Targeted social assistance programs and local economies: The case of conditional cash transfer in Indonesia

Draft as 26 December 2019 (Do not cite!)

Anna T. Falentina[1,2], Budy P. Resosudarmo[1]

Abstract

Social assistance programs have been implemented to alleviate poverty in many developing countries. However, little is known whether these social assistance programs inducing local economy development, an important area for policy making.

Exploiting variation in the timing of conditional cash transfer implementation in Indonesian subdistricts, the paper examines the effects of a key social assistance program on the performance of local micro and small enterprises (MSEs) in Indonesia. MSEs are crucial engines of the local economy in many developing countries. MSEs also contributes to welfare through providing source of employment and income. Nonetheless, the productivity of MSEs remains low, reflecting low living standard of those engaged in production process.

The analysis is based on a linear subdistrict fixed effects model, combining data from surveys of manufacturing MSEs with village census data and geophysical information. Results show that exposure to the program contributes to an increase in labour productivity in the medium term. Women engaged in MSEs were also benefited from the program. The overall effect is driven by increased productivity in urban areas, in villages close to cities and in non-coastal areas. No immediate impacts are observed. Relaxing credit constraints appears to be a mechanism through which the program affects MSEs in the local area.

The key findings emphasised the importance of the sustainability of such programs for a minimum of 5 years so that the trickledown effect of the program can penetrate in the local economy. Findings also suggest that access to credit is crucial for MSEs to support their business. While MSEs appear to obtain loans from non-bank sources, policy-makers could ease credit access for MSEs so that entrepreneurs can run their business smoothly.

JEL: I38, O12, O18, L25

Keywords: targeted social assistance programs, cash transfer, micro and small enterprises, labor productivity, Indonesia

[1] Arndt-Corden Department of Economics, Australian National University
[2] Statistics Indonesia (BPS)

1. Introduction

Targeted social assistance programs have been carried out to alleviate poverty in many developing countries. The programs have become popular globally and are being expanded following experiments and pilot projects in the early 2000s. For the poor, targeted social assistance programs not only provide additional income but also encourage improvement in individuals' health and education. There is an increasing commitment for targeted social assistance programs as many countries tend to spend more on programs over time. During 2008–2014, developing countries spent an average of 1.5% of GDP on social assistance programs (World Bank 2017).[3] This increase in spending has resulted in a significant increase in program coverage around the world (Gladieu 2018).

A large body of literature has provided evidence that targeted social assistance programs reduce poverty, improve health and education access (Baird, McIntosh, and Özler 2011; Fiszbein et al. 2009; World Bank 2019). Additionally, the existing literature indicates that these programs may have a domino effect on other things, for instance, on improving liquidity and trade at the local economy. Cash transfers received from the programs relax the budgetary constraints on the poor, thereby increasing consumption and demand for goods and services. Similarly, conditionality on health and education encourages the poor to invest more on health and education leading to the accumulation of human capital which eventually improves productivity (Banerjee & Duflo, 2011; Barrientos, 2012).

Understanding the local economy-wide impact of targeted social assistance programs is important since it will provide evidence-based analysis to policy-makers, who are usually budget-constrained, into the side effects of the substantial investment in such programs. If that

[3] The World Bank calculated social assistance spending following the definition of social assistance as non-contributory cash or in-kind transfer programs targeted in some manner to the poor or vulnerable (World Bank, 2012)

investment can also expand the local economy, the implications would be substantial because the poor rely on the local economy for their livelihood.

Only a handful of studies have addressed the question of whether targeted social assistance programs stimulate the development of local economies. For instance, a study on *Oportunidades*, a conditional cash transfer program focusing on human development in Mexico, find that not only beneficiaries but also ineligible households experienced an increase in consumption (Angelucci and Giorgi 2009). Sadoulet, De Janvry, & Davis (2001) show that recipients of *Procampo*, a productive transfer programs to small-sized farm owners in Mexico, managed to put the money they received into productive activities that multiplied the transfers into larger income effects. These studies, however, focus on the assets and consumption of beneficiaries, rather than entire societies.

Some studies have focused on evaluating social assistance programs that are specifically designed to encourage entrepreneurship among beneficiaries. These kinds of programs not only transferred resources but also provided training on business activities to beneficiaries. Gobin, Santos, & Toth (2017) evaluated the impact that randomised cash transfers had on entrepreneurship among ultra-poor women in remote northern Kenya. They show that the new petty trade enterprises set-up due to the program is the main channel through which the program increased the welfare of ultra-poor women. Other work conducted by Blattman, Green, Jamison, Lehmann, & Annan (2016), which examined another cash transfer program for enterprise development in Uganda, shows that the program increased microenterprise ownership and income from petty trading.

Other studies also looked at the macro perspective of grant programs. For instance, Buera, Kaboski, and Shin (2014) evaluated the aggregate and long-run effects of asset grants on occupational choices and income in developing countries using a quantitative theory to interpret and extrapolate the micro-evidence. They found that the wealth grants have a positive effect on aggregate total factor productivity (TFP) but a relatively larger negative impact on aggregate capital.

Some studies specifically evaluated conditional cash transfers (CCT or *Program Keluarga Harapan*/ PKH) in Indonesia. Cahyadi et al. (2018) and the World Bank (2011) find that the PKH increased the utilisation of health and education services among the poor. Triyana & Shankar (2017) show that the PKH improved antenatal care coverage for women. These studies, however, utilised the RCT design of the PKH, which constitute a fraction of the total treated regions in which the external validity might not hold. Research done by Christian, Hensel, & Roth (2018) found that PKH reduced the rate of suicides at a subdistrict level. A study conducted by Ferraro & Simorangkir (2018) reveal that PKH has reduced deforestation.

The present study extends the existing literature that estimate the local economy-wide impact of such targeted social assistance programs in developing countries. Specifically, this study extends a study conducted by Bianchi and Bobba (2013) that focused on exntensive margin of receiving *Opportunidades* on entrepreneurship. Our study provides intensive margin analysis on the impact of such programs on the development of local economy. Specifically, the present study exploits variation in the different timings of PKH implementation in Indonesia to examine the causal impact of targeted social assistance programs on the development of local economies, represented by micro and small enterprises (MSEs). In addition, we evaluate the heterogeneity of the effects and examine a possible mechanism through which the program affects local MSEs.

Our study focuses on the impact of targeted social assistance programs on MSEs for the following reasons. MSEs are crucial engines of the local economy in many developing countries. MSEs also contribute to welfare by providing employment and income (Banerjee & Duflo, 2005; Berry et al., 2001) and in some cases, MSEs provide an essential informal safety net mechanism (Resosudarmo, Sugiyanto, and Kuncoro 2012). Nonetheless, the productivity of MSEs in Indonesia remains low (Hill 2001; Mead and Liedholm 1998; OECD 2015).

The results show that there are significant local economic impacts of targeted social assistance programs. Exposure to this program raises the labour productivity of MSEs in the medium term. Nonetheless, no evidence of immediate effects is observed. The effects are heterogeneous across different regions. Women engaged in MSEs are also benefited from the programs. We also show that credit constraint is a mechanism through which the programs affect the local economy. The results justify public policy encouraging the extension of such programs up to 5–6 years so that the trickledown effects can penetrate local economies. The results also highlight the importance for policy-makers to ease credit access for MSEs.

We start by providing a framework that shows the links between the programs and the local economies. In Section 3, we provide the context of targeted social assistance programs in Indonesia. Next, we explain the identification strategy. Then, we present the results and robustness checks. Finally, we conclude the paper by providing the policy implications of the findings.

