Are mothers better at handling expenditures in stressful situations? Evidence from an Unconditional Cash Transfer in Indonesia *†

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Abstract

This paper analyses the effect of a specific unconditional cash transfer in Indonesia on consumption, nutrition, and labor markets. I implement two different methodologies to disentangle the real effect of the cash transfer on recipients from the indirect effect arising from poor households not receiving the transfer. Findings suggest that, while the cash transfer does not significantly raise the consumption level of recipients, poor households not benefiting from the transfer suffer from acute liquidity constraints in terms of food expenditures. When household consumption and food expenditure decisions are made by mothers, the effect of liquidity constraints is stronger for overall consumption expenditure but weaker for food expenditure, implying that credit constrained mothers are willing to give up non-food components of consumption to benefit household nutrition. On the other hand, the cash transfer does not significantly affect hours worked.

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1 Introduction

In the last two decades, Social Protection Programs have increasingly grasped the attention of the sustainable development agenda, reflecting both in an explosion of developing countries implementing Social Safety Nets, from 72 in 2000 to 149 in 2017, and in an increase in their efficiency (World Bank, 2017a). Initially, poverty alleviation programs took the form of subsidies for specific goods; however, this method was problematic as upper and middle classes were more likely to benefit from the subsidies since their consumption levels for most commodities are higher than those of lower income classes. Nowadays, poverty alleviation programs directly target poor household by providing them with direct cash transfers (Unconditional Cash Transfer), or transfers aimed for specific expenditures such as schooling or medical expenditures (Conditional Cash Transfers). This improvement has been largely connected with the amelioration of information technology in the past decades, which has allowed for more accurate screenings of populations and therefore better understanding of who the poorest households are and where they live (Olken, 2019).

Indonesia has also embarked on this novice wave and its implementation of social safety nets has gone hand in hand with that of other countries worldwide. In this paper, I analyse the effect of a specific Indonesian Unconditional Cash Transfer (UCT) program on consumption smoothing and liquidity constraints amongst poor Indonesian households. The Bantuan Langsung Sementara Masyarakat (BLSM), meaning Temporary Community Assistance, is the successor of the more famous Bantuan Langsung Tunai (BLT) cash transfer program, whose aim is to compensate very poor households facing unprecedented price increases, and is carried out from the Government of Indonesia to complement their drastic fuel price subsidy cuts in 2005, 2008 and 2013. Though the 2013-14 transfer is smaller in absolute size as compared to the previous ones, its effectiveness in terms of reaching poor and near-poor households has greatly increased (World Bank, 2017b). This is likely to be a consequence of the implementation of the Social Protection Cards (KPS) system, developed under the Unified Database to increase the eligibility accuracy of various social programs.

I analyse the effect of the program on food consumption and overall consumption levels, exploiting the fact that household eligibility for the program depends on a Proxy Mean Test score, a score that uses household characteristics to proxy income levels and to therefore define the poorest households. I contextualise this research with consumption smoothing theories, according to which I would expect households to smooth their additional income from the BLSM transfer, and with liquidity constraints theories, according to which households just below the threshold of program eligibility might be credit rationed and therefore reduce their consumption levels. To disentangle the two effects, I apply two different econometric methods.

Firstly, I implement a Fuzzy Regression Discontinuity design to test the difference in consumption levels between individuals just below the eligibility threshold who did not receive the transfer and those just above who received the cash transfer. This effect, however, is likely to incorporate both a consumption smoothing behavior of households just above the threshold, which would alleviate the difference in consumption levels, and a liquidity constraints behavior of households just below the threshold, which would increase the difference in consumption levels between the two groups. For this reason, I complement my analysis with an Intent to Treat model using an Instrumental Variable estimation, where I use KPS card ownership to instrument the effect of the cash transfer on consumption. This way, though the estimated effect is still "local" in the sense that it only considers compliers, it no longer restricts the number of households analysed to those around the threshold, thus decreasing the effect of liquidity constraints and mainly testing for consumption smoothing. The exogeneity assumption of this method relies on the fact that, although the KPS card can be used to redeem transfers from other social protection programs which could then also affect household consumption levels, the BLSM program has been the first program to implement the KPS card and by 2014, the year in which I analyse consumption patters, no other social protection program had officially started using the card (World Bank, 2017b).

I then extend this analysis to intra-household resource allocation and labor market effects. The idea that mothers are more likely to spend money from cash transfers on nutrition and health has been first studied by Thomas (1990), and has now become an advanced argument in favor of poverty alleviation programs targeting women (Duflo, 2003); however, the liquidity constrained behaviors of mothers suffering from fuel price increases in Indonesia has not been investigated in depth. My motivation to study labor market effects is to support Banerjee et al. (2017) in disproving the myth that households receiving cash transfers are fundamentally "lazy" and therefore would work less when receiving benefits. This aspect is particularly relevant when analysing the BLSM transfer and the impact of fuel subsidy cuts as lower income households tend to live in peripheral areas and commute daily to the city centers (Regmi and Eng, 2018). According to the theory of laziness of poor households, one would expect the laxity of cash recipients, who are shielded from the increase in fuel prices, to decrease their working hours as they do not need to bear and pay for increases in their commuting expenses.

Overall, I contribute to the existing literature on cash transfers in that I am - to the best of my knowledge - the first to analyse the effectiveness of the 2013-14 BLSM transfer in terms of consumption, nutrition and labor supply. Additionally, my research is instrumental as I am also the first to implement two different econometric models to disentangle the effect of cash transfers on consumption smoothing and liquidity constraints, and to extend this analysis to intra-household resource allocation.

My findings suggest that: (i) the BLSM cash transfer does not significantly affect overall consumption, (ii) poor households not receiving the transfer suffer from acute liquidity constraints in terms of food consumption, (iii) households not receiving the transfer and whose expenditure decisions are made by mothers are more sensitive to constraints in overall consumption but are not affected by constraints in terms of food consumption, and (iv) receiving the transfer has no effect on labor supply.

The rest of the paper is structured as follows: Section 2 presents a general overview on the history and previous literature findings on Social Protection Programs worldwide and in Indonesia; Section 3 explains in detail the theoretical models upon which my predictions are made; Section 4 provides statistics for the variables used and explains the construction of the Proxy Mean Test score; Section 5 outlines the main empirical strategies and Section 6 explains the robustness checks relative to each strategy; Sections 7 and 8 presents my main results and robustness checks; and Section 9 concludes.

2 Literature Review

2.1 History and Evidence on Cash Transfers: A Global Perspective

At the forefront of the Cash Transfers "movement" is a program launched in Mexico in 1997. PROGRESA, the "Programa de Educacion, Salud y Alimentacion" is a Conditional Cash Transfer (CCT) aimed at improving education, health, and nutrition of the poor through the provision of regular monetary transfers to women, conditional on healthcare visits and school attendance of their children (Millán et al., 2019). There are two main reasons behind the enormous success and influence of PROGRESA; not only was the program successful because of its positive results on Mexican households, but, and perhaps most importantly, the program's broad consensus derived from the confidence, or internal validity, supporting the estimated results. The Mexican government, facing budgetary constraints and therefore unable to provide transfers to the whole intended target group, decided to focus on a much smaller range of communities among which half was randomly selected to receive the benefits of the program. Known as a Randomized Controlled Trial (RCT), this evaluation scheme is argued to benefit from the strongest internal validity, as the random allocation of treatment ensures no selection bias between the individuals receiving the treatment and those not receiving it. Thanks to this design, the positive results on health and education arising from the evaluation of PROGRESA's first trial provided the confidence needed for the program to be scaled up to a broader selection of communities and to be expanded to other countries with the financial support of International Financial Institutions such as the World Bank (Duflo and Kremer, 2005).

Rigorous program evaluations in other Latin American countries helped to build upon PROGRESA's base model, especially in the context of education, where households are likely to be facing savings constraints that hinder their financial capabilities to face large expenses at the beginning of the school years. In Colombia, problems arising from financial constraints were successfully overcome with the implementation of a CCT that redistributed the total amount of the bi-monthly cash transfers in such a way that households would benefit from a lump-sum at the beginning of the school year and slightly lower regular payments (Barrera-Osorio et al., 2011).

