

**Table 4-3. RDD Estimation Results of URBAN Village**

| | Dependent Variables: | | | | | |
|---|---|---|---|---|---|---|
| | NL (1) | ER (2) | IMR (3) | LS (4) | POOR (5) | SME (6) |
| *Panel A: Sumatra* | | | | | | |
| IDT | -0.326 | -0.023 | -16.555 | -0.100 | 0.038 | 0.178 |
| | [1.338] | [0.022] | [22.633] | [0.642] | [0.035] | [0.488] |
| $R^2$ | 0.056 | 0.091 | 0.048 | 0.061 | 0.015 | 0.052 |
| Clusters | 8 | 8 | 8 | 8 | 8 | 8 |
| Observations | 175 | 175 | 175 | 156 | 172 | 144 |
| *Panel B: Java* | | | | | | |
| IDT | 0.351* | -0.031** | -4.071 | -0.257 | 0.026 | -0.226 |
| | [0.164] | [0.007] | [2.773] | [0.445] | [0.033] | [0.167] |
| $R^2$ | 0.044 | 0.022 | 0.004 | 0.024 | 0.024 | 0.008 |
| Clusters | 5 | 5 | 5 | 4 | 5 | 5 |
| Observations | 565 | 565 | 565 | 556 | 562 | 536 |
| *Panel C: Bali and Nusa Tenggara* | | | | | | |
| IDT | 0.570 | -0.071* | -19.048 | -1.415* | 0.116 | -0.867 |
| | [1.764] | [0.029] | [9.735] | [0.600] | [0.066] | [1.102] |
| $R^2$ | 0.099 | 0.167 | 0.243 | 0.371 | 0.132 | 0.147 |
| Clusters | 4 | 4 | 4 | 4 | 4 | 4 |
| Observations | 31 | 31 | 31 | 31 | 30 | 28 |
| *Panel D: Kalimantan* | | | | | | |
| IDT | 0.679 | -0.003 | 14.379 | 0.682 | 0.023 | 0.952 |
| | [4.062] | [0.016] | [32.406] | [0.395] | [0.015] | [0.512] |
| $R^2$ | 0.065 | 0.117 | 0.05 | 0.071 | 0.08 | 0.080 |
| Clusters | 4 | 4 | 4 | 4 | 4 | 4 |
| Observations | 29 | 29 | 29 | 19 | 26 | 26 |
| *Panel E: Sulawesi and Papua* | | | | | | |
| IDT | -2.501 | 0.101** | -27.5 | -0.192 | 0.006 | -1.853* |
| | [1.357] | [0.033] | [51.291] | [0.419] | [0.084] | [0.830] |
| $R^2$ | 0.338 | 0.203 | 0.046 | 0.17 | 0.014 | 0.208 |
| Clusters | 6 | 6 | 6 | 6 | 6 | 6 |
| Observations | 39 | 39 | 39 | 37 | 36 | 34 |

*Notes:* Panel A examines the impact of IDT program on dependent variables in Sumatra island. Panel B, C, D, and E present the results of Java, Bali and Nusa Tenggara, Kalimantan and Sulawesi and Papua, respectively. In column 1, the dependent variable is the log (0.01 + average luminosity) of the village. Dependent variables in column 2, 3, 4, 5, and 6 are school enrolment rate population aged between 7-15 years, infant mortality rate per 1000 live birth, the log total number of livestock in the village, percentage of poor household per total household in the village, and log number of small and micro enterprises, respectively. Quadratic RD polynomial and bandwidth equal to 2 are used in the estimation. Standard errors are clustered at the provincial level.

*** significant at 1%, ** significant at 5%, * significant at 10%.

### 4.5.2 Mechanism: IDT and Structural Change

While the IDT program improved the welfare of rural villages in the central islands of Indonesia, in this section we provide further evidence that the mechanism through which injections of capital alone (i.e. Capital Fundamentalism) affect village welfare is through structural transformation, as captured by the number of households in agriculture.

We provide two pieces of evidence in this regard. First, as shown in Figure 4-3, we provide simple correlations, which demonstrate that villages that comprised more households exiting agriculture fared better in terms of their welfare indicators. In other words, greater proportions of households reliant upon agriculture in particular villages are associated with lower productivity, lower enrolment rates, higher infant mortality rates, higher livestock numbers, a higher incidence of poor households and fewer small and micro enterprises.

Secondly, again turning to our main empirical specification, we further provide causal estimates of the *IDT95* program on the percentage of agricultural households in recipient villages, the results of which are shown in Table 4-4, which presents the results for each island grouping (panels A-E) as well various specifications of the polynomials and bandwidths. Our results show that the *IDT95* program significantly reduced the percentage of households working in agriculture, most starkly in the case of Java (16 percentage points) and Sumatra (15 percentage points) and to a lesser extent in Bali and Nusa Tenggara (6 percentage points). We find no statistical (and negligible economic) evidence that the *IDT95* program had any effect whatsoever on structural transformation in the case of Kalimantan and Sulawesi and Papua.

Taken together, our evidence suggests that the IDT program exerted by far the largest impacts on rural villages in the central islands of Java, Sumatra and Bali and Nusa Tenggara. Concurrently, it was only these islands that experienced structural transformation as a result of the *IDT95* program. These results suggest that structural transformation was a necessary condition for a region to benefit from the injections of capital from the IDT program. In other words, if a region was able to use funds from *IDT95* to shift their factors of production away from agriculture and into higher productivity sectors, that region also experienced parallel improvements in their welfare. For example, in Sumatra, falling numbers of households in agriculture were accompanied by a boost to productivity, lower infant mortality rates, fewer poor households and a dramatic increase in the number of small and micro enterprises. These results are consistent with previous studies, including: Gollin et al (2002), Lagakos and Waugh, (2013) and Gollin et al (2014), which collectively demonstrate that structural transformation impacts positively on productivity.

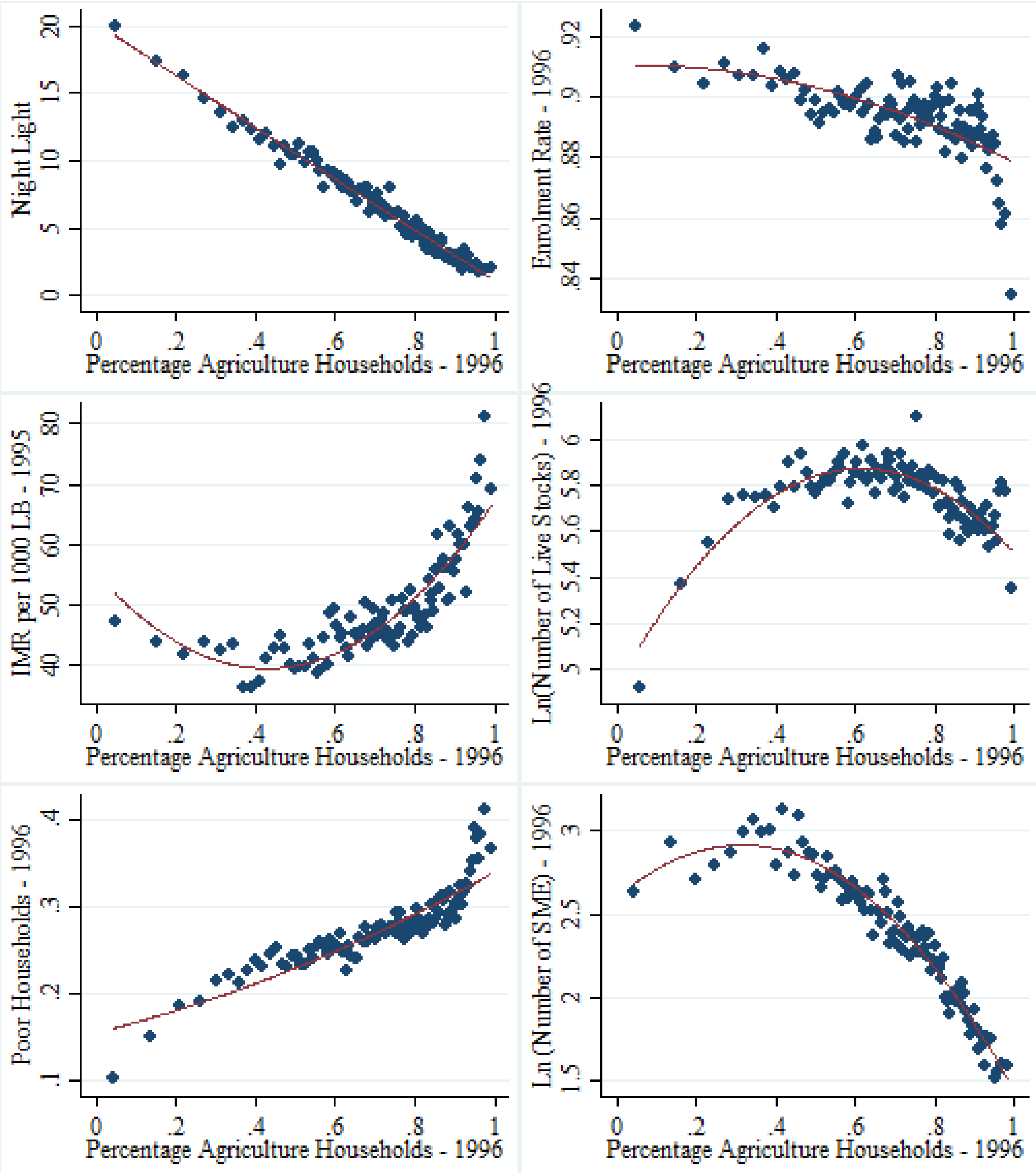



**Figure 4-3. Correlation between Structural Transformation and Outcomes**

*Notes*: This figure plots simple correlation between welfare measures and percentage household working in agriculture. The solid line plots predicted values.

**Table 4-4. RDD Estimation of the IMPACT of IDT on Structural Change**

| | Bandwidth (BW): 2 | | | BW: 3 | BW: 4 | BW: 5 | BW: 10 |
|---|---|---|---|---|---|---|---|
| | Quadratic | Linear | Cubic | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| *Panel A: Sumatra* | | | | | | | |
| IDT | -0.149*** | -0.157*** | -0.149*** | -0.155*** | -0.154*** | -0.155*** | -0.157*** |
| | [0.026] | [0.018] | [0.026] | [0.019] | [0.017] | [0.015] | [0.015] |
| $R^2$ | 0.179 | | | 0.176 | 0.187 | 0.199 | 0.197 |
| Clusters | 52 | | | 53 | 54 | 55 | 61 |
| Observations | 1,781 | | | 3,015 | 4,205 | 5,367 | 10,504 |
| *Panel B: Java* | | | | | | | |
| IDT | -0.159*** | -0.159*** | -0.159*** | -0.159*** | -0.154*** | -0.160*** | -0.159*** |
| | [0.013] | [0.009] | [0.013] | [0.010] | [0.009] | [0.008] | [0.007] |
| $R^2$ | 0.209 | | | 0.198 | 0.194 | 0.191 | 0.172 |
| Clusters | 81 | | | 82 | 83 | 86 | 90 |
| Observations | 3,258 | | | 5,299 | 7,390 | 9,218 | 16,198 |
| *Panel C: Bali and Nusa Tenggara* | | | | | | | |
| IDT | -0.064*** | -0.086*** | -0.064*** | -0.082*** | -0.083*** | -0.082*** | -0.079*** |
| | [0.019] | [0.019] | [0.019] | [0.020] | [0.020] | [0.018] | [0.017] |
| $R^2$ | 0.115 | | | 0.104 | 0.094 | 0.085 | 0.103 |
| Clusters | 37 | | | 39 | 39 | 39 | 39 |
| Observations | 511 | | | 832 | 1,116 | 1,354 | 2,285 |
| *Panel D: Kalimantan* | | | | | | | |
| IDT | 0.023 | 0.010 | 0.023 | 0.004 | 0.013 | 0.014 | 0.006 |
| | [0.028] | [0.021] | [0.028] | [0.024] | [0.020] | [0.017] | [0.019] |
| $R^2$ | 0.013 | | | 0.014 | 0.018 | 0.032 | 0.056 |
| Clusters | 24 | | | 25 | 25 | 25 | 25 |
| Observations | 596 | | | 1,012 | 1,395 | 1,765 | 3,139 |
| *Panel E: Sulawesi and Papua* | | | | | | | |
| IDT | 0.011 | 0.010 | 0.011 | 0.010 | 0.018 | 0.010 | 0.010 |
| | [0.020] | [0.013] | [0.020] | [0.016] | [0.012] | [0.011] | [0.009] |
| $R^2$ | 0.006 | | | 0.014 | 0.012 | 0.020 | 0.061 |
| Clusters | 47 | | | 48 | 48 | 48 | 50 |
| Observations | 938 | | | 1,525 | 2,063 | 2,535 | 4,419 |

*Notes:* This table presents the impact of IDT program on percentage of the household working in Agriculture. The dependent variable is the percentage of the household working in agriculture. BW represents the Bandwidth used in the estimations. Standard errors are clustered at the district level. Quadratic, Linear, and Cubic represent different functional forms, $f(.)$, for the RD polynomial.