2. Framework: From targeted social assistance programs to local economies

This section briefly discusses the potential mechanisms by which targeted social assistance programs lead to the development of local economies. There are two main mechanisms for how changes in household income affect the local economy, namely resource transfers and conditionality. These two mechanisms would then affect a set of other mechanisms at the local-economy level. Figure 1. summarises how targeted social assistance programs affect local economies.

The literature suggests three processes by which resource transfers received from the programs affect local economies. Firstly, resource transfers, in the form of cash or in-kind, relax liquidity constraints. It is widely acknowledged that households in poverty are credit constrained. They do not have the collateral to get loans from financial institutions and they tend to face default on these loans. The resources received from the program increases the poor's capacity to save, and improves their access to credit. Therefore, poor households that are often excluded from credit markets can have better access to credit.

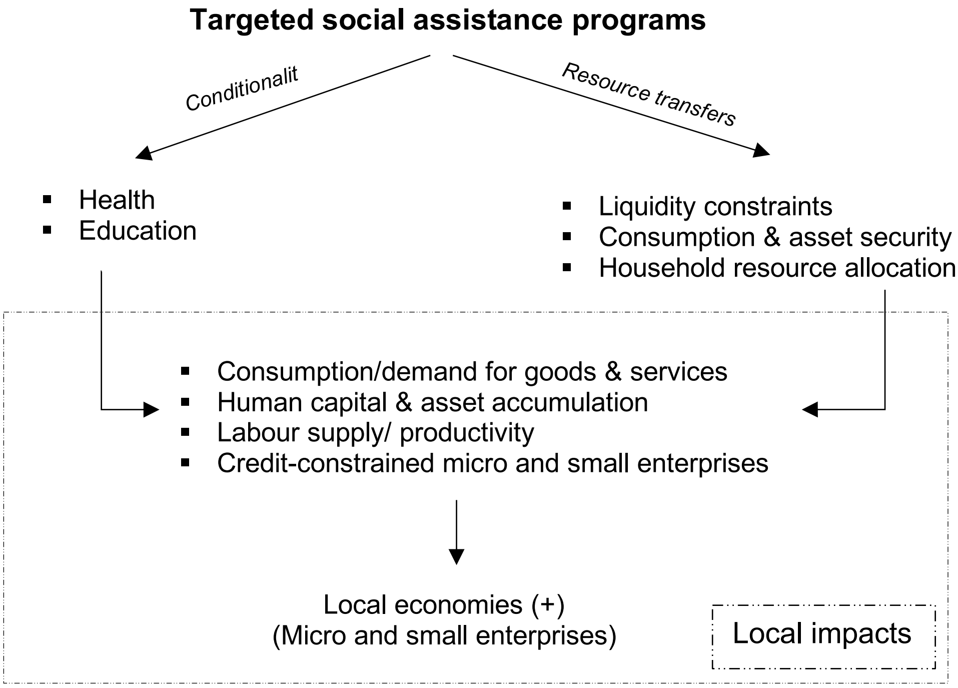


Figure 1. The links between targeted social assistance programs and local economy

Secondly, resource transfers improve consumption and asset security. The insurance market rarely reaches the poor meaning that the poor are less protected from hazards. The transfers provide protection for poor households' consumption and assets against vulnerabilities, thus increasing physical or financial assets or technological adoption that in turn facilitates production expansion, for instance, through agricultural intensification (Sadoulet, De Janvry, and Davis 2001; Shortle and Abler 1999; World Bank 1992). The increase in households' consumption due to the programs raises the demand for goods and services. Thus, resource transfers from the programs represent a massive demand shock. Because of this shock, cash are going into enterprises, which then improve the way the enterprises get access to credit by, for instance, having resource for collateral.

Thirdly, resource transfers improve household resource allocation. The existing literature indicates that unequal intra-household resource allocation in poor households might affect their capacity to take economic opportunities. The resource from transfers could help to change intra-household resource allocation and enable them to benefit from the economy. For instance, cash transfers paid to the mother of beneficiary households could improve her bargaining power within the household, thus enabling greater investment in children's health and education (Banerjee & Duflo, 2011).

In addition, program conditionality might act as another plausible mechanism by which targeted social assistance programs lead to the development of local economies. Targeted social assistance programs conditional on health or schooling utilisation are expected to boost investment in human capital greater than additional income effects from the transfer (Barrientos 2012). Therefore, improvement in access to healthcare, education and other non-income effects of targeted social assistance programs facilitate investment in human capital that affect labour supply as well as productivity of those engaged in production process.

3. Targeted social assistance programs in Indonesia

The social assistance system in Indonesia has evolved over time. The World Bank (2012) provides a brief history of the evolution of social assistance in Indonesia. During the Soeharto era (1965–1997), the Government of Indonesia (GoI) introduced government-funded social policies, publicly-provided basic education and health services to fulfil the state's responsibility to provide for the rights of the citizens and care for the poor, and to provide social security as stipulated in the constitution.

During the Asian Financial Crisis in 1997–1999, the GoI reduced costly universal subsidies for food, fuel and electricity and replaced these with safety net programs and scaled up existing programs, such as *Inpres Desa Tertinggal*. A set of new social safety net programs, known collectively as the *Jaring Pengaman Sosial* (JPS) was introduced in early 1998. Over the next decade, many of the JPS initiatives evolved into permanent programs with financing shifting from donors to the GoI regular budget. In the early 2000s, the GoI started to establish the financial and legal foundations of targeted social assistance programs to support sustainable growth. Starting in October 2005, an unconditional cash transfer (UCT) was introduced. The UCT provided quarterly cash transfer as much as IDR 300,000 per household per quarter to 19.1 million poor and near poor households to reduce the inflationary shocks following the removal of the universal fuel subsidy in 2005.

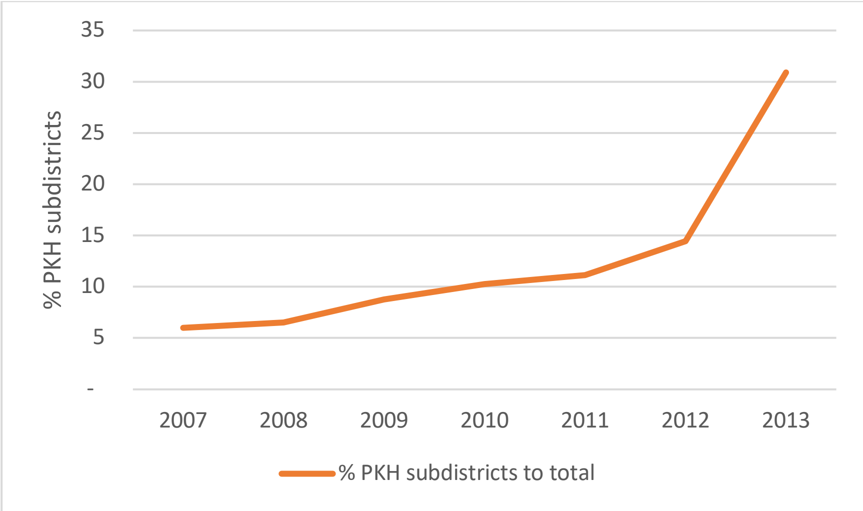
In 2007, as a part of the efforts to increase the efficiency and improve the effectiveness of targeted social assistance programs, the GoI introduced the PKH, a conditional cash transfer program that provides assistance to the targeted poor households. The program provided a substantial amount of money quarterly to households with school age children, or to lactating or expecting mother to an amount up to IDR 600,000–2,200,000 (USD 45 to 165) per year for up to six years when individuals meet specified health or education requirements. This money is equal to 10% of the annual pre-program beneficiary household expenditure. It is reported that between 2011 and 2016, the government spent an average of 8.5% of annual national public expenditure on PKH implementation and the program covered 6 million households (10% of the country population) by the end of 2016 (World Bank 2017). Previous studies have shown that PKH improved welfare and health-seeking behaviour and that PKH households have greater access to health and education (Cahyadi et al. 2018; World Bank 2011). PKH also improved antenatal care coverage for women (Triyana and Shankar 2017).