More related to the focus of this study, the impact of CCTs on consumption and labor market participation has also been an important attribute to such programs. Fiszbein and Schady (2009) provide a review of program results on the above mentioned aspects. In most Latin American countries reviewed, with the exception of Ecuador, CCTs were found to significantly increase per capita consumption for the median household, with the magnitude of the increase being proportional to the size of the transfer. Moreover, beneficiaries were found to consume foods with higher-quality nutrients. While CCTs were, a-priori, plausible candidates for positive impacts on food, several theories highlighted the potential negative impact on labor force participation. This hypothesis is based on households experiencing an "income effect" and working less when earning more, or on households willingly working less in order to still be entitled for CCTs in the future. Evidence on this matter from programs in Cambodia, Ecuador and Mexico has however shown no significant reduction in adult work efforts (Fiszbein and Schady, 2009). On this matter, Banerjee et al. (2017), find a negative correlation between the fraction of GDP devoted to cash transfers and the population's belief that poverty is a result of laziness rather than of an unfair allocation of resources in the society. To debunk this stereotype of cash recipients being "lazy" amongst countries with lower levels of social protection programs, they provide evidence from seven RCTs in different developing countries, finding no consistent evidence that recipients of welfare programs are less motivated to work.

Soon after the success of PROGRESA, many Latin American countries, such as Brazil, Nicaragua and Colombia, started implementing similar social transfer programs, echoing the positive effects of the Mexican program. This chain of positivity brought international agencies, amongst which the World Bank, to exhort developing countries in other world regions to implement CCTs. Such efforts led to debates as to whether CCTs are a "one size fits all" programs. On the matter, Schubert and Slater (2006) outline four main concerns related to the applicability of CCTs in African countries. Firstly, they worry that the increase in demand for education and health brought about from such programs is at high risk of not being met by the supply-side of health and education services administered by the governments. Secondly, they argue that the capacity to enforce and monitor the conditions behind CCTs - such as monitoring whether kids are sent to school or to the doctor - is very weak in low-income African countries, thus threatening the effectiveness of the program as a whole. Another major problem related to the administration of conditionality concerns the additional costs that such conditionality implies, which imposes a greater burden to low-income countries. Lastly, they argue that socio-cultural differences could lead to differential program effects and that an in-depth analysis of indigenous attitude towards conditionality is needed before implementing CCTs.

Baird et al. (2011) argue that critics of conditionality should, by default, be in support of their theoretical counterpart, Unconditional Cash Transfers (UCTs), since in UCTs the administration of conditionality is no longer a threat and therefore the marginal contribution of individuals is not observed. This has led to a strain of literature investigating whether the positive results of CCTs are solely due to their conditionality. Findings from evaluations that exploit peculiar cases, in which faulty program implementations in Mexico and Ecuador have led households to think the transfers were not conditional, suggest that without conditionality the positive effects on education would vanish (De Brauw and Hoddinott, 2011; Schady et al., 2008).
To test the differential effect between UCTs and CCTs, Baird et al. (2011) set up an experimental design in Malawi in which households are randomly selected into three groups, one receiving CCTs, one receiving UCTs and a control group receiving no transfers. This pioneering experiment finds that both UCTs and CCTs have positive effects on school participation but that the impact of CCTs is higher, while UCTs are more effective in reducing teenage and pregnancy rates as those provide a financial buffer for young girls. The impact of Cash Transfers and government's interventions on fertility and Sexually Transmitted Infections (STIs) in Kenya are further studied by Duflo et al.

(2015), who find that UCTs alone reduce fertility rates but not STIs, and that the combination of the two programs instead reduces STIs but not fertility rates. They reconcile their findings with cash transfers having an impact on fertility because higher incomes disincentive committed relationships at younger ages, while the combination of transfers and governmental curricula stressing the importance of sexual abstinence until marriage was more effective at reducing the likelihood of causal relationships but fostered pregnancy rates. An important takeaway from these studies is that both UCTs and CCTs can be, if thoughtfully implemented, effective tools to improve welfare aspects of poor households.

In Sub-Saharan Africa, a study on the Zambia Child Grant Program highlights the positive effects of UCTs on household consumption, food consumption, diet diversity and food security (Seidenfeld et al., 2014), and in Kenya, an RCT confirms the positive effects of UCTs on monthly consumption and psychological well-being. Moreover, exploiting differences in the magnitude of the transfers and timing, transfers in the form of lump-sums are found to be more effective in increasing expenditure on durables, highlighting the role of credit constraints (Haushofer and Shapiro, 2016).

Another important aspect of Cash Transfers that has been investigated upon is the role of the recipient's gender. Thomas (1990) is the first to empirically examine the role of household composition in allocation of resources and finds that women are more likely to spend additional income on factors that contribute positively to the family's health. Duflo (2003) then contextualizes this finding with cash transfers and finds that when the black population became entitled to pension programs in South Africa, women recipients would invest more in their granddaughters, especially in fields of nutrition and health. This highlights that empowering women can improve the efficiency of transfers and increase investments in health, nutrition and education regardless of conditionality, thus making the next generations better off.

In summary, the extensive body of literature on the development and impact of Cash Transfers provides evidence on the effectiveness of both CCTs and UCTs, and is mostly focused on four aspects of welfare, those being health, education, nutrition and fertility, and most of these impacts seem to be positively amplified when transfers are given to women.

2.2 Brief History of Social Protection Programs in Indonesia

The beginning of Social Protection Programs in Indonesia dates back to the aftermath of the Asian Financial Crisis of 1997-1998, as an attempt to mitigate the drastic effects of the Crisis on food prices and real wages, which greatly damaged the poorest part of the population.

The first wave of poverty alleviation programs introduced by the Government of Indonesia (GOI) provided social safety net programs (JPS), covering education, health, community empowerment and employment creation. JPS also included a separate program - the Open Market Operations (OPK), later called Raskin - aimed at subsidizing rice for poor households (Sumarto and Bazzi, 2011). Though the magnitude of these social protection programs was unprecedented in Indonesia's history, targeting errors were extremely high. Sumarto et al. (2002) estimate that only 10% of the poorest households were correctly targeted, while 20% of households in the highest quintile also benefited from the OPK. Such targeting errors reflect the lack of adequate measures to collect household information; for example, indicators such as the ability to fulfill religious obligations were used to determine household welfare status.

The second generation of social protection programs were implemented between 2005 and 2008, as a way to protect poor households from rising oil and fuel prices complemented by governmental subsidy cuts. In 2005, the GOI carried out the first Socioeconomic Data Collection (PSE), a survey to identify households entitled to Unconditional Cash Transfers to mitigate the adverse effects of oil price shocks (BLT program). The PSE classified households based on 14 generally accepted socio-economic variables and was also used for health insurance programs and to better target Raskin recipients. In 2008, the PSE framework was updated with a new Data Collection for Social Protection Programs (PPLS 2008), which included eight additional socio-economic indicators and ranked households using a Proxy Means Tests methodology (TNP2K, 2015), which will be further discussed in Section 2.2.2. PPLS 2008 was also used to target families for the PKH Conditional Cash Program.

2.2.1 BLSM and the Unified Database

The Unified Database for Social Protection Programs (UDB) was developed using the 2011 updated Data Collection for Social Protection Programs (PPLS 2011), which relies on the 2010 update of the Indonesian Population Census, thus benefiting from increased coverage and targeting accuracy. Established in 2012, the UDB aims to provide the first Indonesian unified targeting system for all Social Protection Programs. Improvements in the methodology of data collection include: (i) complementing initial poverty lists obtained through mapping with improvised discussions and consultations; (ii) including a greater span of variables to measure household well-being used to proxy income levels; and (iii) greater data collection coverage, covering 40% of the population (TNP2K, 2015).