*** significant at 1%, ** significant at 5%, * significant at 10%.

### 4.5.3 Factors that Expedite Structural Change

In the final part of our analysis, we further examine which factors might expedite this process of structural change in those islands for which the *IDT95* program had an effect (namely: Java Sumatra and Bali and Nusa Tenggara). Motivated, first by the observation that the positive effects of the IDT95 program were largely confined to Indonesia's central islands and secondly by the existing literature that highlights the importance of infrastructure in the process of structural change (Lee and Wolpin, 2006, Gibson and Olivia, 2010, Gollin and Rogerson, 2010, Adamapoulos, 2011, Herrendorf et al. 2012 and Asher and Novosad, 2019), we posit that rural villages in Indonesia might be doubly disadvantaged, both by their disadvantageous locations and further by their lack of capital,

Accordingly, we investigate whether village characteristics pertaining to the available infrastructure prior to receiving capital injections via the IDT program, expedited the process of structural change. To this end, we interact the predicted variable from our first stage, $\widehat{IDT}$, with indicator variables ($IND_{v,p}$) that equal unity: if the distance between a village and the nearest district office is less than the median of the comparable distance for other villages in that district (*close*), if a village has access to a local market (*market*), if an asphalt road is readily available (*quality road*) and finally if modern transportation is available (*modern transport*). We estimate the following regression:

$$\begin{aligned} Out_{v,p} = \ & \beta_0 + \beta_1 \widehat{IDT}_{v,p} + \beta_2 \left(P - villscore_{v,p}\right) + \beta_3 \left(P - villscore_{v,p}\right) * \widehat{IDT}_{v,p} \beta_0 \\ & + \beta_4 \widehat{IDT}_{v,p} * IND_{v,p} + \beta_5 \left(P - villscore_{v,p}\right) * IND_{v,p} \\ & + \beta_6 \left(P - villscore_{v,p}\right) * \widehat{IDT}_{v,p} * IND_{v,p} + \vartheta_p + \varepsilon_{v,p}. \end{aligned} \tag{4}$$

The results of this exercise are presented in Table 4-5. The top section of each panel in Table 4-5 presents the coefficients on the IDT variable and the interaction terms captured by $IND_{v,p}$. The bottom section of each panel rather presents the total effect, i.e. the sum of the two constituent terms from the upper section.

Our results suggest broadly that rural villages in remote areas of Indonesia (i.e. Kalimantan, Sulawesi and Papua) received few benefits from the *IDT95* program. To further elaborate on this hypothesis, we examine whether living in remote communities affect the incidence of structural transformation. Our results, in Column 2 of Table 4-5, show that villages closer to the district office experience a faster rate of structural transformation, thereby lending additional support for the central thesis of Asher and Novosad (2019).

Turning next to village access to markets, which facilitate the flow of goods trade, our results (see Column 3 of Table 4-5) suggest, in all three island groups, that market availability actually slowed the process of the structural transformation; although the effect is only statistically significant in Java. This is because, as suggested by GoI activity reports at the time, a significant number of the poor households spent their IDT monies in the trading sector. For example, in Java almost 33 percent of poor households used the IDT funds in this way. In such cases, poor households spent their IDT funds to purchase goods from the local market to resell in their small shops, which are typically located close to or next to their dwelling. Local market availability therefore likely reduced households' willingness to involve themselves in such activities, due to other households having taken up such activities and this crowding out effect resulted in IDT beneficiaries being reluctant to engage in such activities, opting instead to remain in the agricultural sector.

Column 4 of Table 4-5 further reports the result of interacting the IDT variable with an indicator equal to 1 if villages had access to a quality (asphalt) road. This interaction effect on structural change is large and statistically significant in the case of Sumatra, the sixth largest island in the world, in which travelling distances are often extremely long, meaning that rural villages significantly benefit from reduced travelling times. In the cases of Java however, the world's most populous island and Bali and Nusa Tenggara, much of which has experienced significant development, we find no statistically significant results. Despite the result in Java being small and statistically insignificant, its magnitude was nevertheless positive. Our interpretation is that during the time of the implementation of the IDT, the majority of Javanese villages already had access to asphalt roads, especially in comparison to the other Indonesian islands.[40]

Finally, in relation to access to modern transportation, its impact is small and statistically insignificant across all three islands as reported in Column 5 of Table 4-5. This result could be driven by the fact that by the time of the implementation of the IDT program the majority

[40] For example, in 1993, only 8% of Javanese villages had soil roads, compared 19.48% and 29.33% in Sumatra and Bali and Nusa Tenggara, respectively.

of villages across Indonesia had already accessed modern transport. For example, at this time according to PODES data, almost 84 percent villages in both Java and Sumatra and 77 percent of villages in Bali and Nusa Tenggara had access to modern transport.

In summary, the effects of the IDT program on structural transformation were both hampered and expedited by varying types of village infrastructure. These findings are directly in line with previous studies that examine the role of infrastructure on the process of the structural transformation (Gollin and Rogerson, 2010, Adamapoulos, 2011, Herrendorf et al. 2012, Asher and Novosad, 2019) through increasing mobility of goods and people mobility (Herrendorf et al, 2012, Adamopolous, 2011 and Gollin and Regerson, 2010).

**Table 4-5. RDD Estimation with Interaction Results of the RURAL AREA in the Island:**

**Panel A: Sumatra**

| | Variable Dependent: Percentage working in Agriculture | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| IDT | -0.157*** | -0.143*** | -0.159*** | -0.147*** | -0.188*** |
| | (0.018) | (0.022) | (0.016) | (0.022) | (0.023) |
| IDT x *Close* | | -0.040** | | | |
| | | (0.018) | | | |
| IDT x *Market* | | | 0.065 | | |
| | | | (0.064) | | |
| IDT x *Quality Road* | | | | -0.034* | |
| | | | | (0.020) | |
| IDT x *Modern Transport* | | | | | 0.039 |
| | | | | | (0.024) |
| Observations | 1,781 | 1,781 | 1,781 | 1,781 | 1,781 |
| Clusters | 52 | 52 | 52 | 52 | 52 |
| $R^2$ | 0.179 | 0.182 | 0.180 | 0.183 | 0.183 |
| IDT Effect (*Close*) | | -0.183*** | | | |
| | | (0.013) | | | |
| IDT Effect (*Market*) | | | -0.095*** | | |
| | | | (0.076) | | |
| IDT Effect (*Quality Road*) | | | | -0.180*** | |
| | | | | (0.015) | |
| IDT Effect (*Modern Transport*) | | | | | -0.149*** |
| | | | | | (0.018) |

**Panel B: Java**

| | Variable Dependent: Percentage working in Agriculture | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| IDT | -0.159*** | -0.145*** | -0.158*** | -0.160*** | -0.168*** |
| | (0.009) | (0.009) | (0.009) | (0.011) | (0.015) |
| IDT x *Close* | | -0.040*** | | | |
| | | (0.013) | | | |
| IDT x *Market* | | | 0.044* | | |
| | | | (0.025) | | |
| IDT x *Quality Road* | | | | 0.013 | |
| | | | | (0.012) | |
| IDT x *Modern Transport* | | | | | 0.013 |
| | | | | | (0.016) |
| Observations | 3,258 | 3,258 | 3,258 | 3,258 | 3,258 |
| Clusters | 82 | 82 | 82 | 82 | 82 |
| $R^2$ | 0.209 | 0.216 | 0.215 | 0.213 | 0.211 |
| IDT Effect (*Close*) | | -0.185*** | | | |
| | | (0.014) | | | |
| IDT Effect (*Market*) | | | -0.114*** | | |
| | | | (0.025) | | |
| IDT Effect (*Quality Road*) | | | | -0.147*** | |
| | | | | (0.010) | |
| IDT Effect (*Modern Transport*) | | | | | -0.156*** |
| | | | | | (0.009) |

**Panel C: Bali and Nusa Tenggara**

| | Variable Dependent: Percentage working in Agriculture | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| IDT | -0.086*** | -0.083*** | -0.094*** | -0.113*** | -0.093*** |
| | (0.019) | (0.024) | (0.019) | (0.013) | (0.021) |
| IDT x *Remote* | | -0.005 | | | |
| | | (0.028) | | | |
| IDT x *No Market* | | | 0.020 | | |
| | | | (0.063) | | |
| IDT x *No Quality Road* | | | | -0.024 | |
| | | | | (0.041) | |
| IDT x *No Modern Transport* | | | | | 0.008 |
| | | | | | (0.031) |
| Observations | 511 | 511 | 511 | 511 | 511 |
| Clusters | 37 | 37 | 37 | 37 | 37 |
| $R^2$ | 0.109 | 0.115 | 0.143 | 0.226 | 0.136 |
| IDT Effect (*Remote*) | | -0.088*** | | | |
| | | (0.022) | | | |
| IDT Effect (*No Market*) | | | -0.075*** | | |
| | | | (0.052) | | |
| IDT Effect (*No Quality Road*) | | | | -0.137*** | |
| | | | | (0.039) | |
| IDT Effect (*No Modern Transport*) | | | | | -0.085*** |
| | | | | | (0.023) |

*Notes:* IDT is indicator equal 1 if village received IDT program in 1995, *Close* is indicator equal 1 if the distance between village and the nearest district office is lower than median distance on each district, and *Market* is indicator equal 1 if village has market. *Quality Road* is indicator equal 1 if road constructed using asphalt and hardened form and *Modern Transport* is indicator equal 1 if public transport used by villagers to the city are either motorcycle, three-wheels, or four-wheels transportation mode. Quadratic RD polynomial and bandwidth equal to 2 are used in the estimation. All standard errors are clustered at the district level. *** significant at 1%, ** significant at 5%, * significant at 10%. Panel A is Sumatra, B is Java, and C is Bali and Nusa Tenggara Islands.

## 4.6 Conclusion

Capital Fundamentalism endures as one of the ‘Big Ideas’ of the golden era of development economics and is at the core of many of the most important contributions of the period (Harrod 1939, Rosenstein-Rodan 1943, Domar 1946, Lewis 1954, Rostow 1960). More recently, the centrality of Capital Fundamentalism has been questioned (King and Levine, 1994b), with capital being advocated as part of the process of development, as opposed to constituting a catalyst of development in and of itself. This view has been generally accepted, despite the fact that a fundamental assessment has yet to be judiciously conducted.

In this paper we therefore provide the first causal estimates of the effects of capital injections on household welfare and structural transformation in local economies in the context of the Government of Indonesia’s Inpres Desa Tertinggal (IDT or Left Behind Village) Program. In other words, we provide evidence that capital injections alone can catalyse economic development.

Our results provide evidence that the IDT program significantly improved the welfare of rural households in Java, Sumatra and Bali and Nusa Tenggara, through the process of structural transformation. In the outlying islands, the program had no effect on structural transformation and subsequently little development occurred in these areas. These results suggest that structural transformation was a necessary condition for regions to benefit from capital injections. In other words, capital injections alone are found, at least for the more central islands of Indonesia, to spur economic development in and of themselves, which therefore lends credence to idea of Capital Fundamentalism remaining relevant. While technology no doubt is key in elucidating the growth process, our results nevertheless suggest that capital plays a key role in economic development, at least in regards to poor rural Indonesia villages in the mid-1990s, for which technology no doubt played a more relevant role as these entities developed further.

## 4.7 Reference


Adamopoulos, T., 2011. Transportation Costs, Agricultural Productivity, And Cross-Country Income Differences. *International Economic Review*, 52(2), pp.489-521.

Adelman, I. and Chenery, H.B., 1966. The foreign aid and economic development: the case of Greece. *The Review of Economics and Statistics*, pp.1-19.

Aghion, P. and Howitt, P., 1992. A Model of Growth through Creative Destruction. *Econometrica*, 60 (1992), pp. 323-351.

Akkemik, K.A. 2005. October. Labor productivity and inter-sectoral reallocation of labor in Singapore (1965-2002). In *Forum of international development studies* (Vol. 30, No. 2005.9).

Akita, Takahiro, and Jesse Szeto. 2000. "*Inpres Desa Tertinggal* (IDT) Program and Indonesian Regional Inequality." *Asian Economic Journal* 14, no. 2:167–86.

Alatas, Vivi. 2000. "Evaluating the Left Behind Villages Program in Indonesia: Exploiting Rules to Identify Effects on Employment and Expenditures." PhD diss., Department of Economics, Princeton University.

Arndt, C., Jones, S. and Tarp, F., 2016. What is the aggregate economic rate of return to foreign aid?. *The World Bank Economic Review*, *30*(3), pp.446-474.

Asher, Sam and Novosad, Paul. 2018. Rural Roads and Local Economic Development. *Policy Research Working Paper*. No. 8466. World Bank, Washington, DC.

Au, C.C. and Henderson, J.V., 2006. How migration restrictions limit agglomeration and productivity in China. *Journal of development economics*, 80(2), pp.350-388.

BAPPENAS (National Development Planning Agency), 1994, IDT Program Implementation Guidance. BAPPENAS, Jakarta.

Bazzi, S., Gaduh, A., Rothenberg, A.D. and Wong, M., 2016. Skill transferability, migration, and development: Evidence from population resettlement in Indonesia. *American Economic Review*, 106(9), pp.2658-98.

Berthélemy, J.C. and Söderling, L., 2001. The role of capital accumulation, adjustment and structural change for economic take-off: Empirical evidence from African growth episodes. *World Development*, *29*(2), pp.323-343.

Besley, T. and Burgess, R., 2004. Can labor regulation hinder economic performance? Evidence from India. *The Quarterly journal of economics*, *119*(1), pp.91-134.

Bryan, G., Chowdhury, S. and Mobarak, A.M., 2014. Underinvestment in a profitable technology: The case of seasonal migration in Bangladesh. *Econometrica*, 82(5), pp.1671-1748.

Caselli, F. 2005. *Accounting for cross-country income differences*. Aghion P., Durlauf S.N. (Eds.), Handbook of Economic Growth, North Holland, New York (2005).

Cattaneo, M.D., Jansson, M. and Ma, X., 2019. Simple local polynomial density estimators. *Journal of the American Statistical Association*, (just-accepted), pp.1-11.

Chenery, H.B., Robinson, S., and Syrquin. M. 1986. *Industrialization and growth: a comparative study*. Oxford University Press, New York (1986).