The PKH used a dual-targeting system that targeted regions and households. During the first stage of the program, the central government decided the province and district level quotas of PKH recipients. In 2007, the PKH was implemented as a pilot program in six provinces: West Java, East Java, North Sulawesi, Gorontalo, East Nusa Tenggara (NTT) and DKI Jakarta. The top 20% of income quintile districts were excluded from PKH eligibility within the selected provinces. Then from among these eligible districts, the provincial and district governments selected subdistricts based on an index that reflected supply-side readiness in terms of education providers and health care services. From 2008 to 2010, the PKH was further expanded in Nanggroe Aceh Darussalam, North Sumatera, Banten, South Kalimantan, West

Nusa Tenggara, and Yogyakarta provinces so that by 2010, the program covered all Indonesian provinces.

The second stage of the program targeted households. The government extracted a list of eligible beneficiaries within these supply-side ready subdistricts utilising a unified database combined with a proxy mean test method (World Bank 2011). After this, the local office of Social Affairs Ministry validated and updated the basic information on eligible beneficiaries and registered eligible household after which the households received their first payment. During the year, local coordinators verified the compliance of beneficiaries with the conditions. Finally, beneficiaries received a second and then subsequent payments. However, the verification system started in 2010 was not always imposed.

As seen in Figure 2, the program reached 6% of all subdistricts in 2007 and by 2012 the program covered more than 14% of all Indonesian subdistricts. The vast majority of the PKH was rolled out in 2013, in line with the intention of the government to expand the programs to all provinces. The requirement for every beneficiary's eligibility and conditionality on meeting the target to be verified meant that households did not necessarily receive the PKH in a consecutive pattern. For instance, due to a natural exit from the program in households that had passed over the poverty line, meaning that they were no longer eligible for the PKH in the following year. As a result, there are some gaps between years up to when each subdistrict received the PKH for the subsequent time.



Source: Bappenas (for PKH subdistricts based on actual payment) and BPS (for total number of subdistricts)

Figure 2. Expansion of the PKH over time

In addition to the PKH, there are other active targeted social assistance programs, such as subsidised rice for the poor, subsidised social health, and cash transfers for poor and at risk students. Although the coverage of PKH is much lower than that of the other targeted social assistance programs, the PKH is noted as being one of the most effective Indonesian targeted social assistance programs due to its targeted nature (World Bank 2017). The PKH also introduced innovations in facilitation approach, such as the 2013 "Family Development Sessions (FDS) that provided a group-level training in early childhood education, parenting, health and nutrition and improved the outcome of the program.

4. Empirical framework

4.1 Data

We combined data for the period 2004–2012 from the manufacturing MSEs survey (2004, 2005, 2009, 2010, 2011 and 2012), village census-PODES (2003, 2005, 2008 and 2011), and the list of PKH subdistrict recipients from the Ministry of National Development Planning (Bappenas) (2007–2012). We limited the study period to 2012 as the PKH expanded to a large degree by covering all provinces in 2013 so that the timing of receiving the PKH can be predicted easily.

The MSEs survey is an annual cross-sectional survey that sampled MSEs in the manufacturing sector across Indonesia. MSEs are categorised simply based on the number of workers. Enterprises with 1–4 workers are micro, while those with 5–19 workers are small enterprises. The information collected in the MSEs survey includes owner and enterprise characteristics. The village census (*Potensi Desa* or PODES) is conducted every two or three years and provides information on all rural villages and urban areas in Indonesia, including details on infrastructure and the availability of educational institutions and health care providers. The list of PKH subdistrict recipients outlines the subdistrict and the year when the residents received the PKH annually.

The data on MSEs are enterprise level data, while the PKH identifier is at subdistrict level. We merged the data from the PODES with the pooled MSEs survey data based on a village identifier. After this, we merged it with the list of PKH recipients based on subdistrict identifier. Subdistricts that do not appear in the list are considered as non-beneficiaries. The data on MSEs come from surveys, therefore the panel of subdistrict is a non-balanced one since a subdistrict might not be sampled in every MSE survey round/year.

The enterprises included in the sample are MSEs selected at the time of the survey. In total we have 146,208 enterprise-observations spread over 18,613 villages and 6 survey years. The combined data allowed me to match the subdistrict where MSEs were located with the introduction and presence of PKH in that specific year. That is, the data constitutes subdistrict identifiers with variation in outcome variables and PKH by year of survey and subdistrict.

Geophysical information came from various sources. Data on rainfall were from CHRIPS dataset of University of California Santa-Barbara, while data on elevation, slope, distance to river are from Hydrosheds dataset of WWF-USGS. Distance to port and nighttime lights in 1993 were collected from World Port Index and DMSP-NOAA, respectively.

Table 1. shows descriptive characteristics for the pooled data. The sample of enterprises is dominated by male-owned enterprises, with a share of around 55%. The average age of owners in the sample is 44 years old and on average owners attained primary school education. On average, the sampled enterprises established in 1992, operate in a resource-intensive industry, and over 50% hold a license.

Table 1. Descriptive statistics of enterprise data and village characteristics

	Mean	SD
Panel A. Enterprise level data (MSEs survey, n=146,208)		
Enterprise characteristics		
Total output (million IDR per month)	1.609	2.214
Output per worker (million IDR per month)	0.847	1.259
Value added (million IDR per month)	0.636	0.975
Value added per worker (million IDR per month)	0.338	0.557
Number of workers	2.075	1.635
Year established	1992.696	13.490
% of enterprises with license	49.55	
% of enterprises in labour intensive industry	40.89	
% of enterprises in resource intensive industry	42.04	
% of enterprises in capital intensive industry	17.06	
Owner characteristics		
Age (years)	44.141	11.950
Education	2.137	1.021
Sex (Male)	54.53	
Panel B. Village information (PODES, n=18,613 in 6-year)		
% of villages with asphalt road	76.950	
% of electrified household	73.965	
% of villages with light on main roads	80.810	
% of villages with primary school	97.990	
% of villages with secondary school	56.900	
% of villages with hospital	6.010	
% of villages with maternity hospital	14.120	
% of villages with community health centre (*puskesmas*)	22.560	

	Mean	SD
% of villages with maternal & natal health centre (*posyandu*)	98.870	
Elevation (metre above sea level)	200.189	284.468
Slope (percentage rise)	3.458	4.769
Distance to port (metre)	64,848.860	45,652.600
Distance to river (metre)	1,975.799	4,370.326
Lights in 1993	6.947	13.314

Source: MSEs survey (2004-2005: SUSI, 2010-2012 *Survei IMK*), and PODES 2003-2011

There is a substantial variation in key infrastructure characteristics in respect to village features. Over the four PODES data, over 75% of villages are accessible by an asphalt road and over 72% of households in the villages are connected to the electricity grid. With respect to health services, on average only 6% of villages have hospitals, while maternity hospitals, community health centres (*puskesma*s), and maternal and natal health centres (*posyandu*) are found in 14%, 22% and 99% of the villages. In terms of educational institutions, 98% of villages have primary schools and 56% have secondary schools.