BLSM beneficiaries were elicited if amongst the poorest 25% according to the UDB, therefore putting the effectiveness of UDB targeting at the core of the success of the BLSM program. Generally, there are two main channels through which targeting accuracy is measured: *leakage*, or inclusion error, which refers to the share of non-beneficiaries receiving the program, and *undercoverage*, or exclusion error, which refers to the share of eligible households not receiving the program (Cornia and Steward, 1995). Bah et al. (2019) find that the UDB implementation reflects a substantial reduction in the leakage of BLSM benefits to non-beneficiaries, as it is more progressive than its predecessors BLT 2005 and BLT 2008. The total magnitude of the cash transfers is however lower for BLSM as compared to previous programs, both because of lower cash transfer size and lower household coverage, which contributed to an increase in undercoverage (Bah et al., 2019; World Bank, 2017b).

2.2.2 Proxy Means Tests

In order to elicit eligibility for the BLSM transfer, households are ranked on the basis of Proxy Means Tests (PMT), a common measure that prevents from relying solely on household incomes, and is especially used in developing countries where a great portion of the population is not formally employed and therefore lacks an official statement of income records. PMT methodology has been used for cash transfer programs such as PROGRESA in Mexico and relies on government collected information on household assets and characteristics in order to create a "proxy" for household consumption or income. Its main counterpart, community based methods, relies on allowing the community to select beneficiaries. Evidence from a field experiment evaluated by Alatas et al. (2012) finds that, in Indonesia, PMT scores perform better than community based methods, though without significantly affecting outcomes of poverty alleviation programs.

2.3 Evaluations of poverty alleviation programs in Indonesia

Sumarto et al. (2005) evaluate the impact of the first generation programs on consumption and poverty levels. Overall, their results suggest that social safety net programs have significantly contributed to increased levels of consumption amongst poor households. More specifically, they estimate that households who benefited from the programs had a per-capita consumption level around 4 to 10 % higher than those who did not participate. When evaluating the impact of the programs on the probability of being poor, only the subsidized rice program - known as OPK at the time - was found to significantly decrease this probability.

Bazzi et al. (2015) evaluate the impact of the BLT 2005 unconditional cash transfer on consumption smoothing of recipients. Exploiting the fact that some beneficiaries only received one of the two planned disbursements, they find that delayed payments decrease consumption by 7.5 percentage points as compared to non-recipients. Households who received both disbursements on time instead do not experience significant consumption differences compared to non-recipients. They reconcile these findings with theories on consumption smoothing and liquidity constraints, which will be further discussed in Section 3.

Cahyadi et al. (2018) investigate longer-run effects of the PKH Conditional Cash Program exploiting an experimental set-up in which the program is not extended to control group villages but rather to new ones. They find the program to have drastically increased human capital levels of recipients, which is in line with the aim of the PKH to target education and health. The economic status of recipients, on the other hand, did not experience significant changes.

Banerjee et al. (2017) evaluate seven randomized controlled trials from governmental cash transfers throughout six developing countries, amongst which one is the PKH program in Indonesia, to find that working hours amongst individuals receiving the transfers do not significantly and systematically differ from those not receiving the transfers.

On a broader note, Yusuf (2018) uses a Computable General Equilibrium model to analyse the effect of cash transfers on the Indonesian economy as a whole, finding that, despite a great reduction in poverty levels, the transfers impose a substantial burden to the Indonesian GDP, especially when domestically financed. However, when cash transfers are financed by cutting fuel subsidies, as in the case of BLT and BLSM programs, the programs impose a substantially lower burden to the economy while at the same time increasing inequality reduction.

3 Theoretical Framework

Following a similar theoretical reasoning as (Bazzi et al., 2015), I test for conventional consumption smoothing under the permanent income hypothesis as well as the effect of liquidity constraints when households are credit rationed. I then proceed to analyse the effect of receiving the transfer on hours worked of the household head in primary and - if applicable - secondary job.

3.1 Consumption under uncertainty and the Random-Walk hypothesis

I start by predicting consumption patterns using a model with time-varying interest rate and constant relative risk aversion, where households maximise expected utility as an additive function of future utilities discounted by a discount factor, $\beta < 1$ (which is the same as $\frac{1}{1+\delta}$, where δ is the rate of time preference):

$$E(U) = E_1\left(\sum_{t=1}^{T} \beta^t u(C_t)\right) \tag{1}$$

The first order condition (FOC), also called Euler equation, of equation 1 for a two time period is found when the Marginal Rate of Substitution, $MRS = \frac{dC_2}{dC_1}$ (i.e. the slope of the indifference curve), equals the intertemporal price, $-(1 + R_t)$ (i.e. the slope of the budget constraint), yielding:

$$\frac{u'(C_1)}{\beta u'(C_2)} = (1 + R_t) \tag{2}$$

which can be rewritten as:

$$u'(C_{t-1}) = \beta(1 + R_t)\, E_{t-1}[u'(C_t)] \tag{3}$$

Using a constant relative risk aversion utility of the form $u(C) = \frac{C^{1-\theta}}{1-\theta}$, with the constant relative risk aversion parameter $\theta > 0$, the marginal utility of consumption is $u'(C) = C^{-\theta}$ which can be substituted in equation 3 resulting in:

$$E_{t-1}\left[\left(\frac{C_t}{C_{t-1}}\right)^{-\theta}\right] = \frac{1}{\beta(1 + R_t)} \tag{4}$$

Noting that the growth in consumption can be written as $g_t = \frac{C_t - C_{t-1}}{C_{t-1}} = \frac{C_t}{C_{t-1}} - 1$, I make use of first-order Taylor approximation of $(1 + g)^{-\theta}$ around $g = 0$ to replace the highly non-linear term $\frac{C_t}{C_{t-1}}$. This approximation yields $(1 + g)^{-\theta} \approx 1 - \theta g$ [1] which I substitute in equation 4 to get:

$$E_{t-1}[1 - \theta g] = 1 + (-\theta E_{t-1} g_t) = \frac{1}{\beta(1 + R_t)} \tag{5}$$

of which I take log of both sides to get $-\theta E_{t-1} g_t = \delta - R_t$, or equivalently $E_{t-1}(g_t) = 1/\theta(R_t - \delta)$. Lastly, using the fact that[2] $g_t \approx \Delta ln(C_t)$, I get the final result

$$\Delta ln(C_t) = \frac{1}{\theta}(R_t - \delta) + \epsilon_t \tag{6}$$

[1] To see why this is the case, I start by writing the general first order Taylor approximation formula as $f(x) \approx f(x_0) + f'(x_0)(x - x_0)$, which can be applied to $(1 + g)^{-\theta}$ around $g = 0$ resulting in $(1 + g)^{-\theta} \approx (1 + 0)^{-\theta} + (-\theta)(1 + 0)^{-\theta-1}(g - 0) \approx 1 - \theta g$

[2] From $ln(1 + g_t) = ln(\frac{C_t}{C_{t-1}}) = \Delta ln(C_t) \approx g_t$

where $E_{t-1}(\epsilon_t) = 0$. Equation 6 is of great importance as it highlights that, if the time-varying interest rate R_t equals the household discount factor δ, the logarithmic value of consumption follows a random walk. Reconciling this model with my analysis suggests that household should smooth the additional income they get from the subsidy in order to smooth consumption between now and the future. While one might not usually expect poor household to save part of their cash transfer as transfers are usually received on a regular basis, this behavior is consistent with the BLSM transfer being allocated in one or two disbursements (World Bank, 2017b), and therefore with households having to administer the transfer over the whole time of the subsidy cut.