Cheng, M.-Y., J. Fan, and J. S. Marron. 1997. On Automatic Boundary Corrections. *Annals of Statistics* 25(4): 1691–1708.

Collins, S.M., Bosworth, B.P. and Rodrik, D., 1996. Economic growth in East Asia: accumulation versus assimilation. *Brookings papers on economic activity*, 1996(2), pp.135-203.

Denison, E.F., 1962. Sources of economic growth in the United States and the alternatives before us. Committee for Economic Development, New York (1962)

Denison, E.F., 1967. Why growth rates differ, Washington DC. *The Brookings Institution*.

Domar, E.D., 1946. Capital expansion, rate of growth, and employment. *Econometrica, Journal of the Econometric Society*, pp.137-147.

Domar, E.D., 1947. Expansion and employment. *The American Economic Review, 37*(1), pp.34-55.

Easterly, W., 1999. The ghost of financing gap: testing the growth model used in the international financial institutions. *Journal of development Economics, 60*(2), pp.423-438.

Easterly, William. 2001. *The Elusive Quest for Growth: Economists' Adventures in the Tropics*. Cambridge: MIT Press.

Fallon, P.R. and Lucas, R.E., 1993. Job security regulations and the dynamic demand for industrial labor in India and Zimbabwe. *Journal of development Economics*, *40*(2), pp.241-275.

Gelman, Andrew and Guido Imbens, 2018. Why High-Order Polynomials Should Not Be Used in Regression Discontinuity Designs. *Journal of Business and Economic Statistics*, 2018, pp. 1–10.

Gibson, John and Susan Olivia, 2010. The Effect of Infrastructure Access and Quality on Non-farm Enterprises in Rural Indonesia. *World Development*, 38(5), 717–726.

Gollin, D., 2014. The Lewis model: A 60-year retrospective. *Journal of Economic Perspectives*, 28(3), pp.71-88.

Gollin, Douglas et al. (2014) The agricultural productivity gap. *Quarterly Journal of Economics*. 129 (2), 939–993.

Gollin, D., Parente, S. and Rogerson, R., 2002. The role of agriculture in development. *American economic review*, 92(2), pp.160-164.

Gollin, D. and Rogerson, R., 2010. Agriculture, roads, and economic development in Uganda (No. w15863). *National Bureau of Economic Research*.

Grossman, G.M. and Helpman, E., 1991. Quality ladders in the theory of growth. *The review of economic studies*, 58(1), pp.43-61.

Harrod, R.F., 1939. An essay in dynamic theory. *The economic journal*, *49*(193), pp.14-33.

Harrod, R.F., 1948. The Fall in Consumption. 1. *Bulletin of the Oxford University Institute of Economics and Statistics*, 10(5), pp.162-167.

Hayashi, F. and Prescott, E.C., 2008. The depressing effect of agricultural institutions on the prewar Japanese economy. *Journal of political Economy*, 116(4), pp.573-632.

Henderson, J.V., Storeygard, A. and Weil, D.N., 2012. Measuring economic growth from outer space. *American economic review*, 102(2), pp.994-1028.

Herrendorf, B., Schmitz, Jr, J.A. and Teixeira, A., 2012. The role of transportation in US economic development: 1840–1860. *International Economic Review*, 53(3), pp.693-716.

Hirshman, A. 1958. *The Strategy of Economic Development*. New Haven: Yale University Press.

Hodler, R. and Raschky, P.A., 2014. Regional favoritism. *The Quarterly Journal of Economics*, 129(2), pp.995-1033.

Imbens, Guido and Thomas Lemieux. 2008. Regression Discontinuity Designs: a Guide to Practice. *Journal of Econometrics*, 2008,142(2), 615–635.

King, R.G. and Levine, R., 1994a. *Capital fundamentalism, economic development, and economic growth* (Vol. 1285). World Bank Publications.

King, R., G, and R. Levine, 1994b, Capital fundamentalism, economic development and economic growth. In *Carnegie-Rochester Conference Series on Public Policy* (Vol. 40).

Krugman, P. 1993. "Toward a Counter-Revolution in Development Theory." In *Proceedings of the World Bank Annual Conference on Development Economics*, ed. L. Summers and S. Shah, pp. 15–38. Washington, DC: World Bank.

Krugman, P., 1994. The myth of Asia's miracle. *Foreign affairs*, vol. 73, no. 6 (November/December), pp.62-78.

Krugman, P.R., 1997. *Development, geography, and economic theory.* Vol. 6. Cambridge: MIT Press.

Lagakos, D. and Waugh, M.E., 2013. Selection, agriculture, and cross-country productivity differences. *American Economic Review*, 103(2), pp.948-80.

Lee, D.S. and Lemieux, T., 2010. Regression discontinuity designs in economics. *Journal of economic literature*, 48(2), pp.281-355.

Lee, D. and Wolpin, K.I., 2006. Intersectoral labor mobility and the growth of the service sector. *Econometrica*, 74(1), pp.1-46.

Lewis, W.A. 1954. Economic Development with Unlimited Supplies of Labour. *Manchester School of Economics and Social Studies*, 22 (1954), pp. 139-191.

Mankiw, N.G., Romer, D. and Weil, D.N., 1992. A contribution to the empirics of economic growth. *The quarterly journal of economics*, 107(2), pp.407-437.

Manning, C., 2014. Labour market regulation and employment during the yudhoyono years in Indonesia. In *Trade, Development, and Political Economy in East Asia*. ISEAS Publishing.

McCrary, J. 2008. Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics*, 142(2): 698–714.

McMillan, M., and D. Rodrik. 2014. Globalization, Structural Change and Productivity Growth with an Update on Africa. *World Development*. 63. pp. 11–32.

Messina, J., 2006. The role of product market regulations in the process of structural change. *European Economic Review*, 50(7), pp.1863-1890.

Michalopoulos, S. and Papaioannou, E., 2013. National institutions and subnational development in Africa. *The Quarterly Journal of Economics*, 129(1), pp.151-213.

Molyneaux, John, and Paul Gertler. 1999. “Evaluating Program Impact: A Case Study of Poverty Alleviation in Indonesia.” Haas School of Business, University of California, Berkeley.

Munshi, K. and Rosenzweig, M., 2016. Networks and misallocation: Insurance, migration, and the rural-urban wage gap. *American Economic Review*, 106(1), pp.46-98.

Murphy, K.M., Shleifer, A. and Vishny, R.W., 1989. Industrialization and the big push. *Journal of political economy*, 97(5), pp.1003-1026.

Nelson, R.R. and Pack, H. 1999. The Asian Miracle and Modern Growth Theory. *The Economic Journal*, 109 (457) (1999), pp. 416-436.

Nickell, S.J., Swaffield, J.K. and Redding, S.J., 2002. Educational Attainment, Labor Market Institutions and the Structure of Production. *Working Paper*, *Centre for Economic Performance*, London School of Economics, London.

Otsu, T., K.-L. Xu, and Y. Matsushita. 2014. Estimation and Inference of Discontinuity in Density. *Journal of Business and Economic Statistics*, 31(4): 507–524.

Ngai, L.R. and Pissarides, C.A. 2007. Structural Change in a Multisector Model of Growth. *The American Economic Review*, 97 (1) (2007), pp. 429-443.

Rosenstein-Rodan, P.N., 1943. Problems of industrialisation of eastern and south-eastern Europe. *The economic journal*, 53(210/211), pp.202-211.

Rodrik, D., 2016. The return of public investment. *Project Syndicate*. January 13, 2016.

Rostow, W. W., 1960. *The Five Stages of Growth-A Summary*. Cambridge: Cambridge University Press.

Solow, R.M., 1957. Technical change and the aggregate production function. *The review of Economics and Statistics*, pp.312-320.

Suryadarma, D. and Yamauchi, C., 2013. Missing public funds and targeting performance: Evidence from an anti-poverty transfer program in Indonesia. *Journal of Development Economics*, 103, pp.62-76.

Syrquin, M. 1995. *Patterns of Structural Change*. Chenery H., Srinivasan T.N. (Eds.), Handbook of Development Economics, Vol. 1, Elsevier (1995), pp. 203-273.

Stiglitz, J. 1996. Some Lessons from the East Asian Miracle. World Bank Research Observer. 1 (2). pp. 151–77.

Tohari, A., Parsons, C. and Rammohan, A., 2019. Targeting poverty under complementarities: Evidence from Indonesia's unified targeting system. *Journal of Development Economics*, 140, pp.127-144.

World Bank. 2012. More and Better Jobs for South Asia. Washington, DC

Yamauchi, C., 2010. Community-based targeting and initial local conditions: Evidence from Indonesia’s IDT Program. *Economic Development and Cultural Change*, 59(1), pp.95-147.

Young, A., 1992. A Tale of Two Cities: Factor Accumulation and Technical Change in Hong Kong and Singapore. In Oliver J. Blanchard and Stanley Fisher (eds) *NBER Macroeconomics Annual 1992*, Cambridge MA, MIT Press, p13-54.

Young, A., 1994. Lessons from the East Asian NICs: a contrarian view. *European economic review*, 38(3-4), pp.964-973.

Young, A., 1995. The tyranny of numbers: confronting the statistical realities of the East Asian growth experience. *The Quarterly Journal of Economics*, 110(3), pp.641-680.

## 4.8 Appendices

### 4.8.1 Share of Agriculture to GDP and IDT Periods

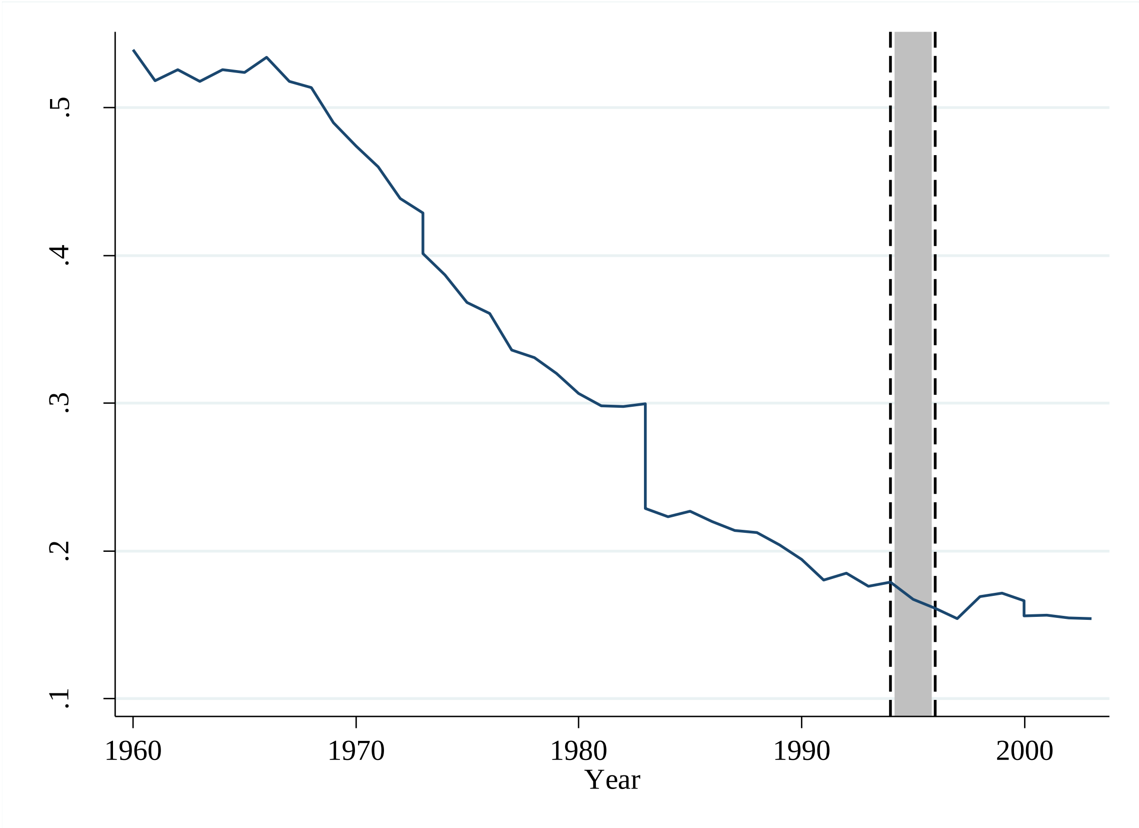



**Figure 4-4. Share of Agriculture to GDP and IDT Periods**

Notes: This figure plots fall in the share of agriculture in GDP during the periods from 1960 to 2000. The area within the vertical dashed lines represents the period of the IDT program.