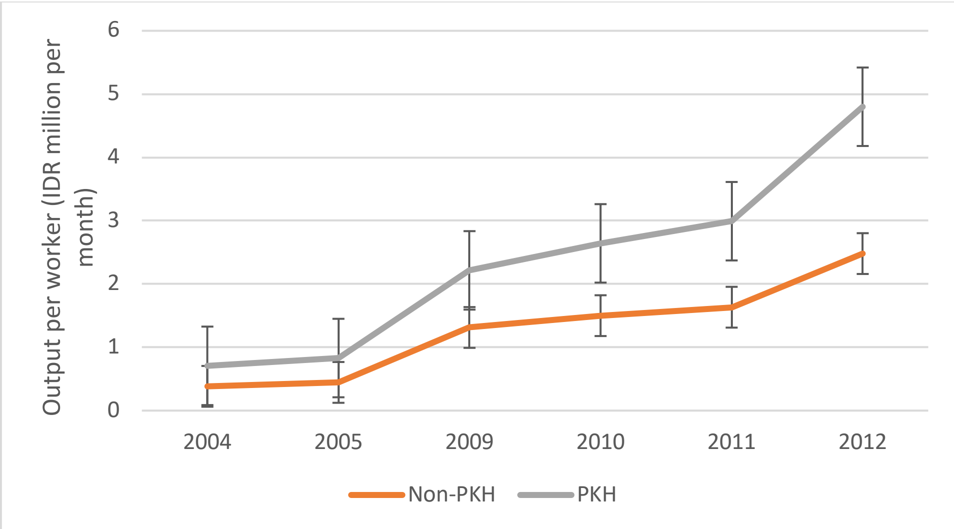
In this study, we focus on labour productivity (output per worker and value added per worker) and the number of workers as the dependent variables (outcomes). Gross output-based productivity captures disembodied technical change, whereas value added based labour productivity reflects an industry's capacity to contribute to economy-wide income and final demand (OECD 2001). Labour productivity is a proxy of the standard of living of those engaged in production process after controlling for other factors, while the number of workers reflects the effect on employment the program has in response to the expected increase in demand. Table 2. provides an overview of the development of output per labour from 2004–2012.

Table 2. Evolution of outcome measures over time

Outcome	2004	2005	2009	2010	2011	2012
Output per worker	0.323	0.387	0.901	1.158	1.374	2.301
Value added per worker	0.139	0.167	0.723	0.537	0.610	0.736
Number of workers	2.146	2.067	2.010	2.112	2.073	1.772

Unit: IDR million per month, except number of workers (persons). Source: MSEs surveys

Figure 3 shows that PKH subdistricts and non-PKH subdistricts have similar pre-program outcome trends. However, they differ in some important economic attributes (Table 3). In regards to primary school and hospital availability, PKH subdistricts tend to be better with similar trends in *posyandu* availability. Nonetheless, it appears that there is no difference in terms of road access, electricity access, secondary school, maternity hospital and *puskesmas* availability between the two groups.



Note: Non-PKH subdistricts are those subdistricts never get PKH during 2007-2012, while PKH subdistricts are those received PKH at least once. Source: MSEs surveys

Figure 3. Output per labour (IDR million per month) by year

Table 3. Economic attributes based on group in 2003

	Mean		t-test
	Non-PKH	PKH	p-value
Asphalt road (1=yes, 0=no)	0.744	0.733	0.399
Proportion of electrified households	0.708	0.709	0.955
Lights on main road (1=yes, 2=no)	1.212	1.161	0.000
Primary school availability (1=yes, 2=no)	0.982	0.989	0.036
Secondary school availability (1=yes, 2=no)	0.544	0.539	0.765
Hospital availability (1=yes, 2=no)	1.929	1.951	0.001
Maternity hospital availability (1=yes, 2=no)	1.822	1.834	0.305
Community health centre (*puskesmas*) availability (1=yes, 2=no)	1.751	1.761	0.398
Maternal & natal health centre (*posyandu)* availability (1=yes, 2=no)	1.020	1.012	0.017

Note: Non-PKH subdistricts are those subdistricts never received PKH during 2007-2012, while PKH subdistricts are those received PKH at least once during 2007-2012. Source: PODES 2003

4.2 Identification strategy and estimation

The main identification strategy exploits variations occurring from the different timing of PKH implementation across subdistricts. It has been documented that the variation in the timing for receiving the PKH is due to the pressure to cover all provinces and at the same time to stay within the budget during the expansion of the program (Cahyadi et al. 2018; Ferraro and Simorangkir 2018). Although subdistricts located in eligible districts are more likely to receive the PKH compared to that outside the districts, no one really knows the exact timing of when a subdistrict will receive the PKH.

Moreover, a natural exit from the program and conditionality compliance also drive variation in the sequence of receiving the subsequent PKH. Households receiving a transfer during a specific year might not necessarily receive one in the following year as, for instance, they might have exceeded the poverty line or no longer have children of school age. As a result, we have variation at subdistrict level in the sequence of receiving the next PKH. It has been reported that compliance is around 80% for both the education and the health component in the randomised control trial (RCT) villages (World Bank 2017). Nonetheless, the enforcement of compliance only started after 2010 and is very weak (Cahyadi et al. 2018).

A similar approach has been used in previous studies. For instance, Stevenson & Wolfers (2006) utilised natural variation in the introduction of unilateral divorce law in the US to evaluate its impact on suicide and spousal homicide. Hartwig et al., (2018) exploited the different timing of local subsidized health services (*Jamkesda*) to evaluate the impact of the program on maternal care from 2004 to 2010. The closest study to mine is Ferraro & Simorangkir (2018) which used a similar approach to assess the impact of the PKH on deforestation at the village level. However, their main estimation considered that once a village received the PKH then the village continued to receive the PKH for the rest of study period.

Other studies that evaluated the PKH include work done by the World Bank (2011) and Cahyadi et al. (2018). They focused on the education and health effects and utilised the RCT design of the PKH that constitutes a subsample of the whole PKH subdistricts instead of the whole community as this study. Christian et al. (2018) examined the effect of PKH on suicide by using two-stages of the PKH roll-out: the first stage of subdistricts who received the treatment from 2007-2011 and the second stage of subdistricts who received the treatment in 2012 and 2013.

Utilising a linear subdistrict fixed effects specification, we estimate the average effect of targeted social assistance program by the timing of receiving PKH on the performance of MSEs as indicates in labour productivity (output per worker and value added per worker) and the number of workers. The observation also allows me to identify pre-treatment period (2004 and 2005) and post-treatment period (2009-2012).

$$log\, y_{ivst} = \beta_0 T_{st} + X'_{ivt}\gamma + Z'_{vt}\vartheta + \delta_s + \delta_t + \varepsilon_{ijt} \quad (1)$$

$$log\, y_{ivst} = \beta_1 t_{1st} + \beta_2 t_{2st} + \beta_3 t_{3st} + \beta_4 t_{4st} + \beta_5 t_{5st} + X'_{ivt}\gamma + Z'_{vt}\vartheta + \delta_s + \delta_t + \varepsilon_{ijt} \quad (2)$$

where y_{ivt} represents one of the three outcome variables for enterprise *i* in village *v* subdistrict *s* at year *t*. In equation (1), T_{st} is a dummy variable equals 1 if people living in subdistrict *s* received the PKH at year *t,* and 0 otherwise. Subdistrict is an administrative area, one level above village. In equation (2) the main variables of interest are t_1, t_2, t_3, t_4, and t_5 that are a dummy variable indicating whether a subdistrict whose residents received the PKH during a certain year, received it as the first, second, third, fourth or fifth time. We have five dummies of the PKH timing as data indicates that during 2007–2012 a subdistrict received the PKH a maximum of five times. Note, t_1–t_5 equals 0 for subdistricts that never received the PKH from 2007 to 2012. By construction, $T_{st} = \sum_1^5 t_{st}$.