3.2 Liquidity constraints

Households who did not receive the BLSM transfer and whose PMT score falls just below the threshold for program eligibility are, instead, "credit rationed" as they are unable to access the cash transfer to shield them from the increase in fuel prices. While their income level might be sufficient to provide them a buffer for a first period of increased fuel prices, they might suffer from liquidity constraints in a later period. Liquidity constraints can lower the amount of household consumption below the optimum value as predicted from the FOC in equation 3, both when the constraint currently binds and when the constraint might only bind in the future. To see why a constraint that might bind in the future can affect current consumption, I consider a simple three period model with zero real interest rate ($R_t = 0$) and zero time preference ($\beta = 1$ or $\delta = 0$), in which utility is quadratic such that $u(C) = C - \frac{a}{2}C^2$. Consumption in period 3 is determined by household income in that period (Y_3), plus whatever financial wealth the household has accumulated from the previous periods (A_2), so that $C_3 = A_2 + Y_3$, where $A_2 = A_1 + Y_2 - C_2$. In period 2 the household elicits C_2 such to maximise:

$$E(U) = (C_2 - \frac{a}{2}C_2^2) + E_2[(A_1 + Y_2 + Y_3 - C_2) - \frac{a}{2}(A_1 + Y_2 + Y_3 - C_2)^2] \tag{7}$$

where the first part represents the expected utility of the current period's consumption while the second part represents the expected utility of consumption in period 3. Maximization with respect to C_2 yields the optimal solution:

$$C_2^* = \frac{1}{2}(A_1 + Y_2 + E_2(Y_3)) \tag{8}$$

Households are thus able to consume, in period 2, the optimal value C_2^* if the constraint does not bind. If, conversely, the constraint is binding, households will consume the full amount that is available in period 2, $C_2 = A_1 + Y_2$. If the constrain does not bind in period 1, consumption is expected to follow a random walk, i.e. $C_1 = E_1(C_2)$; however, if there is a chance that the constraint binds in period 2, this will affect consumption in period 1 such that:

$$C_1 = E_1[C_2] < E_1[C_2^*] = E_1[\frac{A_1 + Y_2 + E_2(Y_3)}{2}] = \frac{A_0 + Y_1 - C_1 + E_1[Y_2] + E_1[Y_3]}{2} \tag{9}$$

Note that the last step of this equation assumes that the law of iterated expectations[3] holds. Solving the inequality for C_1 yields the final result:

$$C_1 < \frac{A_0 + Y_1 + E_1[Y_2] + E_1[Y_3]}{3} \tag{10}$$

which is lower than the optimum amount $C_1^* = \frac{A_0+Y_1+E_1[Y_2]+E_1[Y_3]}{3}$, therefore showing that uncertainty with respect to future binding constraints decreases current consumption.

3.3 Labor Market Effects

When turning my attention to the potential labor market implications of cash transfers, theoretical implications become more ambiguous, providing arguments for cash transfers both potentially increasing and decreasing labor supply and thus hours worked. Banerjee et al. (2017) outline the main theoretical arguments in favor of both views. The most known argument in favor of households working less as a consequence of receiving benefits is the so-called "income effect": if leisure is a normal good, additional income will lead households to work less. The second argument is the "tax effect": households who receive the transfer are less likely to work because if they get richer they will no longer qualify for cash transfers. On the other hand, cash transfers might increase labor supply because they allow households to escape the "poverty trap" and thus increase their labor productivity; additionally, they reduce credit constraints and can potentially allow households to start a business. These arguments are in line with the so-called "substitution effect", according to which people who receive additional income have incentives to work more.

When contextualising these arguments with fuel subsidy cuts, I imagine both effects to be augmented: households receiving the transfer might either work less because they do not have to worry about compensating for higher fuel costs, or they might work more because their incentives are higher.

[3] The law of iterated expectations states that $E_1\big(E_2(Y_3)\big) = E_1(Y_3)$

4 Data

Data is collected from the 5^{th} wave of the Indonesian Family Life Survey (IFLS), a longitudinal survey representative of 83% of the Indonesian population. IFLS is one of the few large-scale surveys for developing countries and enables to track household and community level data from before and after the Asian Economic Crisis. Data collection for the 5^{th} wave took place between September 2014 and March 2015 and was the first wave to move from interview questionnaires filled by hand to a computer-assisted personal interview system (CAPI), which improved accuracy and cut costs.

4.1 Descriptive Statistics

I begin by describing main household and household head characteristics used to to construct PMT scores. Summary statistics for these variables are reported in Table 11 in the Appendix, from which I understand that, in my sample, 82% of household heads are male, 80% are married and have an average age of 44. The most common employment sectors in the sample are agriculture, retail, manufacturing and social services. On average, households are composed of 5 to 6 individuals, but reach a maximum of 40. Following Alatas et al. (2016), I calculate dependency ratios as the amount of household members below 14 or above 65 divided by the number of members between 14 and 65 years old; on average, households in the sample have a dependency ratio around 60%, but extremes can score up to 500%, meaning that they have 5 times more members not in the labor force as compared to those working. Moreover, the highest concentration of children is found in elementary schools as compared to Junior and Senior high schools. 60% of households in our sample live in urban areas and 77% report having access to a doctor in their village; 17% own a BLT card, meaning they have been able to participate in previous BLT programs.

Panel A of Table 1 shows the intra-household distribution of expenditure decisions. From this table, I understand that, in my dataset, mothers are more likely to be responsible for food expenditures rather than overall consumption expenditures; more precisely, mothers are responsible for consumption expenditure decision in 18% of the households, while they are in charge of decisions regarding nutrition in 46% of the households.

Panel B of Table 1 gives a detailed overview of household ownership of the Social Security Card (KPS), and of the BLSM transfer recipients. Out of the 14,174 households in the sample, the percentage of those owning a KPS card, 10%, is lower than those receiving BLSM transfers, 12%;

Table 1: Statistics on intra-household distribution of expenditure decisions and on BLSM recipients and KPS card owners. Percentage values in parentheses.

Panel A	Mother	Other hhld member	Don't know	Total
In charge of	2,555	8,117	3,502	14,174
consumption expenditure	(18)	(57)	(25)	(100)
In charge of	6,561	4,111	3,502	14,174
food expenditure	(46)	(29)	(25)	(100)
Panel B	Yes	No	Don't know	Total
KPS Card Ownership	1,406	12,725	43	14,174
	(10)	(90)	(0)	(100)
Received BLSM transfer	1,698	12,475	1	14,174
	(12)	(88)	(0)	(100)

this means that a portion of BLSM transfers is still allocated to households who are not entitled to it, or that KPS cards are not correctly assigned.

Table 2 describes monetary variables such as overall per capita consumption, per capita food consumption and the amount of BLSM transfer received per capita. Although BLSM transfers are received as a total amount and not per capita, I show per capita levels to ease comparability amongst monetary variables. Households in the sample spend on average around 888,000 Rp (approx 60$) per capita on overall food and non-food consumption [4], while the amount spent on food is almost half of that spent on non-food consumption. The BLSM transfer, which should in total amount to

Table 2: Summary statistics of monetary variables, each expressed in Rp per capita

Variable	Mean	St. Dev.	p10	p25	p50	N
Consumption	888,084.3	1,550,473	148,175.0	271,872	507,349.7	14,174
Food	381,658.5	395,612.4	78,214.3	145,714.3	266,250	14,174
BLSM transfer	67,242.8	42,286.0	27,272.7	40,000.00	80,000.00	1,666

600,000 Rp per receiving household, averages to 67,242.8 Rp per capita. On a more indicative note to understand the size of the cash transfer, as the transfer is supposed to target the poorest 25% of households, I present percentile values for all variables. This is insightful as we understand that the average cash transfer amounts to almost 50% of monthly food expenditure for the households

[4] Non-food consumption includes: electricity, water, fuel, household items, transportation, recreation, furniture, clothing, medical costs, gifts and ritual ceremonies and other such items

in the lowest quartile of food expenditure, and therefore has the potential to make a significant change for recipients. Even more, the average cash transfer per capita is almost equivalent to the monthly food expenditure per capita of households in the lowest 10th percentile.

Table 12 in the Appendix summarizes the variables used to analyse the effect of receiving the transfer on working hours. I have information on both primary and secondary jobs in form of average weekly hours worked. The average individual in the sample works roughly 41 hours per week, which is higher than the normal full-time employment; I understand, in fact, that individuals report working up to 84 hours per week on their primary jobs, an amount that goes well beyond labor laws in Indonesia according to the International Labor Organization [5]. The number of individuals employed in a secondary job is 2,629, roughly 22% of individuals working, and the average hours spent weekly on secondary jobs is around half of that spent on primary jobs. Panels B and C report summary statistics for men and women respectively. Out of the 11,691 individuals who reported working, 13% are women while the great majority, 87%, are men. With respect to secondary jobs, the proportion of women working is lower than for primary jobs, roughly 9%. On average, men report working more hours as compared to women.