### 4.8.2 Variables were used to select targeted villages under the IDT Program

**IDT 1994**

| | Rural | Urban |
|---|---|---|
| 1. | Type of local Community Organisation | Type of local Community Organisation |
| 2. | Type of main road | Type of main road |
| 3. | Main sector | Main sector |
| 4. | Average agriculture area per household (are) | Average agriculture area per household (are) |
| 5. | Distance to district capital | Distance to district capital |
| 6. | Education facility | Education facility |
| 7. | Health facility | Health facility |
| 8. | Type of Paramedics | Type of Paramedics |
| 9. | Communication Facility | Communication Facility |
| 10. | Type of market | Type of market |
| 11. | Density | Density |
| 12. | Source of Drinking Water | Source of Drinking Water |
| 13. | Is there any Epidemic last year | Is there any Epidemic last year |
| 14. | Type of fuel | Type of fuel |
| 15. | Type of Garbage Dump | Type of Garbage Dump |
| 16. | Type of Toilet | Type of Toilet |
| 17. | Type of Electricity | Type of Electricity |
| 18. | Ratio place of worship/1000 citizens | Ratio place of worship/1000 citizens |
| 19. | Crude Birth Rate per 1000 citizens | Crude Birth Rate per 1000 citizens |
| 20. | Crude Mortality Rate per 1000 citizens | Crude Mortality Rate per 1000 citizens |
| 21. | Enrolment rate (7-15 years old) | Enrolment rate (7-15 years old) |
| 22. | Number of livestock | Number of livestock |
| 23. | Percentage of households having TV | Percentage of households having TV |
| 24. | Percentage of households having telephone | Percentage of households having telephone |
| 25. | Socio culture status | Socio culture status |
| 26. | Percentage Agriculture Households | |
| 27. | Type of transportation mode | |

**IDT 1995**

| | Rural | Urban |
|---|---|---|
| 1. | Type of main road | Main sector of Work of the Villagers |
| 2. | Main sector of Work of the Villagers | Education facility |
| 3. | Education facility | Health facility |
| 4. | Health facility | Communication Facility |
| 5. | Type of Paramedics | Density |
| 6. | Communication Facility | Source of Drinking Water |
| 7. | Density | Source of fuel |
| 8. | Source of Drinking Water | Type of Garbage Dump |
| 9. | Source of fuel | Type of Toilet |
| 10. | Percentage of households with Electricity | Percentage of households with Electricity |
| 11. | Percentage of households having TV | Percentage of households having TV |
| 12. | Percentage of Agriculture Households | Percentage of Agriculture Households |
| 13. | Percentage of Households having motor cycles | Percentage of Households with college students |
| 14. | Socio Economic status of the villagers | Percentage of Households with car or boat |
| 15. | Access to Health Facility | Socio Economic status of the villagers |
| 16. | Is there any subscriber of newspaper/magazine | Access to Health Facility |
| 17. | Access to Markets | Access to Markets |
| 18. | Access to Stores | |

### 4.8.3 The IDT94 vs IDT95 recipients

| | | | IDT 1995 Recipients | | |
|---|---|---|---|---|---|
| | | | IDT | Non-IDT | Villages |
| IDT 1994 Recipients | Not in the list | *n* | 126 | 519 | 645 |
| | | % | 0.57 | 1.2 | 0.99 |
| | IDT | *n* | 18,179 | 2,319 | 20,498 |
| | | % | 82.28 | 5.35 | 31.33 |
| | Non-IDT | *n* | 3,789 | 40,492 | 44,281 |
| | | % | 17.15 | 93.45 | 67.68 |
| | Villages | | 22,094 | 43,330 | 65,424 |
| | | | 100 | 100 | 100 |

### 4.8.4 The example of the administrative data and map for IDT Program

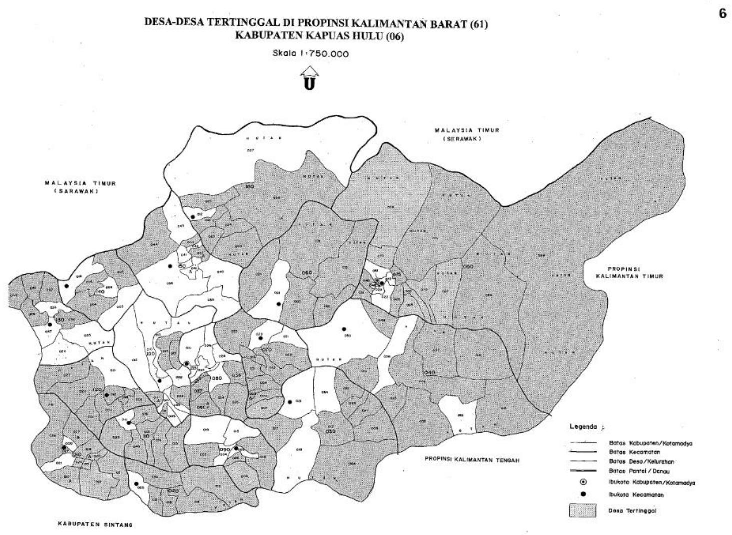

Daftar Nama Desa Menurut Kabupaten/Kotamadya
dan Kecamatan 1995

PROPINSI : (61) KALIMANTAN BARAT
KABUPATEN/KODYA: (06) KAPUAS HULU
KECAMATAN : (010) SILAT HILIR

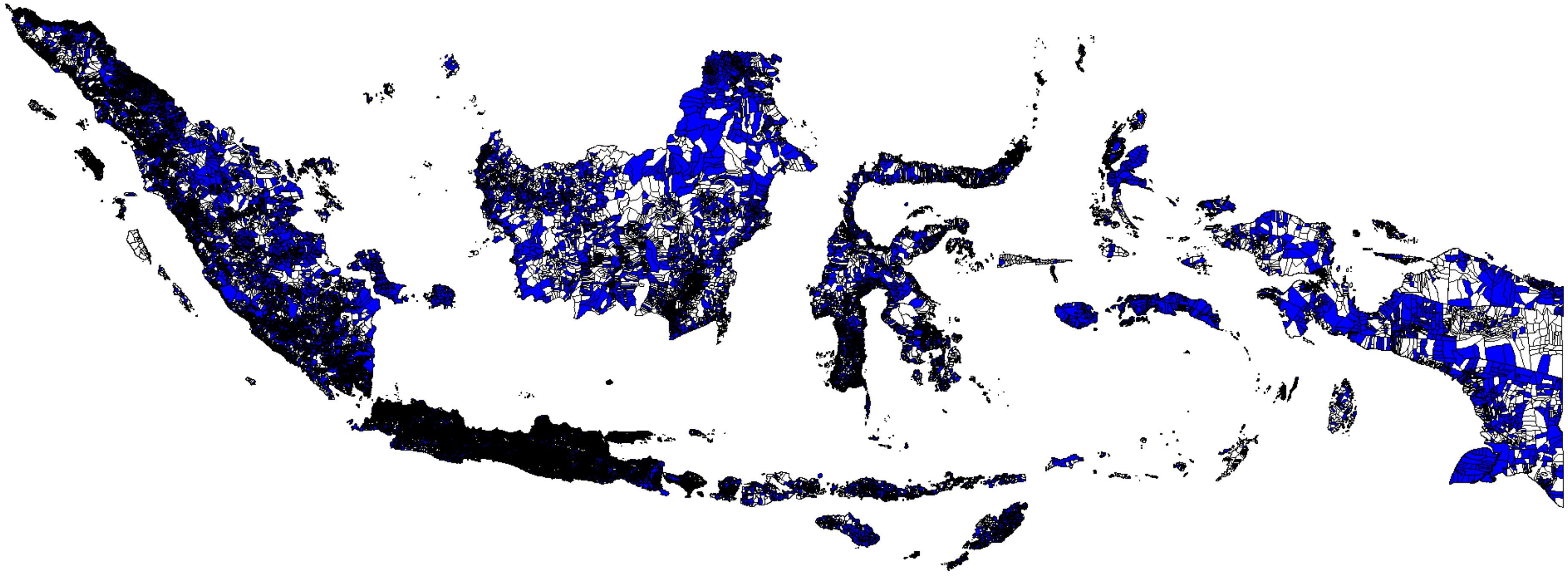
| NAMA DESA/KELURAHAN | STATUS IDT 1996/1997 | STATUS PERKOTAAN | STATUS HUKUM |
|---|---|---|---|
| (007) NANGANUAR | IDT | DESA | DEFINITIF |
| (015) MIAU MERAH | IDT | DESA | DEFINITIF |
| (019) SETUNGGUL | IDT | DESA | DEFINITIF |
| (020) SUNGAI SENA | IDT | DESA | DEFINITIF |
| (021) PANGERAN | NON IDT | DESA | DEFINITIF |
| (024) PULAU BERGERAK PENAI | IDT | DESA | DEFINITIF |
| (027) BARU | IDT | DESA | DEFINITIF |
| (028) PERIGI | NON IDT | DESA | DEFINITIF |
| (031) BONGKONG I | IDT | DESA | DEFINITIF |

PROPINSI : (61) KALIMANTAN BARAT
KABUPATEN/KODYA: (06) KAPUAS HULU
KECAMATAN : (020) SILAT HULU

| NAMA DESA/KELURAHAN | STATUS IDT 1996/1997 | STATUS PERKOTAAN | STATUS HUKUM |
|---|---|---|---|
| (012) NANGA LUAN | IDT | DESA | DEFINITIF |
| (015) NANGA LUNGU | IDT | DESA | DEFINITIF |
| (018) LANDAU BADAI | IDT | DESA | DEFINITIF |
| (021) NANGA NGERI | IDT | DESA | DEFINITIF |
| (028) NANGA DANGKAN | NON IDT | DESA | DEFINITIF |
| (030) BELIMBING | IDT | DESA | DEFINITIF |

### 4.8.5 Spatial location of villages which received IDT Programs in 1995



### 4.8.6 List of variables from PODES 1993 and IDT Village Census 1994

| PODES 1993 | IDT Village Census 1994 |
|---|---|
| Pre -93- Population Density | Pre -94- Percentage LGA Households |
| Pre -93- Source of Drinking Water | Pre -94- Percentage Construction Households |
| Pre -93- Cooking Fuel | Pre -94- Percentage Trade Households |
| Pre -93- Type of Garbage Dump | Pre -94- Percentage Transport Households |
| Pre -93- Type of Toilet | Pre -94- Percentage Financial Households |
| Pre -93- Percentage of households having Electricity | Pre -94- Percentage Service Households |
| Pre -93- Percentage of households having Television | Pre -94- Percentage Others Households |
| Pre -93- Percentage Agriculture Households | Pre -94- Percentage daily/manual Households |
| Pre -93- Percentage Mining Households | Pre -94- Percentage of Households having university child |
| Pre -93- Percentage Industry Households | Pre -94- Percentage of Households having 4 wheels |
| Pre -93- Percentage LGA Households | Pre -94- Percentage of Households having motorcycle/Boat |
| Pre -93- Percentage Construction Households | Pre -94- Village has access to road |
| Pre -93- Percentage Trade Households | Pre -94- Road type: Asphalt |
| Pre -93- Percentage Transport Households | Pre -94- Road type: Hardened |
| Pre -93- Percentage Financial Households | Pre -94- Road type: Soils |
| Pre -93- Percentage Service Households | Pre -94- Road type: Others |
| Pre -93- Percentage Others Households | Pre -94- Road can be used by 4 wheels or more whole year |
| Pre -93- Percentage daily/manual Households | Pre -94- Public Transportation :1. Bicycle Taxi |
| Pre -93- Percentage of Households having university child | Pre -94- Public Transportation :2. Pedicab |
| Pre -93- Percentage of Households having 4 wheels | Pre -94- Public Transportation :3. Horse-drawn cart |
| Pre -93- Percentage of Households having motorcycle/Boat | Pre -94- Public Transportation :4. horse-drawn buggy/carriage |
| Pre -93- Public Transportation :1. Bicycle Taxi | Pre -94- Public Transportation :5. Motor cycle taxi |
| Pre -93- Public Transportation :2. Pedicab | Pre -94- Public Transportation :6. 3 wheeled motor vehicles |
| Pre -93- Public Transportation :3. Horse-drawn cart | Pre -94- Public Transportation :7. 4 wheeled motor vehicles |
| Pre -93- Public Transportation :4. horse-drawn buggy/carriage | Pre -94- Public Transportation :8. Rowboat |
| Pre -93- Public Transportation :5. Motor cycle taxi | Pre -94- Public Transportation :9. Motor boat |
| Pre -93- Public Transportation :6. 3 wheeled motor vehicles | Pre -94- Public Transportation :10. Motor ship |
| Pre -93- Public Transportation :7. 4 wheeled motor vehicles | Pre -94- Public Transportation :11. Others |
| Pre -93- Public Transportation :8. Rowboat | Pre -94- Main Transportation Mode |

| PODES 1993 | IDT Village Census 1994 |
|---|---|
| Pre -93- Public Transportation :9. Motor boat | Pre -94- School Enrol rate population aged 7-15 years |
| Pre -93- Public Transportation :10. Motor ship | Pre -94- Infant Mortality Rate per 1000 live birth |
| Pre -93- Public Transportation :11. Airplane | Pre -94- Percentage Husbandry Households: 1. Dairy cow |
| Pre -93- Public Transportation :12. Others | Pre -94- Percentage Husbandry Households: 2. Cattle |
| Pre -93- Percentage of population aged 7-15 years who work | Pre -94- Percentage Husbandry Households: 3. Buffalo |
| Pre -93- Infant Mortality Rate per 1000 live birth | Pre -94- Percentage Husbandry Households: 4. Horse |
| Pre -93- Type of Main Road | Pre -94- Percentage Husbandry Households: 5. Goat/Sheep |
| Pre -93- Whether Village has access to public transport | Pre -94- Percentage Husbandry Households: 6. Pig |
| Pre -93- Distance village to subdistrict office | Pre -94- Percentage Husbandry Households: 7. Broiler Chicken |
| Pre -93- Distance village to subdistrict office | Pre -94- Number of Livestock: 1. Dairy cow |
| | Pre -94- Number of Livestock: 2. Cattle |
| | Pre -94- Number of Livestock: 3. Buffalo |
| | Pre -94- Number of Livestock: 4. Horse |
| | Pre -94- Number of Livestock: 5. Goat/sheep |
| | Pre -94- Number of Livestock: 6. Pig |
| | Pre -94- Number of Livestock: 7. Broiler Chicken |