We prefer to use the specification in equation (2) because the duration of receiving the PKH differs among subdistricts. Out of the eligible subdistricts included in the analysis, most of the subdistricts received the PKH only once (39.61%) or twice (33.31%) during 2007-2012. Those who received the PKH three times are nearly 21.37%, while those received the PKH four or five times account for 5% and less than 1%, respectively. Furthermore, a subdistrict might receive the PKH in a non-consecutive pattern due to a natural exit or a central government budget constraint. The impacts might also differ due to a cumulative process (Cahyadi et al. 2018). The sign of the variables of interest is expected to be positive if the program positively affects local economies.

We control for village characteristics Z'_{vt}, such as infrastructure (electrification rate, road access, education institutions, health care providers), rainfall, nightlights in 1993, elevation, slope, distance to port, and distance to river. The vector X'_{ivt} controls for owner (gender, age and education) and enterprise characteristics (year established, industry and license). Time-invariant subdistrict characteristics are controlled by including δ_s subdistrict fixed effects, while δ_t year fixed effects control for common shocks. The design of the PKH, in which provincial governments determine target subdistricts suggests there might be a correlation within province due to unobserved random shocks at province, therefore we clustered the standard errors by province.

In the absence of unobserved confounding factors, equation (2) will yield an unbiased estimation of the PKH. The subdistrict fixed effects eliminate any time invariant factors such as topography, institutions and endowments, while inclusion of owner, enterprise and village characteristics should minimise bias due to time variant omitted variables.

The main confounding factor that we do not control for in the specification is the introduction/presence of other targeted social assistance programs where the timing might coincide with the PKH. In addition to the PKH, in a certain year residents of a village might receive other welfare programs, such as *Askeskin*, and a village may also receive community-driven development programs. In the robustness check, we evaluate whether the results suffer from omitted variable bias by controlling for other welfare programs such as *Askeskin* and other development programs. In addition, we assess whether adding fixed assets in the specification has effect on the main variable coefficients. Data on fixed assets are available for most years, except for 2011.

We also evaluate the possibility of self-selection bias by estimating the impact only for subdistricts that eventually received PKH by 2012. Any difference in the main coefficients would be evidence of confounding trends between controls and treatment. We also estimate spatial regression for spillover effects as adjacent subdistricts might receive PKH and have impacts to its neighbouring subdistricts (Anselin 1988). In order to evaluate reverse causality, we examine whether current productivity drives the possibility of receiving PKH at (t+1). Furthermore, we examine the impact heterogeneity by type of regions (urban/rural, villages that are near/far from the city, coastal/non-coastal, Java & Bali and other islands).

5. Results

5.1 Impact of PKH

Table 4 presents the average effects of receiving PKH based on equation (1) and (2). There are two panels, A and B, for log output per worker and other outcomes, respectively. Column (1) shows the coefficient of T_{st} as in equation (1) controlling for all covariates, while the remaining columns show coefficient t_1 until t_5 based on equation (2). Column (2) shows the coefficients for different timing of receiving the PKH in the base specification controlling for subdistrict fixed effects. Column (3) shows the coefficients controlling for year fixed effects. Column (4) accounts for owner and enterprise characteristics, while column (5) is the full specification that also controls for village characteristics. Overall, significant effects of the PKH on output per worker appear during the fifth time the PKH is received.

As it can be seen in Column (1), controlling for all covariates and using a dummy variable to indicate whether a subdistrict receive PKH, we find that the coefficient T_{st} is not statistically significant. The next columns present the results using decomposition for timing of receiving the PKH. The results in Column (2) show that there is a positive association between PKH and labour productivity. That is, output per worker is higher if receiving PKH regardless of the timing it is was received such as the first, second, third, fourth or fifth time. Nonetheless, this correlation seems to be a spurious one because as we add year fixed effects and control variables, the correlation in the first, second, third, and fourth time becomes weaker.

Table 4.4 Effect of targeted cash transfer program

Variables	A. Main estimations					B. Other outcomes	
	log output per worker					log value added per worker	log number of workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dummy of receiving PKH = 1	-0.0415						
	(0.0382)						
1st time receiving PKH = 1		0.612***	-0.0208	-0.0144	-0.0132	-0.0652	0.0320**
		(0.0875)	(0.0419)	(0.0407)	(0.0426)	(0.0595)	(0.0141)
2nd time receiving PKH = 1		0.651***	-0.0621	-0.0631	-0.0617	-0.107	0.0126
		(0.0886)	(0.0603)	(0.0607)	(0.0590)	(0.0655)	(0.0313)
3rd time receiving PKH = 1		0.607***	-0.0481	-0.0523	-0.0576	0.0112	-0.0108
		(0.0557)	(0.0389)	(0.0415)	(0.0434)	(0.0521)	(0.0186)
4th time receiving PKH = 1		0.665***	-0.140	-0.0741	-0.0871	-0.145	-0.0853***
		(0.0883)	(0.0881)	(0.0750)	(0.0777)	(0.137)	(0.0284)
5th time receiving PKH = 1		1.732***	0.318***	0.252***	0.230***	0.512	0.0971***
		(0.118)	(0.0503)	(0.0531)	(0.0612)	(0.314)	(0.0199)
Subdistrict FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	N	Y	Y	Y	Y	Y
Owner & enterprise characteristics	Y	N	N	Y	Y	Y	Y
Village characteristics	Y	N	N	N	Y	Y	Y
Observations	146,208	146,208	146,208	146,208	146,208	124,697	146,208
R-squared	0.644	0.519	0.609	0.642	0.644	0.606	0.352

Control variables not displayed for convenience: owner characteristics (gender, age and education), enterprise characteristics (year established, industry and license), and village characteristics (electrification rate, road access, education institutions, health care providers, rainfall, nightlights in 1993, elevation, slope, distance to port, and distance to river). Clustered standard errors by province in parentheses. *** p<0.01, ** p<0.05, * p<0.1

A positive effect appears when we use a decomposition specification. The results in Column (5) suggest no evidence of any significant effect from receiving the PKH in the first and the second time (short term) on output per worker. That local MSEs were not able to increase their production capacity in such a short time might be due to constraints they faced, hindering their productive capacity. Similar results were also found in less integrated markets such as in Uganda, where local trader markets faced difficulties in increasing the supply of goods to meet the increased demand following short-term cash injections (Creti 2010). Likewise, there is no evidence of significant effect when the PKH has been received for the third and fourth time. It is widely acknowledged that MSEs are more credit-constrained than larger enterprises. In the penultimate section, we examined whether credit constraint is a reason for the lack of such immediate effects.

In contrast to the short term, we found positive and significant effects when the PKH was received a fifth time (medium term). As the duration of receiving the PKH gets longer, perhaps entrepreneurs discovered ways to increase their production or perhaps they acquired more capital, and thereby where able to supply more to the market to catch up with demand. On average, the PKH led to an increase in output per worker by 23% during the fifth time the cash transfer was received.