4.2 Proxy Mean Test score approximation

I proceed by explaining the model used to reconstruct the Proxy Mean Test score for all households in the dataset. The official governmental test used in the Unified Database includes three branches of variables: household head characteristics, household characteristics and characteristics of the village in which the household lives. Table 3 reports the full set of variables, each of which is assigned a given weight in the official PMT calculation.

For privacy reasons, the IFLS database does not publicly disclose households' village codes, and I am therefore unable to retrieve the variables in the third column of Table 3, except for the variable related to the availability of a doctor, as households in the survey are asked if, were they to be sick, they would have access to a doctor in their village.

Due to limited accessibility to variable specific PMT weights as well as limited information on village characteristics in the IFLS database, I proceed by estimating the probability of each household receiving the program using a logit specification, following specific guidelines found in the literature (Alatas et al., 2016; Bazzi et al., 2015; Tohari et al., 2019). I therefore predict the propensity score of

[5] The amount stipulated in the Act 13 of 2003 is 40 weekly hours with 14 being the maximum overtime weekly hours, thus amounting to a total of 54 legal working hours per week

Table 3: PMT variables used by the Government

HH head indicator	**HH indicator**	**Village characteristics**
Male	Size	Distance to district
Age	Dependency Ratio	*Existence of*
Married	Number of children 0-4	Primary school
Educational attainment	*Children's education*	High School
Elementary	Elementary	Health Clinic
Junior High	Junior High	Hospital
Senior High +	Senior High +	Maternal facilities
Employment type	*Assets*	*Availability of*
Agriculture	Earth Floor	Doctor
Industry	Brick or cement wall	Midwife
Service	Private toilet	Semi Permanent market place
Formal	Clean water	Credit facility
Informal	Electricity	Asphalt road
	Access to other programs and credit	

each household using an additive function of all observable underlying characteristics contributing to the official PMT score. The estimated equation is as follows:

$$Pr(BLSM_h > 0) = F\left(\alpha X_h^{head} + \beta X_h^{fam} + \gamma X_h^{house} + \delta X_h^{other} + \omega_h\right) \tag{11}$$

where X_h^{head} is a vector of characteristics of the household head, such as her or his education and employment status, age, gender and marital status; X_h^{fam} is a vector of family characteristics such as the household size, dependency ratio and the number of children currently attending different schooling levels; X_h^{house} is a vector of house characteristics such as the type of roof, floor, whether toilet access is private or shared, the availability of drinkable water *etc*; lastly, X_h^{other} includes characteristics such as the availability of a doctor in the village, whether the household has previously been considered eligible for BLT programs and whether the household lives in an urban area. I also employ province fixed effects, captured by the variable ω in Equation 11, as to capture spacial variation of infrastructure differences that are captured by the official PMT weights but that I do not have access to. F is the logistic Cumulative Distribution Function (CDF), which I use because the social protection programs are allocated on the base on the ranking of each households' PMT scores (Bazzi et al., 2015), and therefore the probability of a household receiving the transfer does not depend solely on its PMT score but also on where its PMT score is collocated compared to the whole population.

Table 4 reports all variable as well as the marginal effect, computed through the coefficients of the logit regression, of each variable on the probability of receiving the program. From Table 4 I understand that being eligible for the program depends: (i) negatively on the household head being highly educated or formally employed, as well as owning a house with high quality floors and toilets; (ii) positively on the household head being self-employed, higher dependency ratios and having more kids currently attending school; (iii) positively also on the household owning a vehicle, which can be reconciled with the program targeting households who would suffer directly from increased fuel prices, and not only through their indirect effect on other prices. Other characteristics such as having previously been eligible for the BLT program or the availability of a doctor in the village also positively contribute to the probability of receiving the program.

Table 4: Underlying Variables of PMT score

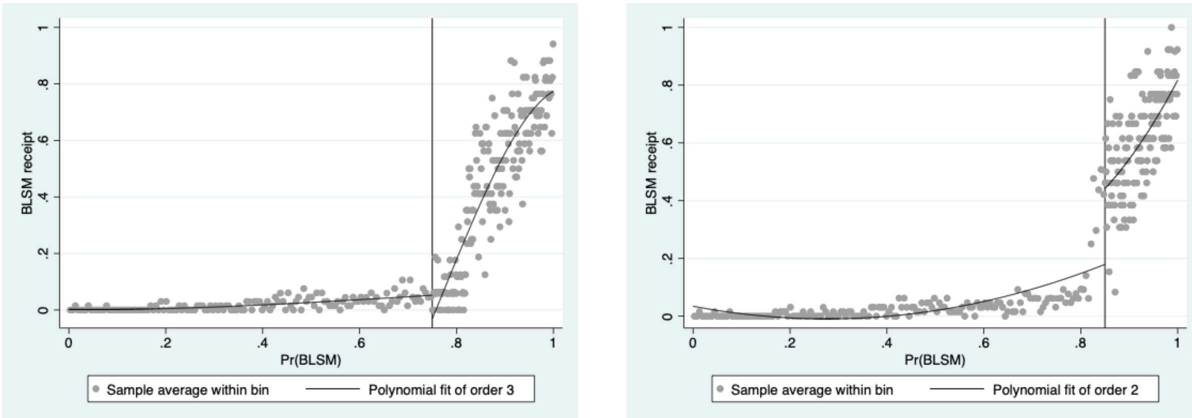
Variable	Marginal Effect	St.Err.	Variable	Marginal Effect	St. Err.
Head of HH characteristics			Household characteristics		
Male	-0.009	(0.008)	Size	0.000	(0.001)
Age	-0.000	(0.003)	Dependency Ratio	0.016***	(0.005)
Married	0.008	(0.008)	N of Children $\leq$ 4	0.001	(0.003)
Education			*N of Children* in:		
Elementary	0.007	(0.008)	Elementary	0.013***	(0.003)
Junior High	-0.001	(0.013)	Junior High	0.015***	(0.004)
Senior High +	-0.032**	(0.013)	Senior High	0.013***	(0.004)
Employed	-0.010***	(0.004)	*Assets*		
Employment type			Vehicle	0.016**	(0.007)
Self-Employed	0.011**	(0.005)	Appliances	0.009	(0.006)
Self-empl. non-perm	-0.010*	(0.006)	Private toilet	-0.016**	(0.007)
Self-empl. perm	-0.010	(0.021)	Concrete roof	-0.018	(0.017)
Employment Sector			Brick/cement wall	-0.010	(0.007)
Agriculture	0.007	(0.019)	Quality floor	-0.025***	(0.007)
Mining	0.002	(0.023)	Clean water	-0.009	(0.011)
Manufacturing	0.005	(0.012)	Own House	-0.011**	(0.006)
Electricity	-0.023	(0.030)	Uses gas to cook	0.017*	(0.009)
Construction	0.033**	(0.015)			
Retail	0.002	(0.012)	**Other**		
Transport	0.017	(0.022)	Urban area	0.017***	(0.0.004)
Finance	0.000	(0.018)	Availability of Doctor	0.025***	(0.006)
Social Services	0.007	(0.016)	BLT card ownership	0.217***	(0.002)

Comparing the official variables from Table 3 with the variables from Table 4, which I use to reconstruct the PMT score, is an important step because it allows me to understand in what way the village-related omitted variables might bias the calculation of the score. As most village characteristics have their counterpart household-related characteristic, I can predict the sign of the correlation between the omitted variables and the variables in my model. For instance, I predict that the existence of schools in the village where a household resides is positively correlated with the number of children in school for each household; similarly, I predict that the presence of health clinics, hospitals and maternal facilities is positively correlated with the number of children and the dependency ratio. Additionally, assuming that a village that has educational, health and financial services is richer than a village without such facilities, I imagine the omitted village variables to have a negative effect on the probability of a household to receive the cash transfer. Combining the positive relationship of the omitted variables with the variables present in equation 11 with the negative relationship of the omitted variables on the estimated probability, I expect my predicted score to suffer from a negative bias and therefore to be an underestimation of the true predicted score. The implications of this bias will be further discussed in Section 5.1.