### 4.8.7 List of variables from IDT Village Census 1995 and PODES 1996

| IDT Village Census 1995 | PODES 1996 |
|---|---|
| Post -95- Population Density | Post -96- Population Density |
| Post -95- Source of Drinking Water | Post -96- Source of Drinking Water |
| Post -95- Cooking Fuel | Post -96- Type of Garbage Dump |
| Post -95- Type of Garbage Dump | Post -96- Type of Toilet |
| Post -95- Type of Toilet | Post -96- Percentage of households having Electricity |
| Post -95- Percentage of households having Electricity | Post -96- Percentage of households having Television |
| Post -95- Percentage of households having Television | Post -96- Percentage Agriculture Households |
| Post -95- Percentage Agriculture Households | Post -96- Percentage Mining Households |
| Post -95- Percentage Mining Households | Post -96- Percentage Industry Households |
| Post -95- Percentage Industry Households | Post -96- Percentage LGA Households |
| Post -95- Percentage LGA Households | Post -96- Percentage Construction Households |
| Post -95- Percentage Construction Households | Post -96- Percentage Trade Households |
| Post -95- Percentage Trade Households | Post -96 Percentage Transport Households |
| Post -95- Percentage Transport Households | Post -96- Percentage Financial Households |
| Post -95- Percentage Financial Households | Post -96- Percentage Service Households |
| Post -95- Percentage Service Households | Post -96- Percentage Others Households |
| Post -95- Percentage Others Households | Pre -96- Percentage of Households having university child |
| Post -95- Percentage daily/manual Households | Post -96- Percentage of Households having 4 wheels |
| Post -95- Percentage of Households having university child | Post -96- Percentage of Households having motorcycle/Boat |
| Post -95- Percentage of Households having 4 wheels | Post -96- Number of Joint Business |
| Post -95- Percentage of Households having motorcycle/Boat | Post -96- Number of Joint Business members |
| Post -95- Public Transportation :1. Bicycle Taxi | Post -96- Percentage of Pre-Prosperous |
| Post -95- Public Transportation :2. Pedicab | Post -96- Percentage of Prosperous Stage I |
| Post -95- Public Transportation :3. Horse-drawn cart | Post -96- Percentage of Prosperous Stage II |
| Post -95- Public Transportation :4. horse-drawn buggy/carriage | Post -96- Percentage of Prosperous Stage III |
| Post -95- Public Transportation :5. Motor cycle taxi | Post -96- Percentage of Prosperous Stage III Plus |
| Post -95- Public Transportation :6. 3 wheeled motor vehicles | Post -96- Percentage of community support to the total village income |
| Post -95- Public Transportation :7. 4 wheeled motor vehicles | Post -96- Percentage central gov. aid to the total village income |
| Post -95- Public Transportation :8. Rowboat | Post -96- Percentage provincial gov. aid to the total village income |
| Post -95- Public Transportation :9. Motor boat | Post -96- Percentage district gov. aid to the total village income |
| Post -95- Public Transportation :10. Motor ship | Post -96- Percentage development expense to the total expense |

| IDT Village Census 1995 | PODES 1996 |
|---|---|
| Post -95- Public Transportation :11.  Others | Post -96- Percentage infrastructure expense to the total expense |
| Post -95- Main Transportation Mode | Post -96- Percentage production expense to the total expense |
| Post -95- School Enrol rate population aged 7-15 years | Post -96- Percentage transport expense to the total expense |
| Post -95- Infant Mortality Rate per 1000 live birth | Post -96- Percentage marketing expense to the total expense |
| Post -95- Percentage Husbandry Households | Post -96- Percentage social expense to the total expense |
| Post -95- Percentage Husbandry Households: 1. Dairy cow | Post -96- Number of community groups |
| Post -95- Percentage Husbandry Households: 2. Cattle | Post -96 Number of community groups receiving IDT |
| Post -95- Percentage Husbandry Households: 3. Buffalo | Post -96- Number of families receiving IDT |
| Post -95- Percentage Husbandry Households: 4. Horse | Post -96- Number of community group supports |
| Post -95- Percentage Husbandry Households: 5. Goat/Sheep | Post -96- Age of Head of village |
| Post -95- Percentage Husbandry Households: 6. Pig | Post -96- Gender of Head of village |
| Post -95- Percentage Husbandry Households: 7. Broiler Chicken | Post -96- Education Head Village: No Educ |
| Post -95- Number of Livestock: 1. Dairy cow | Post -96- Education Head Village: Primary |
| Post -95- Number of Livestock: 2. Cattle | Post -96- Education Head Village: Junior High |
| Post -95- Number of Livestock: 3. Buffalo | Post -96- Education Head Village: Senior High |
| Post -95- Number of Livestock: 4. Horse | Post -96- Education Head Village: University High |
| Post -95- Number of Livestock: 5. Goat/sheep | Post -96- Number of SMEs in the Village |
| Post -95- Number of Livestock: 6. Pig | Post -96- Education H Village: categorical |
| Post -95- Number of Livestock: 7. Broiler Chicken | Post -96- Main Transportation Mode |

### 4.8.8 List of regulations

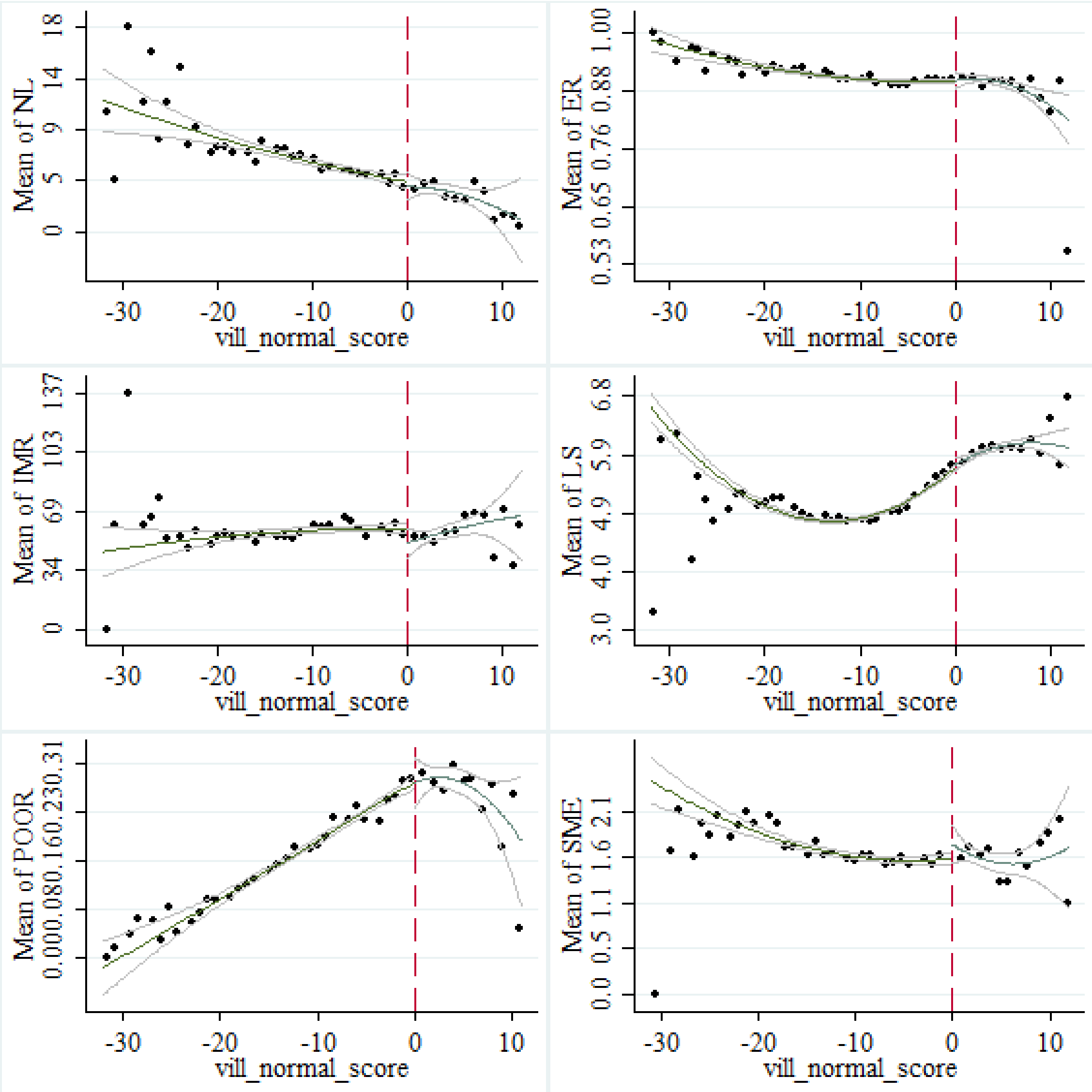
| No | Regulations | Year | Number of Villages |
|---|---|---|---|
| 1 | Government Regulation No. 44 | 1986 | 28 |
| 2 | Presidential Decree No. 44 | 1990 | 54 |
| 3 | Law No. 7 | 1990 | 44 |
| 4 | Government Regulation No. 49 | 1991 | 22 |
| 5 | Government Regulation No. 50 | 1991 | 126 |
| 6 | Government Regulation No. 53 | 1991 | 24 |
| 7 | Government Regulation No. 54 | 1991 | 23 |
| 8 | Government Regulation No. 60 | 1991 | 165 |
| 9 | Government Regulation No. 61 | 1991 | 139 |
| 10 | Government Regulation No. 62 | 1991 | 19 |
| 11 | Government Regulation No. 63 | 1991 | 84 |
| 12 | Government Regulation No. 64 | 1991 | 77 |
| 13 | Law No. 6 | 1991 | 163 |
| 14 | Government Regulation No. 1 | 1992 | 43 |
| 15 | Government Regulation No. 16 | 1992 | 116 |
| 16 | Government Regulation No. 26 | 1992 | 139 |
| 17 | Government Regulation No. 28 | 1992 | 50 |
| 18 | Government Regulation No. 29 | 1992 | 55 |
| 19 | Government Regulation No. 3 | 1992 | 252 |
| 20 | Government Regulation No. 32 | 1992 | 23 |
| 21 | Government Regulation No. 35 | 1992 | 226 |
| 22 | Government Regulation No. 42 | 1992 | 55 |
| 23 | Government Regulation No. 44 | 1992 | 229 |
| 24 | Government Regulation No. 46 | 1992 | 48 |
| 25 | Government Regulation No. 50 | 1992 | 274 |
| 26 | Government Regulation No. 59 | 1992 | 66 |
| 27 | Government Regulation No. 69 | 1992 | 22 |
| 28 | Government Regulation No. 12 | 1993 | 23 |
| 29 | Law No. 4 | 1994 | 39 |
| 30 | Presidential Decree No. 33 | 1995 | 144 |
| 31 | Presidential Decree No. 41 | 1995 | 110 |
| 32 | Government Regulation No. 2 | 1995 | 57 |
| 33 | Government Regulation No. 22 | 1995 | 14 |
| 34 | Government Regulation No. 23 | 1995 | 14 |
| 35 | Government Regulation No. 28 | 1995 | 109 |
| 36 | Government Regulation No. 29 | 1995 | 20 |
| 37 | Government Regulation No. 3 | 1995 | 25 |
| 38 | Government Regulation No. 37 | 1995 | 27 |
| 39 | Government Regulation No. 41 | 1995 | 22 |
| 40 | Government Regulation No. 43 | 1995 | 83 |
| 41 | Government Regulation No. 1 | 1996 | 128 |
| 42 | Law No. 5 | 1996 | 45 |
| | Total | | 3,426 |

*Notes*: This table present the government regulations issued in the periods from 1990-1996 which change the village identifier code. Number of villages present how many villages were impacted as a result for regulation issuance.

### 4.8.9 Graphical illustration of the RD design

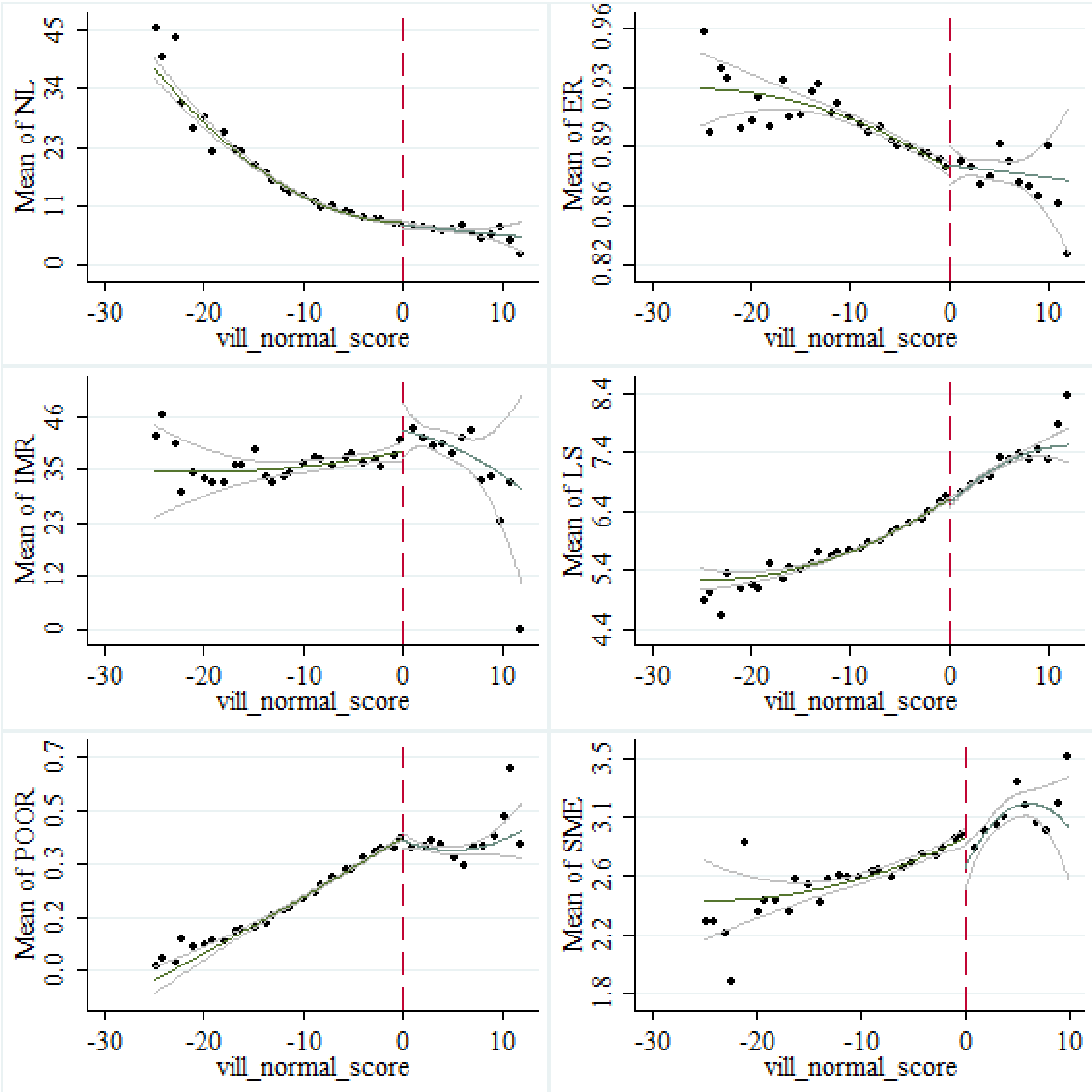
**Figure 4-5. The Discontinuity of the Outcome Variables in the Island:**