Using other measurements for outcome, as shown in Column (6)–(7), we find no evidence of a significant impact on value added per worker nor on the number of workers. Using value added per worker as a dependent variable, none of the coefficients of PKH timing is statistically significant. With regards to the effect on employment, Column (7) shows that at the first time the PKH was received, the coefficient of receiving the PKH for the first time is positive and statistically significant, suggesting the number of workers engaged in manufacturing MSEs increased at the first time of receiving the PKH. However, the coefficient of receiving the PKH for the fourth time is negative and significant. In the fifth time of receiving PKH, the coefficient is positive and statistically significant at 1% level.

5.2 Robustness

Table 5 shows that the estimations are robust to different specifications, strengthening the interpretation of the main specification results as causal effects. we find no evidence of confounding policy effects through other targeted social assistance programs or through fixed assets and no evidence of self-selection bias. Further, there is no evidence of spillover from neighbouring subdistricts that received PKH and the main results is not driven by reverse causality.

Column (2) includes other social assistance program, that is *Askeskin* and other social assistance programs conducted by the local government. The result shows marginal difference of the coefficient from the preferred results in Column (1) that suggests no confounding policy factors. Also, when we add fixed assets per worker in Column (3), the coefficient at the fifth time of PKH stays significant and the magnitude is marginally different from that in Column (1), suggesting no other confounding factors.

Column (4) shows estimates only for subdistricts that eventually received PKH by 2012; we find similar results to that in Column (1). Estimating only on the sample of subdistricts that are eventually exposed to the PKH helps control for unobservable factors that determine exposure to PKH and are held in common by all PKH subdistricts. The result suggests no evidence of self-selection bias.

Column (5) adds the weighted PKH of the neighbouring subdistricts. We find no evidence of spillover from the neighbouring subdistricts that might also receive the PKH as the coefficient of border-shared subdistricts is not statistically significant. On the coefficient of PKH, we found that the point estimates in Column (5) are marginally different from that of the preferred estimation in Column (1).

Table 5. Robustness checks

Variables	Dependent variable					
	log output per worker					dummy of receiving PKH (t+1)
		Robustness				
	Preferred estimation	Include other programs	Include fixed assets per worker	Eligible subdistricts	Spatial Spillovers	Reverse causality
	(1)	(2)	(3)	(4)	(5)	(6)
1st time receiving PKH = 1	-0.0132	-0.0124	-0.00693	-0.0166	0.000625	
	(0.0426)	(0.0437)	(0.0726)	(0.0471)	(0.0440)	
2nd time receiving PKH = 1	-0.0617	-0.0616	-0.0861	-0.0827	-0.0502	
	(0.0590)	(0.0591)	(0.0645)	(0.0690)	(0.0656)	
3rd time receiving PKH = 1	-0.0576	-0.0592	-0.0760	-0.0613	-0.0457	
	(0.0434)	(0.0448)	(0.0584)	(0.0453)	(0.0507)	
4th time receiving PKH = 1	-0.0871	-0.0874	0.0930	-0.0859	-0.0779	
	(0.0777)	(0.0803)	(0.107)	(0.0709)	(0.0875)	
5th time receiving PKH = 1	0.230***	0.225***	0.318***	0.228***	0.234***	
	(0.0612)	(0.0625)	(0.0753)	(0.0687)	(0.0608)	
Other local social assistance programs = 1		0.0134				
		(0.0358)				
Askeskin availability = 1		-0.00228				
		(0.0447)				
log fixed assets per worker			0.151***			
			(0.00801)			
Weighted PKH of border-shared subdistricts					-0.0272	
					(0.0571)	
log output per worker (t)						-0.00313
						(0.00494)
Subdistrict FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Owner & enterprise characteristics	Y	Y	Y	Y	Y	Y
Village characteristics	Y	Y	Y	Y	Y	Y
Observations	146,208	146,208	129,396	66,601	146,208	66,601
R-squared	0.644	0.644	0.678	0.638	0.644	0.571

Column (1)–(5) dependent variable is log output per worker, while that of Column (6) is a dummy of receiving PKH at time t. Control variables not displayed for convenience: owner characteristics (gender, age and education), enterprise characteristics (year established, industry and license), and village characteristics (electrification rate, road access, education institutions, health care providers, rainfall, nightlights in 1993, elevation, slope, distance to port, and distance to river). Column (3) excludes year 2011 as data on fixed assets are not available for that year. Clustered standard errors by province in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In column (6), we examine the presence of simultaneity by assessing correlation between next year's PKH and current productivity. We estimate placebo regression by regressing the probability of receiving PKH at (t+1) on current labour productivity. We find that the coefficient of labour productivity is not statistically significant, suggesting no evidence of simultaneity bias in the main findings.

5.3 Heterogeneity

Previous research has pointed out that regional/infrastructure differences are a source of heterogeneity in the effects of targeted social assistance programs (Creti 2010; Cunha, De Giorgi, and Jayachandran 2011; Hartwig et al. 2018). In villages far from cities, access to market might be limited due to distance. Similarly, coastal area is where poverty rate found to be higher than in non-coastal area. While Java and Bali are where the development is concentrated, the other islands of Indonesia may experience lagging in development. Therefore, we examined the heterogeneity of PKH effects with respect to type of precinct (coastal/non-coastal), access to outside market (near/far from city), and region (Java & Bali compared to other islands). We also conducted heterogeneity for male-/female-owned enterprises as the funds from the program might go more to women.

The heterogeneity impacts results, as shown in Table 6, provide some insight on the impact on different regions and the limitations of the effects. The overall effect of increased productivity is mainly driven by increased productivity the following areas; in villages close to cities, by better access to outside markets; in non-coastal areas, by people relying on the manufacturing sector. Since most of the poor live in remote areas with less access to other markets, these findings suggest the need to recognize the possible effects of the economy wide impact of targeted social assistance programs directed toward poorer households.

Given that villages that are closer to cities might have better access to outside markets, we defined villages as being near to cities if the distance from the village to the nearest city is less than 60km. The results in Column (2) and Column (3) show that in short term there is no evidence of effect in both villages near to cities and those far from cities. However, a positive effect is observed in villages near cities when receiving the PKH for the fifth time.

Columns (4) and (5) differentiate the results for coastal and non-coastal areas. In coastal areas, no evidence of impact of the program is observed. A possible explanation is that people in coastal areas might not rely very much on manufacturing, but instead depend more on other activities, such as fisheries. On the contrary, a positive and significant medium term effect is observed in non-coastal area, but not in the short term.

Java and Bali are where the number of MSEs per 1,000 households is the largest. Column (6) and (7) compare the estimation between Java and Bali, and other islands. During the second and third time, the effect is negative in Java & Bali, while the effect at the second time is positive in other islands. A negative coefficient appears in the fifth time in other islands but no evidence of impact is observed in Java & Bali.

As cash transfers might go more to women, we differentiate the estimation between male- and female-owned enterprises. The results in Column (8) and Column (9) show that in the fifth time of receiving PJH both male- and female-owned enterprises experience an increase in labour productivity. The coefficient for the fifth time of receiving PKH is positive and statistically significant at 1% level for both male- and female-owned enterprises. This indicates that women also benefiting from the targeted social assistance programs.