5 Empirical Strategy

5.1 Fuzzy Regression Discontinuity

My empirical strategy exploits the PMT score threshold above which households are considered eligible for the BLSM program using a Fuzzy Regression Discontinuity (FRD) Design. The reason for using a Fuzzy rather than a Sharp design is that program eligibility does not guarantee the receipt of the disbursements, as the government does not have the monetary capacity to subsidize all individuals above the threshold. For this reason, I do not observe a sharp cutoff at which the probability of program assignment goes from 0 to 1 but, rather, I observe a fuzzy cutoff where the probability of program assignment significantly increases. To implement this method, I start by estimating and ranking individuals' probabilities of receiving the program based on the logistic Cumulative Distribution Function of underlying variables of the PMT score, explained in Section 4.2. I then proceed by establishing whether there is a jump in the probability of receiving the treatment around the 25% poorest households based on my score; this is done with a graphical analysis. Crucially, as mentioned in Section 4.2, my estimation of the score is an underestimation of the true score. The implications of this underestimation can be seen in Figure 1.



(a) Official cutoff

(b) Cutoff used in my analysis

Figure 1: Cutoff choice

In Figure 1a, I observe that, at the 75th percentile of the predicted probability of receiving the transfer - on the x-axis, the actual probability of receiving the BLSM transfer - on the y-axis - is understated, which is consistent with the omitted-variable-bias explanation in Section 4.2. This drives me to consider a higher threshold, which can be seen in Figure 1b, where I observe a clear increase in the probability of receiving the transfer when households are above the 85th percentile; however, for completeness, I also present results for the original cutoff as part of the robustness checks.

The intuition behind the Fuzzy RD method is that, if the jump in the probability of receiving the transfer is matched with a jump in the outcome variable at the exact same point along the running variable (i.e. the predicted probability of receiving the transfer), I can interpret the effect of the jump in the outcome variable as a evidence for a causal effect of receiving the program on the selected outcome. By looking at the effect on the outcome variable around the threshold, this method compares households right before the threshold to households right after the threshold; this is important because it ensures that the counterfactual is a valid counterfactual for the treatment. More specifically, I estimate the following model:

$$log(Y_h) = \alpha + \theta * Pr(BLSM) + \rho T_h + \epsilon_h \tag{12}$$

where Y_h is one of the outcomes of interest, $Pr(BLSM)$ is the predicted probability of receiving the treatment based on the CDF of the PMT score, as explained in Section 4.2, and T_h is a dummy indicating whether a household received the cash transfer.

Defining program eligibility as:

$$D_h = \begin{cases} 1 & \text{if } Pr(BLSM) \geq 0.85 \\ 0 & \text{if } Pr(BLSM) < 0.85 \end{cases} \tag{13}$$

I then estimate equation 12 with a Two Stage Least Square regression, in which the first stage identifies the magnitude of the jump in the probability of receiving the program at the threshold and the second stage measures the magnitude of the jump in the outcome at the same threshold. More specifically, the first stage is estimated as:

$$T_h = \delta + \pi * Pr(BLSM) + \gamma D_h + \eta_h \tag{14}$$

and the reduced form is:

$$log(Y_h) = \beta + \zeta * Pr(BLSM) + \tau D_h + \upsilon_h \tag{15}$$

The treatment effect, ρ, from equation 12 is calculated by dividing the effect of D_h in the reduced form by its effect in the first stage. All regressions are calculated for a specific threshold around the 0.85 cutoff, ranging from 0.75 to 0.95.

5.2 Intent to Treat

To distinguish between liquidity constraint motives and consumption smoothing behaviors, I employ an Intent To Treat (ITT) analysis, which exploits the fact that not all households identified as eligible for Social Protection Programs according to the UBD received the BLSM transfer. The Instrumental Variable, ownership of the Social Protection Card (KPS), can be used to redeem Social Protection Program transfers, such as BLSM, which in turn have a direct effect on consumption. Crucially, by the time the BLSM transfer was disbursed, no other program had implemented the use of the KPS card for eligibility of the transfer, thus excluding a potential violation of the exclusion restriction due to other programs affecting household expenditures.

The instrument serves to filter out those changes in the variable of interest, receiving BLSM benefits, that are not related to the error term and therefore estimate the causal effect. This method is similar to the one discussed in Section 5.1 in that it estimates the following equation:

$$log(Y_h) = \theta + \tau T_h + \sigma Z_h + \lambda_h + \epsilon_h \tag{16}$$

in two stages. The first stage isolates the exogenous variation in the variable of interest due to the instrument:

$$T_h = \delta + \gamma Z_h + \lambda_h + \upsilon_h \tag{17}$$

where T_h is a dummy variable for having received BLSM transfers, and Z_h indicates whether the household owns a KPS card. The reduced form then estimates the indirect effect of the instrument on the outcome variable:

$$log(Y_h) = \alpha + \beta Z_h + \lambda_h + \eta_h \tag{18}$$

where Y_h is the outcome, and λ_h is a set of controls that draws from the variables used to reconstruct the PMT score, in order to control for income levels.

Importantly, this method estimates the effect of BLSM program on compliers: households who receive BLSM transfers if they own the card but do not receive the BLSM transfer when they do not own the card. Like all Instrumental Variable regressions, my estimates yield an Local Average Treatment Effect, which differs from the Average Treatment Effect in that it is based only on compliers and excludes always-takers, i.e. households that receive BLSM transfers regardless of whether they have a KPS card. This, which is usually a drawback of the model, in this case has the advantage of filtering out corruption to some extent, in that it does not consider individuals who received the transfer because of their plausible connections with local authorities rather than being actually eligible.

5.3 Extending the models to account for the role of mothers

While the role of mothers in administering cash transfers has been extensively studied, the way mothers react to consumption smoothing and liquidity constraints when receiving or not a cash transfer has not been deeply investigated.

To delve deeper into the topic, my strategy is to think of mothers being in charge of household expenditures as a potential channel through which cash transfers affect household per capita expenditure levels. To capture the impact of this channel, I re-estimate equation 12 by adding another explanatory endogenous variable represented by the interaction effect between the dummy variable indicating whether the household received the transfer and another dummy variable indicating whether the mother is the household member responsible for consumption or food expenditures, respectively. Therefore, my new regression is:

$$Y_h = \rho_0 + \rho_1 T_h + \rho_2 T_h * Mother_h + \theta * Pr(BLSM) + \epsilon_h \tag{19}$$

The coefficient ρ_2 in Equation 19 captures whether the cash transfer has a differential effect on the outcome variables when mothers are in charge of expenditures. As both the interaction effect and the effect of receiving the transfer are instrumented, the first stage of the Fuzzy RD equation is calculated with the following system of equations:

$$T_h = \beta_0 + \beta_1 D_h + \beta_2 D_h * Mother_h + \theta_h \tag{20}$$

$$T_h * Mother_h = \alpha_0 + \alpha_1 D_h + \alpha_2 D_h * Mother_h + \gamma_h \tag{21}$$

Similarly, I re-estimate equation 16 using the interaction effect between my instrument - owning a KPS card - and the dummy variables indicating whether the mother is responsible for household food or consumption expenditures as instruments for the interaction effects in my new Intent to Treat model. This is captured by the following equation:

$$Y_h = \theta_0 + \tau T_h + \nu T_h * Mother_h + \sigma Z_h + \lambda_h + \eta_h \tag{22}$$

Whose system of first stages is:

$$T_h = \gamma_0 + \gamma_1 Z_h + \gamma_2 Z_h * Mother_h + \lambda_h + \theta_h \tag{23}$$

$$T_h * Mother_h = \mu_0 + \mu_1 Z_h + \mu_2 Z_h * Mother_h + \lambda_h + \gamma_h \tag{24}$$

6 Robustness Analysis

To assess the validity of our empirical strategy, I employ robustness checks for both methods outlined in Section 5.

6.1 Robustness Analysis for the Fuzzy RD method

The Fuzzy regression discontinuity design is subject to three general threats, namely: (i) other variables changing discontinuously at the threshold, (ii) discontinuity at other values of the running variable and (iii) manipulation of the running variable at the threshold. In this section, I explain the methods employed to reassure the results are robust to such threats.