**Panel A: Sumatra**



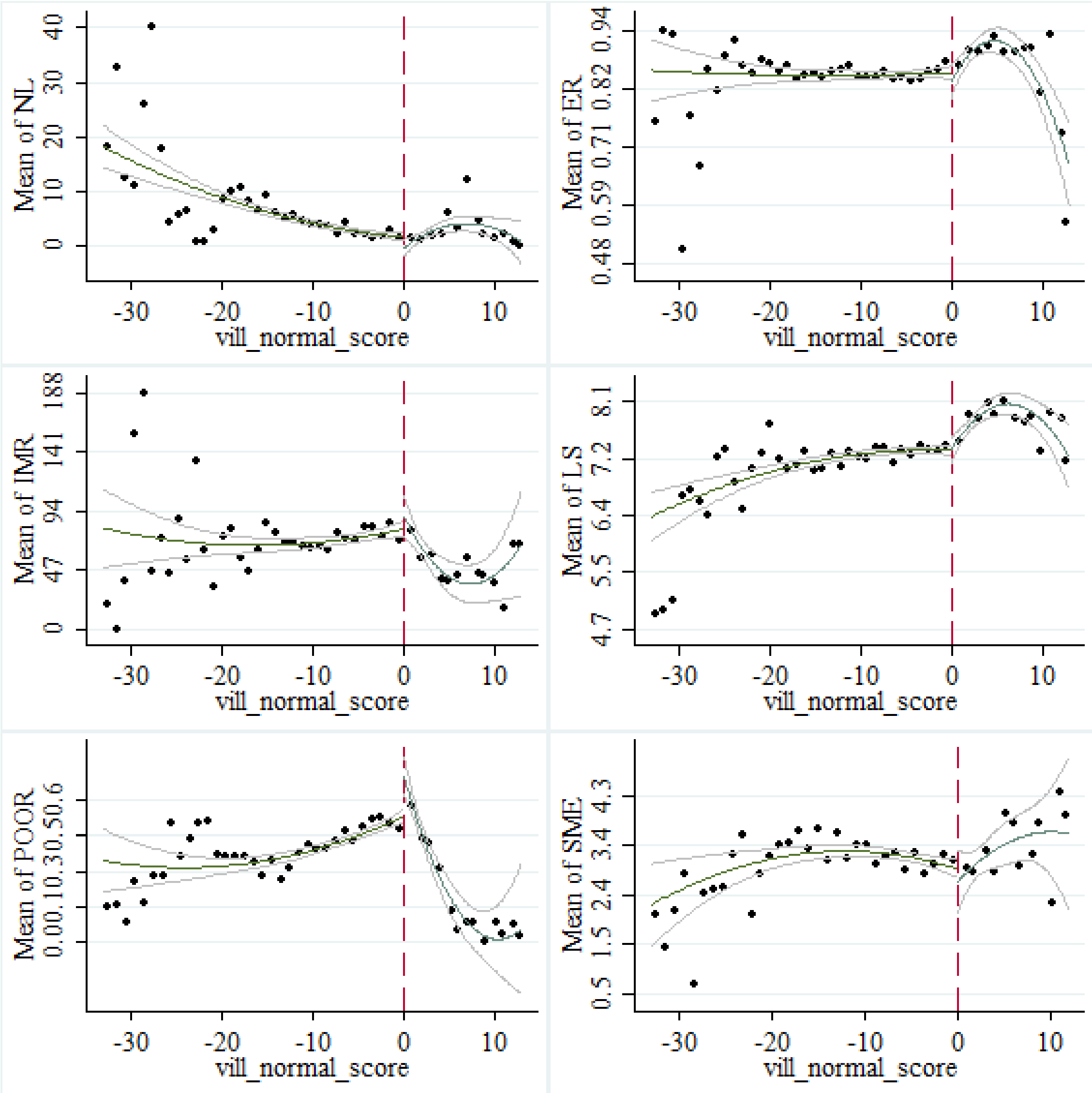

*Notes*: This figure plots welfare measures against the normalized IDT score for Sumatra island, with a negative score indicating the village did not receive IDT Program. Each point represents the average value of the outcome in score spread. The solid line plots predicted values, with separate quadratic vote spread trends estimated on either side of the provincial threshold. The dashed lines show 95 percent confident interval

**Panel B: Java**



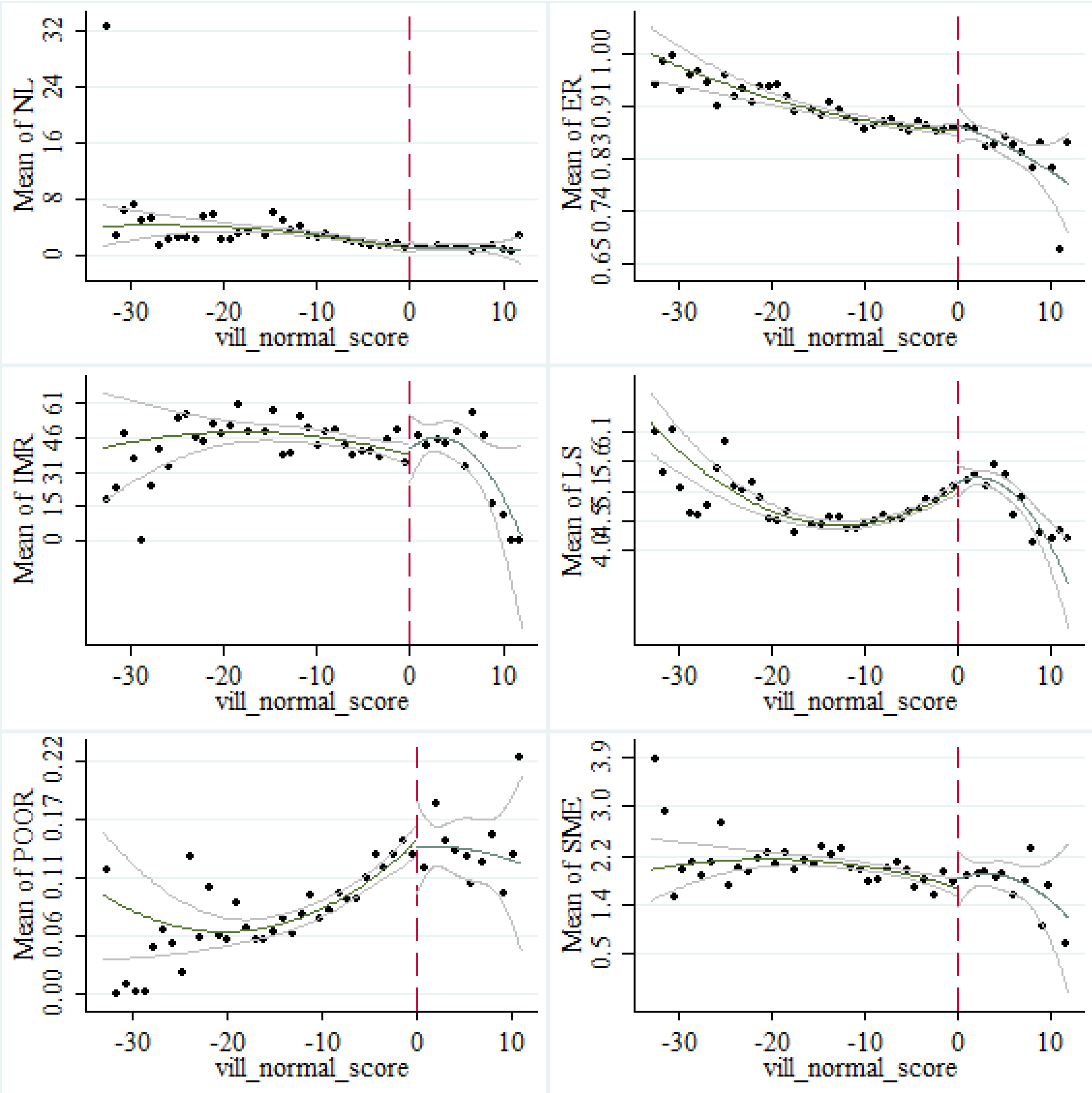

*Notes*: This figure plots welfare measures against the normalized IDT score for Java island, with a negative score indicating the village did not receive IDT Program. Each point represents the average value of the outcome in score spread. The solid line plots predicted values, with separate quadratic vote spread trends estimated on either side of the provincial threshold. The dashed lines show 95 percent confident interval

**Panel C: Bali and Nusa Tenggara**



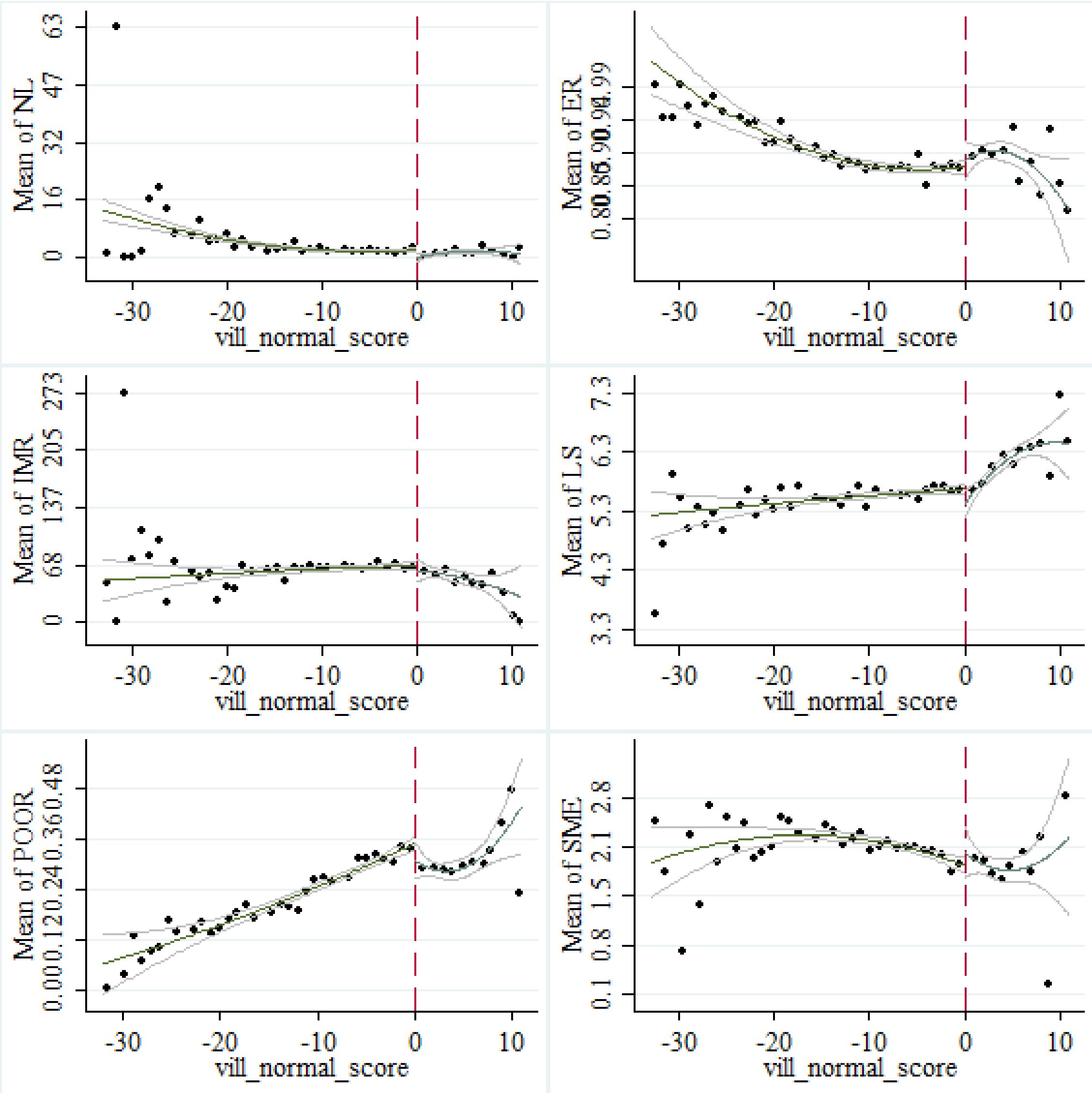

*Notes*: This figure plots welfare measures against the normalized IDT score for Bali and Nusa Tenggara islands, with a negative score indicating the village did not receive IDT Program. Each point represents the average value of the outcome in score spread. The solid line plots predicted values, with separate quadratic vote spread trends estimated on either side of the provincial threshold. The dashed lines show 95 percent confident interval.