Table 6. Effects of targeted cash transfer programs by urban/rural location, coastal/non-coastal, access to city, and region

Variables	Dependent variable: log output per worker								
	Preferred estimation	Near city	Far from city	Coastal	Non-coastal	Java & Bali	Other islands	Male-owned	Female-owned
	(1)	(2)	(3)	(4)	(5)	(6)	(6)	(8)	(9)
1st time receiving PKH = 1	-0.0132	-0.0178	0.0592	-0.0283	-0.00980	-0.0350	0.0187	-0.0454	0.0272
	(0.0426)	(0.0418)	(0.141)	(0.111)	(0.0425)	(0.0554)	(0.0711)	(0.0746)	(0.0439)
2nd time receiving PKH = 1	-0.0617	-0.0706	0.120	0.0747	-0.0674	-0.151*	0.129	-0.130	0.0112
	(0.0590)	(0.0559)	(0.195)	(0.118)	(0.0601)	(0.0622)	(0.0790)	(0.100)	(0.0428)
3rd time receiving PKH = 1	-0.0576	-0.0605	0.152	0.203	-0.0535	-0.0625	0.0439	-0.0404	-0.0193
	(0.0434)	(0.0390)	(0.199)	(0.231)	(0.0475)	(0.0343)	(0.151)	(0.0394)	(0.0478)
4th time receiving PKH = 1	-0.0871	-0.0660	-0.194	-0.0178	-0.0593	-0.0739	-0.138	0.169*	-0.247***
	(0.0777)	(0.0895)	(0.242)	(0.222)	(0.0868)	(0.0920)	(0.261)	(0.0999)	(0.0680)
5th time receiving PKH = 1	0.230***	0.232***			0.228***	0.154^		0.292***	1.467***
	(0.0612)	(0.0631)			(0.0706)	(0.0911)		(0.0611)	(0.0911)
Subdistrict FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Owner & enterprise characteristics	Y	Y	Y	Y	Y	Y	Y	Y	Y
Village characteristics	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	146,208	134,516	11,692	17,036	129,172	95,501	50,707	79,730	66,478
R-squared	0.644	0.643	0.673	0.649	0.647	0.629	0.579	0.656	0.659

Notes: Control variables not displayed for convenience: owner characteristics (gender, age and education), enterprise characteristics (year established, industry and license), and village characteristics (electrification rate, road access, education institutions, health care providers, rainfall, nightlights in 1993, elevation, slope, distance to port, and distance to river). Clustered standard errors by province in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5.4 Credit-constrained enterprises

In this section, we examine a possible mechanism through which social assistance programs affect MSEs in the local area. It is widely acknowledged that MSEs face a number of constraints, for instance credit constraints, when compared to larger enterprises that might limit MSEs productive capacity. Credit is needed for business investment and in the case of MSEs credit is very useful for cash flow so that enterprise could buy materials for production or pay their workers (Kaboski and Townsend 2012).

Using data of those who received loans, we differentiate whether or not the enterprise received loans from institution that required collateral, that is from a bank, cooperative or non-bank financial institutions, e.g., pawnshop, leasing or factoring. We regress a loan dummy on the timing of receiving the PKH controlling for other factors similar to that in the main estimation. The loan dummy equals 1 if enterprises received credit from a bank or cooperative or non-bank financial institution, and 0 otherwise.

Table 7 shows no immediate effect on credit. This result explains the main estimation findings that MSEs were unable to respond to an increase in demand in the short term as they were unable to access credit. Nevertheless, borrowing from a bank, cooperative and non-bank institution rises when receiving the PKH for the fourth and fifth time. There is no evidence of impact on bank-sourced credit, as the estimation of bank-sourced credit shows none of the coefficient is statistically significant.

Table 7. PKH and credit access

Variables	Dependent variable: log output per worker	
	Credit from bank, coop, non-bank	Credit from bank
	(1)	(2)
1st time receiving PKH = 1	0.00611	0.00845
	(0.0189)	(0.00504)
2nd time receiving PKH = 1	-0.00568	0.000308
	(0.0148)	(0.00715)
3rd time receiving PKH = 1	-0.0216	0.00337
	(0.0218)	(0.0160)
4th time receiving PKH = 1	0.0781**	0.000551
	(0.0306)	(0.0106)
5th time receiving PKH = 1	0.286***	-0.0121
	(0.0388)	(0.0111)
Subdistrict FE	Y	Y
Year FE	Y	Y
Owner & enterprise characteristics	Y	Y
Village characteristics	Y	Y
Observations	89,085	89,085
R-squared	0.491	0.241

Control variables not displayed for convenience: owner characteristics (gender, age and education), enterprise characteristics (year established, industry and license), and village characteristics (electrification rate, road access, education institutions, health care providers, rainfall, nightlights in 1993, elevation, slope, distance to port, and distance to river)Clustered standard errors by province in parentheses. *** p<0.01, ** p<0.05, * p<0.1

It seems that MSEs obtained credit mainly from non-bank agencies as significant coefficients are found for credit from all type of sources (Column 1) but not for bank-sourced credit (Column 2). The data indicates that two major reasons for MSEs not borrowing from banks are (i) they do not have collateral (15.31%), and (ii) they do not know the procedure for getting a loan (14.49%). MSEs might not know the procedure for getting a credit, but even had they known the procedure to get a credit, that does not guarantee that they have the collateral needed to get a credit. It is important therefore for policy-makers to ease access to credit for MSEs.

6. Conclusion

We have examined the effect of a targeted cash transfer program on the development of local economies in Indonesia. By exploiting the variation occurring from different timing of conditional cash transfer implementation in Indonesia, and utilising subdistrict fixed effects, we have showed the causal impact of PKH and added to the existing literature by focusing on MSEs in the local area. In general, we found that the PKH benefited MSEs in treatment subdistricts by increasing their output per labour in the medium term by about 23%. Nevertheless, there is no evidence of any immediate effect on labour productivity or impact on employment. The results are robust to an array of robustness checks. Thus, the findings suggest that targeted social assistance programs indeed exert positive side effects on local economies development.

The heterogeneity estimation results provide some insights into the limitations of such programs. The overall effect of the increase in labour productivity is mainly driven by increased labour productivity in villages near city where access to outside markets is better, and in non-coastal area where local people might rely on manufacturing MSEs. The PKH also benefited women engaged in MSEs. The results on a possible mechanism indicated that credit constraint seems to be a channel through which the program affects local MSEs. Furthermore, MSEs who managed to get credit, utilised non-bank sourced credit.

These results have a number of implications for policies regarding targeted social assistance programs and the development of local economies. Firstly, they highlight the importance for sustainability for at least 5 years so that the trickledown effect of the program can penetrate into local economies. Secondly, since most of the poor live in rural areas with less infrastructure and limited access to other markets, the results are pertinent to the need to recognise the limitation of the side effects of such programs on the development of local economies in rural areas and in villages located far from cities. Thirdly, in relation to limited access to credit, policy-makers could ease access to credit for MSEs to help them finance their business activities.

Due to the unavailability of data, however, we are not aware of other channels through which the PKH affect MSEs, for instance an increase in demand. Therefore, future studies might want to look at the consumption levels amongst the local people or the demand from outer regions for goods supplied by MSEs in local areas.

References

Angelucci, Manuela, and Giacomo De Giorgi. 2009. “Indirect Effects of an Aid Program: How Do Cash Transfers Affect Ineligibles’ Consumption?” *American Economic Review* 99 (1): 486–508.

Anselin, L. 1988. *Spatial Econometrics: Methods and Models*. Dordrecht: Kluwer Academic Publishers.

Baird, Sarah, Craig McIntosh, and Berk Özler. 2011. “Cash or Condition? Evidence from a Cash Transfer Experiment.” *The Quarterly Journal of Economics* 126 (4): 1709–53. doi:10.1093/qje/qjr032.Advance.

Banerjee, Abhijit V., and Esther Duflo. 2005. “Chapter 7 Growth Theory through the Lens of Development Economics.” In *Handbook of Economic Growth*, edited by Philippe Aghion and Steven N. Durlauf, 1A:473–552. Cambridge, MA: Elsevier B.V. doi:10.1016/S1574-0684(05)01007-5.