The first threat mentioned could bias the robustness of the results as it implies that there might be another variable other than the assignment variable that also experiences a “jump” at the threshold, thereby being potentially responsible for the treatment effect. I analyse the possibility of this threat violating my result by performing balancing checks. A balancing check essentially tests the distribution of other covariates, not included in the calculation of the PMT score, around the threshold; the validity of the model is then threatened if such covariates are found to be discontinuous, and therefore experience a “jump”, at the threshold.

I test for variables representing characteristics of households similar to those included in the PMT score but not officially contributing to the score, such as whether the house in which the household resides has undergone any renovations since 2007. Testing for such variables is additionally relevant in this case as the PMT score has been reconstructed with household survey data that does not precisely coincide with the data collected for the official PMT score definition. A falsification of this test reassures me that the predicted PMT score does not lack variables that are important for the real determination of the main outcome variables. More precisely, I perform balancing checks for variables such as kitchen renovation, and house expansion, that could have unconsciously affected the score that an interviewer recorded for a household.

The second threat mentioned - discontinuity at other values of the running variable - is addressed through a falsification test where I create fictitious cutoffs in the running variable $Pr(BLSM)$. Re-estimating the effects of program receipt on all dependent variables using the fictitious cutoffs, the results are then falsified if the BLSM program yields significant effects at cutoffs of the variable $Pr(BLSM)$ other than 0.85, conditional on their first-stages being significant - i.e. experiencing a significant increase in program receipt at the cutoffs. Specifically, I consider a cutoff at 0.3, one at 0.55, one at 0.95 and the official 0.75 cutoff, with their respective bandwidths being the cutoff $\pm$ 0.1. I include the official cutoff to understand if, indeed, the cutoff I use is unique and therefore a good replacement for the official one.

Lastly, I account for the threat posed by a possible manipulation of the running variable at cutoff by performing a McCrary density test. Manipulation of the running variable poses a serious threat to the identification strategy because it implies that households have some control over their assignment to the BLSM program. If this were to be the case, I would expect households just below the threshold to slightly change their characteristics in order to be entitled to receive the program benefits, which in turn implies that the density of households is disproportionately higher just above the threshold as compared to just below the threshold.
With a McCrary density test I am able to visualise the density of households around the threshold and test for a significant difference around the threshold.

6.2 Robustness Analysis for the Intent to Treat method

Like other Instrumental Variable methods, the Intent to Treat model relies on three major assumptions: (i) the instrument must have a clear and strong effect on the variable of interest (strong first stage), (ii) it must be uncorrelated to the error term (independence assumption), and (iii) it should have no direct impact on the outcome (exclusion restriction). The first assumption can be easily tested by analysing the F-statistics of the first stage regression, while the second and third assumption cannot be formally tested. Since the KPS card can also be used to redeem other social protection programs, one might doubt of the validity of the independence assumption and exclusion restriction. I argue that such violations are unlikely because the BLSM cash transfer in 2014 has been the first of the bigger social protection programs in Indonesia to have started using the KPS card for eligibility redemption. Nonetheless, I consider potential behavioral implications of receiving the card on household expenditure decision. For example, a household very close to the eligibility threshold could have decreased its consumption in order to appear more poor to ensure program eligibility and therefore, upon receiving the KPS card, increases its consumption. On the other hand, upon receiving the KPS card, a household could decrease its consumption in the hope that this will increase the chances of being one of the eligible households actually chosen for receiving the BLSM transfer.

To account for these possible scenarios, I implement a method that relaxes the exclusion restriction and analyses what the confidence intervals of the estimates would look like if the restriction were to be slightly violated. More specifically, with this method I replace the requirement that σ in equation 16 is precisely 0 with an assumption regarding minimum and maximum values that it may take. For each range of values $[\sigma_{min}, \sigma_{max}]$, I estimate the confidence intervals of σ based on the average value of the range of σ. If the true value of σ was $\sigma_0 \in [\sigma_{min}, \sigma_{max}]$, I can then subtract Z$\sigma_0$ from both sides of equation 16, yielding the following regression:

$$(Y_h - Z_h\sigma_0) = \tau T_h + \epsilon \tag{25}$$

Conley et al. (2012) call this method Union of Confidence Intervals (UCI) because the confidence intervals of τ are bounded to the assumption made on σ. The Confidence Interval calculated is then used to assess whether the coefficient of T in the 2SLS Instrumental Variable regression is still statistically significant for values of σ different than 0.

To account for the possibility of both positive and negative behavioral consequences of the instrument on consumption, I test for the possibility of the exclusion restriction to be both positively and negatively violated, and estimate the confidence interval of the treatment effect for each respective value.

7 Results

7.1 General consumption and food consumption

I begin by analysing the impact of receiving the BLSM transfer on per capita household consumption levels. Column 1 of Table 5 reports the results for equation 12 with the logarithmic value of overall consumption as the outcome variable. The treatment effect, ρ, is represented by the coefficient of the BLSM receipt variable. Column 2 repeats the analysis using the Intent to Treat method, as outlined in equation 16, where the treatment effect noted as τ is the coefficient of the BLSM receipt variable. First stages for the analyses are reported in columns 4 and 5, respectively. In both cases, the instruments used have a positive and significant effect on receiving the BLSM disbursement. The F-statistics are above the commonly accepted threshold of 10, implying that the assumption on the strength of the instruments is satisfied. In the case of the Fuzzy RD design, the strength of the first stage can also be seen by performing a graphical analysis, which I already discussed in Section 5.1. From Figure 1b in Section 5.1, I clearly see a significant jump in the running variable around the threshold, which reassures me that the 0.85 cutoff is a valid instrument for having actually received the benefits.

The negative and significant coefficient of the variable Pr(BLSM), which corresponds to θ in equation 12, simply indicates that as the predicted probability of receiving the cash transfer increases, per capita consumption decreases. This is to be expected, as the predicted probability is a proxy for household income level. For the Intent to Treat analysis, instead of controlling for the predicted probability of receiving the transfer, I control for each individual variable included in the calculation of such probability, so as to assign each variable a given weight in the analysis. The coefficients for each control variable in columns 2 and 4 are reported in Tables 13 and 14 in the Appendix.

The coefficients of the BLSM variable in both columns 1 and 2 of Table 5 indicate that receiving the BLSM disbursements does not significantly affect overall per capita consumption levels; the Fuzzy RD analysis is also graphically represented in Panel a of Figure 2, where one can see a slightly positive, albeit likely insignificant, effect on consumption.

From the perspective of the Intent To Treat analysis, this finding can be reconciled with either the cash transfer not being high enough to affect household per capita consumption levels, or with a consumption smoothing behavior of households who receive the benefits, who save part of the cash transfer received and whose increase in consumption levels is therefore too small to have a significant impact on overall consumption. On the other hand, the coefficient being insignificant

Table 5: Fuzzy RD and IV results for overall consumption and food consumption levels

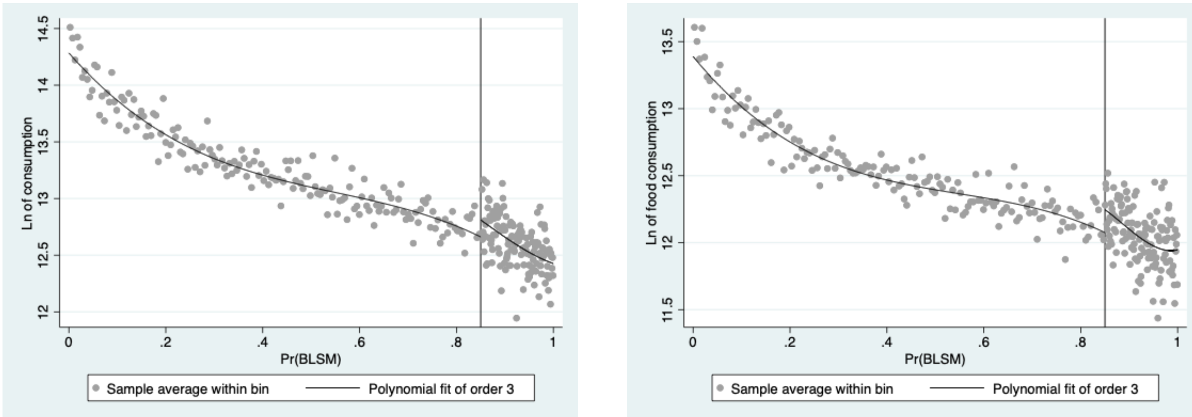
	log(consum)	log(consum)	log(food)	log(food)	*First Stages* BLSM receipt	
	(1)	(2)	(3)	(4)	(5)	(6)
	(FRD)	(IV)	(FRD)	(IV)	(FRD)	(IV)
BLSM receipt	0.250	-0.315	0.496*	-0.133		
	(0.297)	(0.352)	(0.274)	(0.295)		
Pr(BLSM) $\geq$ 0.85					0.147**	
					(0.0547)	
KPS card						0.286***
						(0.0790)
Pr(BLSM)	-1.870**		-2.246***		1.984***	
	(0.835)		(0.723)		(0.256)	
Observations	3,337	12,444	3,331	12,423	3,339	12,423
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
F-stat					26.5	13.13