**Panel D: Kalimantan**




*Notes*: This figure plots welfare measures against the normalized IDT score for Kalimantan island, with a negative score indicating the village did not receive IDT Program. Each point represents the average value of the outcome in score spread. The solid line plots predicted values, with separate quadratic vote spread trends estimated on either side of the provincial threshold. The dashed lines show 95 percent confident interval.

**Panel E: Sulawesi and Papua**




*Notes*: This figure plots welfare measures against the normalized IDT score for Sulawesi and Papua islands, with a negative score indicating the village did not receive IDT Program. Each point represents the average value of the outcome in score spread. The solid line plots predicted values, with separate quadratic vote spread trends estimated on either side of the provincial threshold. The dashed lines show 95 percent confident interval.

### 4.8.10 Robustness Check

4.8.10.1 Placebo Bandwidth

RDD Estimation Results of RURAL Village with Bandwidth equals 1

| | Dependent Variables: | | | | | |
|---|---|---|---|---|---|---|
| | NL | ER | IMR | LS | POOR | SME |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Sumatra* | | | | | | |
| IDT | 0.619* | 0.012 | -16.670** | 1.228*** | -0.106* | 0.624*** |
| | [0.346] | [0.018] | [7.730] | [0.182] | [0.062] | [0.194] |
| $R^2$ | 0.011 | 0.001 | 0.009 | 0.212 | 0.042 | 0.053 |
| Clusters | 48 | 48 | 48 | 47 | 40 | 39 |
| Observations | 615 | 615 | 615 | 611 | 336 | 244 |
| *Panel B: Java* | | | | | | |
| IDT | 0.440*** | 0.053*** | -14.893*** | 0.892*** | -0.092*** | 0.781*** |
| | [0.126] | [0.010] | [4.820] | [0.062] | [0.027] | [0.144] |
| $R^2$ | 0.020 | 0.039 | 0.014 | 0.210 | 0.030 | 0.057 |
| Clusters | 78 | 78 | 78 | 78 | 78 | 78 |
| Observations | 1,046 | 1,046 | 1,046 | 1,046 | 954 | 861 |
| *Panel C: Bali andNusa Tenggara* | | | | | | |
| IDT | 0.012 | 0.018 | -32.875*** | 0.692*** | 0.068 | 0.614* |
| | [0.436] | [0.031] | [10.623] | [0.147] | [0.076] | [0.359] |
| $R^2$ | 0.000 | 0.005 | 0.046 | 0.142 | 0.010 | 0.029 |
| Clusters | 35 | 35 | 35 | 35 | 35 | 27 |
| Observations | 181 | 181 | 181 | 181 | 169 | 104 |
| *Panel D: Kalimantan* | | | | | | |
| IDT | -0.695 | 0.055* | 3.045 | 1.564*** | 0.081* | -0.363 |
| | [0.463] | [0.030] | [12.157] | [0.444] | [0.040] | [0.402] |
| $R^2$ | 0.025 | 0.029 | 0.000 | 0.144 | 0.056 | 0.015 |
| Clusters | 24 | 24 | 24 | 24 | 23 | 18 |
| Observations | 205 | 205 | 205 | 189 | 118 | 83 |
| *Panel E: Sulawesi and Papua* | | | | | | |
| IDT | -0.252 | 0.101*** | -24.377 | -0.267 | 0.064 | -0.119 |
| | [0.253] | [0.036] | [17.296] | [0.392] | [0.063] | [0.313] |
| $R^2$ | 0.003 | 0.048 | 0.014 | 0.005 | 0.011 | 0.002 |
| Clusters | 38 | 38 | 38 | 38 | 36 | 30 |
| Observations | 319 | 319 | 319 | 316 | 243 | 142 |

*Notes:* All specifications in this table are the same with Table 2, except Bandwidth equal to 1.

*** significant at 1%, ** significant at 5%, * significant at 10%.

RDD Estimation Results of RURAL Village with Bandwidth equals 3

| | Dependent Variables: | | | | | |
|---|---|---|---|---|---|---|
| | NL | ER | IMR | LS | POOR | SME |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Sumatra* | | | | | | |
| IDT | 0.612** | 0.019 | -25.286*** | 1.199*** | -0.113** | 0.485*** |
| | [0.296] | [0.016] | [6.516] | [0.151] | [0.055] | [0.165] |
| $R^2$ | 0.009 | 0.012 | 0.024 | 0.193 | 0.045 | 0.031 |
| Clusters | 53 | 53 | 53 | 53 | 52 | 50 |
| Observations | 3,021 | 3,021 | 3,021 | 3,001 | 1,685 | 1,305 |
| *Panel B: Java* | | | | | | |
| IDT | 0.487*** | 0.053*** | -11.095*** | 0.881*** | -0.082*** | 0.755*** |
| | [0.110] | [0.008] | [3.866] | [0.051] | [0.025] | [0.098] |
| $R^2$ | 0.040 | 0.039 | 0.013 | 0.220 | 0.020 | 0.051 |
| Clusters | 82 | 82 | 82 | 82 | 82 | 82 |
| Observations | 5,308 | 5,308 | 5,308 | 5,304 | 4,933 | 4,366 |
| *Panel C: Bali and Nusa Tenggara* | | | | | | |
| IDT | 0.204 | -0.005 | -26.929** | 0.642*** | 0.062 | 0.698** |
| | [0.420] | [0.027] | [11.370] | [0.129] | [0.083] | [0.311] |
| $R^2$ | 0.014 | 0.007 | 0.022 | 0.157 | 0.011 | 0.034 |
| Clusters | 39 | 39 | 39 | 39 | 39 | 33 |
| Observations | 832 | 832 | 832 | 832 | 760 | 431 |
| *Panel D: Kalimantan* | | | | | | |
| IDT | -0.557 | 0.073*** | -19.824 | 1.472*** | 0.034 | -0.430 |
| | [0.328] | [0.023] | [12.011] | [0.276] | [0.034] | [0.370] |
| $R^2$ | 0.035 | 0.050 | 0.015 | 0.127 | 0.035 | 0.033 |
| Clusters | 25 | 25 | 25 | 25 | 24 | 22 |
| Observations | 1,012 | 1,012 | 1,012 | 949 | 566 | 416 |
| *Panel E: Sulawesi and Papua* | | | | | | |
| IDT | -0.271* | 0.080** | -14.049 | -0.238 | 0.058 | -0.258 |
| | [0.161] | [0.032] | [14.194] | [0.346] | [0.048] | [0.247] |
| $R^2$ | 0.008 | 0.042 | 0.006 | 0.004 | 0.022 | 0.011 |
| Clusters | 48 | 48 | 48 | 48 | 46 | 41 |
| Observations | 1,525 | 1,525 | 1,525 | 1,514 | 1,142 | 689 |

*Notes:* All specifications in this table are the same with Table 2, except Bandwidth equal to 3.

*** significant at 1%, ** significant at 5%, * significant at 10%.

RDD Estimation Results of RURAL Village with Bandwidth equals 4

| | Dependent Variables: | | | | | |
|---|---|---|---|---|---|---|
| | NL<br>(1) | ER<br>(2) | IMR<br>(3) | LS<br>(4) | POOR<br>(5) | SME<br>(6) |
| *Panel A: Sumatra* | | | | | | |
| IDT | 0.401 | 0.031* | -27.424*** | 1.132*** | -0.113** | 0.501*** |
| | [0.287] | [0.016] | [6.650] | [0.152] | [0.047] | [0.152] |
| $R^2$ | 0.015 | 0.012 | 0.025 | 0.208 | 0.037 | 0.031 |
| Clusters | 54 | 54 | 54 | 54 | 54 | 51 |
| Observations | 4,211 | 4,211 | 4,211 | 4,177 | 2,420 | 1,841 |
| *Panel B: Java* | | | | | | |
| IDT | 0.471*** | 0.053*** | -11.542*** | 0.913*** | -0.078*** | 0.740*** |
| | [0.095] | [0.007] | [3.162] | [0.049] | [0.022] | [0.085] |
| $R^2$ | 0.055 | 0.038 | 0.010 | 0.226 | 0.022 | 0.050 |
| Clusters | 83 | 83 | 83 | 83 | 83 | 82 |
| Observations | 7,403 | 7,403 | 7,403 | 7,398 | 6,903 | 6,098 |
| *Panel C: Bali and Nusa Tenggara* | | | | | | |
| IDT | 0.261 | 0.003 | -25.713** | 0.658*** | 0.060 | 0.637** |
| | [0.461] | [0.026] | [11.548] | [0.124] | [0.085] | [0.298] |
| $R^2$ | 0.012 | 0.011 | 0.018 | 0.164 | 0.021 | 0.021 |
| Clusters | 39 | 39 | 39 | 39 | 39 | 36 |
| Observations | 1,117 | 1,117 | 1,117 | 1,117 | 1,010 | 598 |
| *Panel D: Kalimantan* | | | | | | |
| IDT | -0.700** | 0.069*** | -14.549 | 1.478*** | 0.049 | -0.528* |
| | [0.331] | [0.020] | [10.514] | [0.228] | [0.030] | [0.285] |
| $R^2$ | 0.029 | 0.056 | 0.018 | 0.112 | 0.033 | 0.021 |
| Clusters | 25 | 25 | 25 | 25 | 24 | 23 |
| Observations | 1,395 | 1,395 | 1,395 | 1,318 | 777 | 597 |
| *Panel E: Sulawesi and Papua* | | | | | | |
| IDT | -0.244 | 0.089*** | -13.449 | -0.307 | 0.073 | -0.267 |
| | [0.145] | [0.027] | [12.672] | [0.344] | [0.050] | [0.221] |
| $R^2$ | 0.007 | 0.039 | 0.006 | 0.010 | 0.015 | 0.012 |
| Clusters | 48 | 48 | 48 | 48 | 47 | 41 |
| Observations | 2,063 | 2,063 | 2,063 | 2,045 | 1,539 | 952 |

*Notes:* All specifications in this table are the same with Table 2, except Bandwidth equal to 4.

*** significant at 1%, ** significant at 5%, * significant at 10%.

RDD Estimation Results of RURAL Village with Bandwidth equals 5

| | Dependent Variables: | | | | | |
|---|---|---|---|---|---|---|
| | NL<br>(1) | ER<br>(2) | IMR<br>(3) | LS<br>(4) | POOR<br>(5) | SME<br>(6) |
| *Panel A: Sumatra* | | | | | | |
| IDT | 0.383 | 0.027** | -28.426*** | 1.154*** | -0.119*** | 0.514*** |
| | [0.285] | [0.013] | [5.900] | [0.143] | [0.044] | [0.145] |
| $R^2$ | 0.025 | 0.016 | 0.026 | 0.222 | 0.038 | 0.031 |
| Clusters | 55 | 55 | 55 | 55 | 55 | 54 |
| Observations | 5,375 | 5,375 | 5,375 | 5,319 | 3,184 | 2,406 |
| *Panel B: Java* | | | | | | |
| IDT | 0.484*** | 0.052*** | -11.327*** | 0.907*** | -0.078*** | 0.740*** |
| | [0.097] | [0.006] | [3.101] | [0.049] | [0.022] | [0.079] |
| $R^2$ | 0.073 | 0.036 | 0.009 | 0.235 | 0.024 | 0.047 |
| Clusters | 86 | 86 | 86 | 86 | 86 | 83 |
| Observations | 9,235 | 9,235 | 9,235 | 9,229 | 8,633 | 7,607 |
| *Panel C: Bali and Nusa Tenggara* | | | | | | |
| IDT | 0.143 | 0.002 | -18.597 | 0.668*** | 0.077 | 0.519** |
| | [0.436] | [0.023] | [11.792] | [0.110] | [0.079] | [0.227] |
| $R^2$ | 0.017 | 0.016 | 0.019 | 0.168 | 0.022 | 0.020 |
| Clusters | 39 | 39 | 39 | 39 | 39 | 36 |
| Observations | 1,355 | 1,355 | 1,355 | 1,355 | 1,211 | 740 |
| *Panel D: Kalimantan* | | | | | | |
| IDT | -0.776** | 0.064*** | -12.351 | 1.466*** | 0.058* | -0.582* |
| | [0.317] | [0.021] | [9.758] | [0.205] | [0.028] | [0.290] |
| $R^2$ | 0.022 | 0.067 | 0.023 | 0.107 | 0.027 | 0.021 |
| Clusters | 25 | 25 | 25 | 25 | 24 | 24 |
| Observations | 1,765 | 1,765 | 1,765 | 1,680 | 982 | 776 |
| *Panel E: Sulawesi and Papua* | | | | | | |
| IDT | -0.124 | 0.077*** | -3.540 | -0.180 | 0.056 | -0.192 |
| | [0.131] | [0.024] | [10.303] | [0.318] | [0.047] | [0.202] |
| $R^2$ | 0.011 | 0.043 | 0.006 | 0.011 | 0.014 | 0.019 |
| Clusters | 48 | 48 | 48 | 48 | 48 | 42 |
| Observations | 2,535 | 2,535 | 2,535 | 2,513 | 1,911 | 1,194 |

*Notes:* All specifications in this table are the same with Table 2, except Bandwidth equal to 5.