Banerjee, Abhit V., and Esther Duflo. 2011. *Poor Economics: A Radical Rethingking of the Way to Fight Global Poverty*. New York: Public Affairs.

Barrientos, Armando. 2012. “Social Transfers and Growth: What Do We Know? What Do We Need to Find Out?” *World Development* 40 (1). Elsevier Ltd: 11–20. doi:10.1016/j.worlddev.2011.05.012.

Berry, Albert, Edgard. Rodriguez, and Henry. Sandee. 2001. “Small and Medium Enterprise Dynamics in Indonesia.” *Bulletin of Indonesian Economic Studies* 37 (3): 363–84. doi:10.1080/00074910152669181.

Bianchi, Milo, and Matteo Bobba. 2013. “Liquidity, Risk, and Occupational Choices.” *The Review of Economic Studies* 80 (2 (283)): 491–511.

Blattman, Christopher, Eric P Green, Julian Jamison, Christian M. Lehmann, and Jeannie Annan. 2016. “The Returns to Microenterprise Support among the Ultrapoor : A Field Experiment in Postwar Uganda.” *American Economic Journal: Applied Economics* 8 (2): 35–64. https://www.jstor.org/stable/24739101.

Buera, Francisco J, Joseph P Kaboski, and Yongseok Shin. 2014. “Macro-Perspective on Asset Grants Programs : Occupational and Wealth Mobility.” *The American Economic Review* 104 (5): 159–64.

Cahyadi, Nur, Rema Hanna, Benjamin Olken, Rizal Adi Prima, Elan Satriawan, and Ekki Syamsulhakim. 2018. “Cumulative Impacts of Conditional Cash Transfer Programs: Experimental Evidence from Indonesia.” *NBER Working Paper Series*, no. 24670. doi:10.3386/w24670.

Christian, Cornelius, Lukas Hensel, and Christopher Roth. 2018. “Income Shocks and Suicides: Causal Evidence From Indonesia.” *Review of Economics and Statistics*, 1–45. doi:https://doi.org/10.1162/rest_a_00777.

Creti, Pantaleo. 2010. “The Impact of Cash Transfers on Local Markets: A Case Study of Unstructured Markerts in Northern Uganda.” London. http://www.cashlearning.org/downloads/resources/calp/impact-of-cash-transfers-on-local-markets-text-only.pdf.

Cunha, Jesse M., Giacomo De Giorgi, and Seema Jayachandran. 2011. “The Price Effects of Cash versus In-Kind Transfers.” *NBER Working Paper Series* 17456. http://www.nber.org/papers/w17456.

Ferraro, Paul J., and Rhita Simorangkir. 2018. “Poverty Alleviation Can Be an Effective Conservation Strategy.” *Mimeo*.

Fiszbein, Ariel, Norbert Schady, Francisco H.G. Ferreira, Margaret Grosh, Niall Keleher, Pedro Olinto, and Emmanuel Skoufias. 2009. “Conditional Cash Transfers: Reducing Presnt and Future Poverty.” Washington DC.

Gladieu, Stephan. 2018. “The State of Social Safety Nets 2018.” *The State of Social Safety Nets 2018*. https://www.worldbank.org/en/topic/socialprotectionandjobs/publication/the-state-of-social-safety-nets-2018.

Gobin, Vilas J., Paulo Santos, and Russell Toth. 2017. “No Longer Trapped? Promoting Entrepreneurship Through Cash Transfers to Ultra-Poor Women in Northern Kenya.” *American Journal of Agricultural Economics* 99 (5): 1362–83. doi:10.1093/ajae/aax037.

Hartwig, Renate, Robbert Sparrow, Sri Budiyati, Athia Yumma, Nila Warda, Asep Suryahadi, and Arjun Bedi. 2018. “Effects of Decentralized Health Care Financing on Maternal Care in Indonesia.” *Economic Development and Cultural Change* 04. doi:10.1086/698312.

Hill, Hal. 2001. “Small and Medium Enterprises in Indonesia: Old Policy Challenges for a New Administration.” *Asian Survey* 41 (2): 248–70. doi:10.1525/as.2001.41.2.248.

Kaboski, Joseph P, and Robert M Townsend. 2012. “The Impact of Credit on Village Economies.” *American Economic Journal: Applied Economics* 4 (2): 98–133. doi:10.1257/app.4.2.98.

Mead, Donald C., and Carl Liedholm. 1998. “The Dynamics of Micro and Small Enterprises in Developing Countries.” *World Development* 26 (1): 61–74. doi:10.1016/S0305-750X(97)10010-9.

OECD. 2001. *Measuring Productivity: Measurement of Aggregate and Industry-Level Productivity Growth*. Edited by OECD. *OECD Productivity Manual*. Paris: OECD

Publicing. doi:10.1787/9789264194519-en.

———. 2015. *Innovation Policies for Inclusive Growth*. Paris: OECD Publicing. doi:http://dx.doi.org/10.1787/9789264229488-en.

Resosudarmo, Budy P., Catur Sugiyanto, and Ari Kuncoro. 2012. "Livelihood Recovery after Natural Disasters and the Role of Aid: The Case of the 2006 Yogyakarta Earthquake." *Asian Economic Journal* 26 (3): 233–59. doi:10.1111/j.1467-8381.2012.02084.x.

Sadoulet, Elisabeth, Alain De Janvry, and Benjamin Davis. 2001. "Cash Transfer Programs with Income Multipliers: PROCAMPO in Mexico." *World Development* 29 (6): 1043–56. doi:10.1016/S0305-750X(01)00018-3.

Shortle, J., and D. Abler. 1999. *Agriculture and the Environment: Handbook of Environmental and Resource Economics*. Cheltenham, UK: Edward Elgar.

Stevenson, Betsey, and Justin Wolfers. 2006. "Bargaining in the Shadow of the Law: Divorce Laws and Family Distress." *The Quarterly Journal of Economics* 121 (1): 267–88.

Triyana, Margaret, and Anuraj H. Shankar. 2017. "The Effects of a Household Conditional Cash Transfer Programme on Coverage and Quality of Antenatal Care: A Secondary Analysis of Indonesia's Pilot Programme." *BMJ Open* 7 (10). doi:10.1136/bmjopen-2016-014348.

World Bank. 1992. *World Development Report 1992: Development and The Environment*. New York: Oxford University Press. http://documents.worldbank.org/curated/en/1993/05/17387636/world-development-report-1992-development-environment.

———. 2011. "Program Keluarga Harapan: Main Findings from the Impact Evaluation of Indonesia's Pilot Household Conditional Cash Transfer Program." Jakarta.

http://pkh.depsos.go.id/index.php.

———. 2012. “History and Evolution of Social Assistance in Indonesia: Social Assistance Program and Public Expenditure Review 8.” Jakarta. http://documents.worldbank.org/curated/en/618431468041436313/pdf/NonAsciiFileName0.pdf.

———. 2017. “Indonesia Social Assistance Public Expenditure Review Update: Towards a Comprehensive, Integrated, and Effective Social Assistance System in Indonesia.” Jakarta. http://documents.worldbank.org/curated/en/535721509957076661/Towards-a-comprehensive-integrated-and-effective-social-assistance-system-in-Indonesia.

———. 2019. “Strengthening Social Protection.” In *World Development Report 2019: The Changing Nature of Work*, 105–22. Washington: The World Bank. doi:10.1596/978-1-4648-1328-3_ch6.