*** significant at 1%, ** significant at 5%, * significant at 10%.

RDD Estimation Results of RURAL Village with Bandwidth equals 10

| | Dependent Variables: | | | | | |
|---|---|---|---|---|---|---|
| | NL | ER | IMR | LS | POOR | SME |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Sumatra* | | | | | | |
| IDT | 0.542 | 0.029** | -28.341*** | 1.166*** | -0.093* | 0.479*** |
| | [0.346] | [0.013] | [5.940] | [0.127] | [0.047] | [0.146] |
| $R^2$ | 0.058 | 0.016 | 0.022 | 0.249 | 0.022 | 0.027 |
| Clusters | 61 | 61 | 61 | 61 | 61 | 59 |
| Observations | 10,517 | 10,517 | 10,517 | 10,304 | 7,234 | 5,146 |
| *Panel B: Java* | | | | | | |
| IDT | 0.527*** | 0.052*** | -9.804*** | 0.905*** | -0.084*** | 0.728*** |
| | [0.089] | [0.006] | [2.396] | [0.048] | [0.021] | [0.067] |
| $R^2$ | 0.145 | 0.030 | 0.005 | 0.271 | 0.052 | 0.039 |
| Clusters | 90 | 90 | 90 | 90 | 90 | 89 |
| Observations | 16,218 | 16,218 | 16,218 | 16,204 | 15,301 | 13,518 |
| *Panel C: Bali and Nusa Tenggara* | | | | | | |
| IDT | 0.220 | 0.003 | -20.528* | 0.677*** | 0.069 | 0.448** |
| | [0.444] | [0.020] | [11.981] | [0.110] | [0.079] | [0.201] |
| $R^2$ | 0.041 | 0.017 | 0.018 | 0.162 | 0.047 | 0.013 |
| Clusters | 39 | 39 | 39 | 39 | 39 | 37 |
| Observations | 2,286 | 2,286 | 2,286 | 2,285 | 2,062 | 1,422 |
| *Panel D: Kalimantan* | | | | | | |
| IDT | -0.804** | 0.062*** | -17.013* | 1.197*** | 0.055* | -0.296 |
| | [0.308] | [0.018] | [8.446] | [0.146] | [0.029] | [0.210] |
| $R^2$ | 0.050 | 0.079 | 0.018 | 0.142 | 0.042 | 0.004 |
| Clusters | 25 | 25 | 25 | 25 | 25 | 25 |
| Observations | 3,139 | 3,139 | 3,139 | 2,962 | 1,908 | 1,590 |
| *Panel E: Sulawesi and Papua* | | | | | | |
| IDT | -0.203* | 0.088*** | -8.157 | -0.061 | 0.033 | -0.289 |
| | [0.117] | [0.020] | [9.724] | [0.285] | [0.045] | [0.181] |
| $R^2$ | 0.035 | 0.030 | 0.004 | 0.021 | 0.021 | 0.016 |
| Clusters | 50 | 50 | 50 | 49 | 50 | 43 |
| Observations | 4,419 | 4,419 | 4,419 | 4,363 | 3,472 | 2,313 |

*Notes:* All specifications in this table are the same with Table 2, except Bandwidth equal to 10.

*** significant at 1%, ** significant at 5%, * significant at 10%.

4.8.10.2 Order polynomial

RDD Estimation Results of RURAL Village with Linear Order Polynomial

| | Dependent Variables: | | | | | |
|---|---|---|---|---|---|---|
| | NL | ER | IMR | LS | POOR | SME |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Sumatra* | | | | | | |
| IDT | 0.516* | 0.024 | -22.968*** | 1.184*** | -0.117** | 0.510*** |
| | [0.295] | [0.014] | [6.706] | [0.146] | [0.053] | [0.141] |
| $R^2$ | 0.013 | 0.005 | 0.026 | 0.209 | 0.048 | 0.033 |
| Clusters | 52 | 52 | 52 | 52 | 51 | 47 |
| Observations | 1,787 | 1,787 | 1,787 | 1,778 | 997 | 755 |
| *Panel B: Java* | | | | | | |
| IDT | 0.506*** | 0.052*** | -11.505*** | 0.891*** | -0.080*** | 0.758*** |
| | [0.100] | [0.007] | [3.473] | [0.049] | [0.023] | [0.086] |
| $R^2$ | 0.031 | 0.040 | 0.010 | 0.204 | 0.022 | 0.055 |
| Clusters | 81 | 81 | 81 | 81 | 81 | 81 |
| Observations | 3,264 | 3,264 | 3,264 | 3,262 | 3,032 | 2,691 |
| *Panel C: Bali and Nusa Tenggara* | | | | | | |
| IDT | 0.271 | -0.002 | -25.698** | 0.645*** | 0.054 | 0.619** |
| | [0.432] | [0.026] | [11.139] | [0.120] | [0.081] | [0.291] |
| $R^2$ | 0.011 | 0.004 | 0.028 | 0.128 | 0.012 | 0.053 |
| Clusters | 37 | 37 | 37 | 37 | 37 | 30 |
| Observations | 511 | 511 | 511 | 511 | 473 | 261 |
| *Panel D: Kalimantan* | | | | | | |
| IDT | -0.779** | 0.068*** | -14.967 | 1.551*** | 0.050* | -0.477 |
| | [0.349] | [0.021] | [11.040] | [0.248] | [0.028] | [0.303] |
| $R^2$ | 0.050 | 0.059 | 0.032 | 0.166 | 0.048 | 0.024 |
| Clusters | 24 | 24 | 24 | 24 | 24 | 21 |
| Observations | 596 | 596 | 596 | 548 | 342 | 237 |
| *Panel E: Sulawesi and Papua* | | | | | | |
| IDT | -0.224* | 0.080*** | -11.165 | -0.188 | 0.057 | -0.258 |
| | [0.132] | [0.027] | [12.966] | [0.328] | [0.046] | [0.220] |
| $R^2$ | 0.009 | 0.033 | 0.003 | 0.006 | 0.020 | 0.016 |
| Clusters | 47 | 47 | 47 | 47 | 45 | 38 |
| Observations | 938 | 938 | 938 | 932 | 698 | 419 |

*Notes:* All specifications in this table are the same with Table 2, except using linear RD polynomial.

*** significant at 1%, ** significant at 5%, * significant at 10%.

RDD Estimation Results of RURAL Village with Cubic Order Polynomial

| | Dependent Variables: | | | | | |
|---|---|---|---|---|---|---|
| | NL | ER | IMR | LS | POOR | SME |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Sumatra* | | | | | | |
| IDT | 0.619* | 0.012 | -16.656** | 1.225*** | -0.106* | 0.624*** |
| | [0.346] | [0.018] | [7.727] | [0.183] | [0.062] | [0.194] |
| $R^2$ | 0.014 | 0.006 | 0.027 | 0.209 | 0.048 | 0.035 |
| Clusters | 52 | 52 | 52 | 52 | 51 | 47 |
| Observations | 1,787 | 1,787 | 1,787 | 1,778 | 997 | 755 |
| *Panel B: Java* | | | | | | |
| IDT | 0.440*** | 0.053*** | -14.893*** | 0.892*** | -0.092*** | 0.781*** |
| | [0.126] | [0.010] | [4.820] | [0.062] | [0.027] | [0.144] |
| $R^2$ | 0.033 | 0.041 | 0.011 | 0.204 | 0.025 | 0.055 |
| Clusters | 81 | 81 | 81 | 81 | 81 | 81 |
| Observations | 3,264 | 3,264 | 3,264 | 3,262 | 3,032 | 2,691 |
| *Panel C: Bali and Nusa Tenggara* | | | | | | |
| IDT | 0.012 | 0.018 | -32.875*** | 0.692*** | 0.068 | 0.614* |
| | [0.436] | [0.031] | [10.637] | [0.147] | [0.076] | [0.360] |
| $R^2$ | 0.014 | 0.008 | 0.035 | 0.129 | 0.018 | 0.055 |
| Clusters | 37 | 37 | 37 | 37 | 37 | 30 |
| Observations | 511 | 511 | 511 | 511 | 473 | 261 |
| *Panel D: Kalimantan* | | | | | | |
| IDT | -0.695 | 0.055* | 3.045 | 1.564*** | 0.081* | -0.363 |
| | [0.464] | [0.030] | [12.178] | [0.445] | [0.040] | [0.402] |
| $R^2$ | 0.051 | 0.060 | 0.043 | 0.166 | 0.053 | 0.026 |
| Clusters | 24 | 24 | 24 | 24 | 24 | 21 |
| Observations | 596 | 596 | 596 | 548 | 342 | 237 |
| *Panel E: Sulawesi and Papua* | | | | | | |
| IDT | -0.251 | 0.100*** | -23.834 | -0.262 | 0.066 | -0.119 |
| | [0.253] | [0.036] | [17.348] | [0.392] | [0.063] | [0.313] |
| $R^2$ | 0.013 | 0.035 | 0.005 | 0.006 | 0.021 | 0.017 |
| Clusters | 47 | 47 | 47 | 47 | 45 | 38 |
| Observations | 938 | 938 | 938 | 932 | 698 | 419 |

*Notes:* All specifications in this table are the same with Table 2, except using cubic RD polynomial.

*** significant at 1%, ** significant at 5%, * significant at 10%.

# Chapter 5

## Conclusion

Poverty reduction is one of the major challenges faced by many developing countries. To address this issue, the governments have initiated several programs and policies. Indonesia, as one of developing countries, has implemented several poverty reduction strategies ranging from improving poverty targeting to delivering poverty programs. The three papers in this thesis evaluate the poverty reduction initiatives, using Indonesia as a case study.

The first paper, using the newly proposed method, finds that the introduction of the UDB significantly increased the targeting performance of social welfare programs in Indonesia. The probability of targeted households receiving all three programs increased by 117 percent compared to previous targeting efforts. Currently, 92 countries are implementing or preparing to roll out unified targeting systems, which cover almost two billion people (Honorati, Gentilini and Yemstov, 2015; Bah et al, 2018). This result confirms the tangible benefits realised as a result of the introduction of the Unified Targeting System.

Another finding of the first paper is that after the implementation of the Unified Targeting System, the proportion of households that benefited from all three social programs more than doubled and those households in receipt of all three programs are at least 30 percentage points better off than those that receive none. Our results therefore serve as a cautionary tale to the results of any policy evaluation that omits complimentary programs since such results might otherwise be upward biased.

The first finding of the second paper shows that households treated with information provision received 30 percentage points more rice under the Raskin program. Interestingly, this result is close to the results of Banerjee et al. (2018) which finds that providing information through the Raskin card increases the rice subsidy received by households by about 26% when compared to the control group. It can therefore be argued that our research provides external validity of Banerjee et al.'s results.

Further, the second paper also finds that receiving information reduced the likelihood of elite capture of the BLSM fund being levied by local leaders by around 25 percentage points. This finding is in accordance with studies by Reinikka and Svensson (2004, 2005), who argued that the provision of information succeeded in increasing household benefits by ensuring that local leaders did not divert the benefits of poverty programs away from their intended beneficiaries.

Another important finding from this paper is that understanding the content of the information campaign improves the likelihood of a household receiving their allocated amount of rice in full. This suggests that the information-based intervention should be mindful as to whether their message is understandable and accessible to their beneficiaries. This is clearly challenging for policymakers in developing countries, particularly in Indonesia.

The first finding of the third paper is that rural villages in Java benefited from the IDT program as measured by several measures of welfare. The estimates from the outer islands however, vary considerably from those previously obtained for the most densely populated and interconnected island, Java. Our results highlight that after Java, Sumatra, Bali and Nusa Tenggara benefited the most from the IDT program. Notably, Sumatra experienced a comparable increase in productivity in comparison with Java, while Bali and Nusa Tenggara experienced none. Both Sumatra and Bali and Nusa Tenggara witnessed significant decreases in their infant mortality rate, with Bali and Nusa Tenggara recording more than 32 percentage point fall; while both Sumatra and Bali and Nusa Tenggara experienced significant increases in livestock numbers. Far fewer impacts of the IDT program are identified in the case of the two most remote parts of the country in Kalimantan and Sulawesi and Papua. The former did experience the largest increases in livestock numbers however, while the latter witnessed a ten-percentage point increase in enrolment rates.

The third paper also shows that the IDT program significantly reduced the percentage of households working in agriculture, most starkly in the case of Java (16 percentage points) and Sumatra (15 percentage points) and to a lesser extent in Bali and Nusa Tenggara (6 percentage points). This study finds no statistical evidence that the IDT program had any effect whatsoever on structural transformation in the case of Kalimantan, Sulawesi and Papua.

Taken together, our evidence suggests that the IDT program exerted by far the largest impacts on rural villages in the central islands of Java, Sumatra and Bali and Nusa Tenggara. Concurrently, it was only these islands that experienced structural transformation as a result of the IDT program. These results suggest that structural transformation was a necessary condition for a region to benefit from the injections of capital from the IDT program. In other words, if a region was able to use funds from IDT to shift their factors of production away from agriculture and into higher productivity sectors, that region also experienced parallel improvements in their welfare. These results are consistent with previous studies, including Gollin et al (2002), Lagakos and Waugh (2013) and Gollin et al (2014), which collectively demonstrate that structural transformation impacts positively on productivity.

Another important finding of this paper is that the effect of the IDT program on structural transformation could be expedited through improving the infrastructure of the village. This paper shows that the effect of IDT on structural change was larger and statistically significant for villages which had better quality of infrastructure. The results are in line with previous evidence about the importance of infrastructure on the process of the structural transformation (Gollin and Rogerson, 2010; Adamapoulos, 2011; Herrendorf et al. 2012; Asher and Novosad, 2019) through increasing mobility of goods and people mobility (Herrendorf, et al, 2012; Adamopolous, 2011).