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

Notes: The table reports Fuzzy RD and IV estimates. The dependent variable in columns 1-4 is the log of per capita household consumption or food expenditure. In columns 5-6, the dependent variable is the dummy for having received the BLSM cash transfer. F-stat is the Kleiberg-Paap Wald F-statistics for weak identification. Robust standard errors, in parentheses, are clustered by province.

also when using a Fuzzy RD model seems to clarify that the insignificant effect is more likely to stem from the cash transfer being too small in magnitude to affect the overall consumption expenditure of households. This is because in the Fuzzy RD analysis I am comparing households just above the 85% threshold who received the benefits with those just below the threshold not receiving the transfer, who are likely suffering from liquidity constraints resulting from the increase in fuel prices, and therefore I would expect any small but positive increase in consumption level stemming from consumption smoothing behavior to appear significant. This argument is further supported by the fact that the variable used for overall consumption comprises items such as gifts, recreation or medical costs who are unlikely to be affected by the cash transfer. Therefore, it seems reasonable to investigate on the effect of the cash transfer on basic household expenditure such as food expenditure.

In light of this, I now turn to the results related to per capita levels of food consumption, reported in columns 3 and 4 of Table 5, and note that households above the 85% threshold who receive the BLSM benefits report spending nearly 50% more on food than those just below the threshold who do not receive the benefits (graphically shown in Panel b of Figure 2). Following the same strain



(a) Overall Consumption

(b) Food Consumption

Figure 2: Second stages of fuzzy RD on overall consumption and food consumpton

of thought as above, I believe this effect could be either attributed to households behaving against consumption smoothing theories, and therefore not precautionarily saving for a possible future with high fuel prices but without transfers, or it could be a sign that household not receiving the transfer are significantly worse off and suffering from liquidity constraints with respect to food expenditures. Again, to validate these preliminary interpretations, I turn to the Instrumental Variable results, reported in column 4. The insignificant effect of BLSM benefits, found when comparing households who own a KPS card and receive the benefits with households who do not own the card and do not receive the benefits, seems to hint that the significant effect found in the Fuzzy RD analysis is a consequence of households suffering from acute liquidity constraints rather than households receiving the benefits not satisfying a consumption smoothing behavior.

7.2 Consumption and food expenditures: the role of mothers

As mentioned in Section 2, mothers are known for administering better expenditures related to health, education and nutrition of their families. The question that naturally follows from this statement is whether the cash transfer has differential effects when mothers are in charge of household food and overall consumption decisions. To analyse this, I augment the Fuzzy RD and IV models previously estimated to account for the interaction effect between receiving the cash transfer and mothers being responsible for consumption and food expenditures, as outlined in Section 5.3. Coefficients of control variables for the IV estimates are reported in Tables 15 and 16 in the Appendix.

Table 6: General consumption and nutrition: the role of mothers

	log(consum)	log(consum)	log(food consum)	log(food consum)
	(1)	(2)	(3)	(4)
	(FRD)	(IV)	(FRD)	(IV)
Panel A				
BLSM receipt	0.346	-0.262	0.626	-0.393
	(0.392)	(0.339)	(0.398)	(0.376)
BLSM receipt	0.176**	-0.299		
x consumption mother	(0.0791)	(0.419)		
BLSM receipt			-0.0552	0.521**
x food mother			(0.104)	(0.262)
Pr(BLSM)	-2.132**		-2.445***	
	(1.036)		(0.887)	
Panel B				
Pr(BLSM) $\geq$ 0.85	-0.034***		-0.083***	
	(0.006)		(0.012)	
Pr(BLSM) $\geq$ 0.85	0.599***			
x consumption mother	(0.041)			
Pr(BLSM) $\geq$ 0.85			0.656***	
x food mother			(0.028)	
KPS card		-0.081***		-0.228***
		(0.014)		(0.026)
KPS card		0.601***		
x consumption mother		(0.188)		
KPS card				0.580***
x food mother				(0.113)
Observations	2,748	10,019	2,748	10,016
Province FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
F-stat	144.18	214.86	561.79	365.52

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

Notes: The table reports Fuzzy RD and IV estimates. The dependent variables in panel A, the second-stage, are the log of per capita household consumption and food expenditure. Panel B reports first-stage estimates. F-stat is the Kleiberg-Paap Wald F-statistics for weak identification. Robust standard errors, in parentheses, are clustered by province.

Results for consumption levels are reported in columns 1 and 2 of Table 6, while results for food consumption are reported in columns 3 and 4. First stages having the interaction effects as dependent variables are reported in Panel B, while the additional first stages having as dependent variable BLSM receipt are reported in Table 17 in the Appendix. The coefficients of the first-stage interacted instruments are positive and significant, while those of the raw instruments are negative.

This is due to the fact that much of the effect on the dependent variable - here being the interaction term between mothers responsible for expenditures and receiving the program - is explained by the respective interacted instruments.

The coefficient for the interaction effect is positive and significant in column 1, while the effect of receiving the cash transfer is still not statistically different from 0. Again, following a similar reasoning as above, I interpret the positive and significant effect of the interaction term either as a sign that mothers belonging to households just above the threshold and who receive the transfer spend significantly more, or as evidence that mothers from households just below the threshold not receiving the transfer feel particularly constrained. In either case, this highlights that mothers' consumption levels are more sensitive to cash transfers and therefore that their income elasticity is higher. The insignificance of the interaction effect in column 2 suggests that the positive effect in column 1 is driven more by liquidity constrained mothers spending less rather than mothers receiving the transfer spending more. Both columns additionally confirm that overall BLSM does not have any significant effect on consumption also when the mother channel is taken into account. Moreover, the F-statistics for all first stages are above the threshold of 10, and the effects of each interacted instrument is highly significant, suggesting that the strong first stage assumption of the models is satisfied.

Turning to the results for food consumption reported in Column 3, I find that, when controlling for the interaction effect, the effect of receiving the BLSM transfer is only marginally significant (at the 11% level) but it still highlights a positive effect of the transfer on food consumption. More interestingly, however, I find that the interaction term is not significant. I interpret this result to be either in support of the hypothesis that mothers, even when facing liquidity constraints, try to relocate their expenditures such not to cut food expenditure, or as a sign that food expenditure of mothers whose household received the transfer are not particularly sensitive to income changes. To disentangle the two effects, I turn to the coefficient of the interaction effect in the Intent to Treat analysis in column 4, which is positive and significant, and thus highlights that the most plausible explanation is not that mothers' food expenditure is not sensitive to receiving the transfer, but rather that mothers, even when their household is suffering from liquidity constraints, try to cut expenses other than food.

7.3 Labor Market Effects

To assess which effect - substitution or income - dominates labor supply decisions of households, and to ultimately understand if the transfer makes recipients more "lazy", I perform a Fuzzy RD and an Intent to Treat analysis, each with two different outcome variables related to labor supply. Specifically, I look at hours worked by the household head in his/her primary job and those worked in the secondary job - if any. Results are reported in Table 7, where the first two columns present the results for the Fuzzy RD and the last two columns refer to the Intent to Treat analysis. Control variables for the latter include only household head related characteristics, and are reported in Tables 18 and 19 in the Appendix.

Table 7: Labor Market Results

	Hours Job 1	Hours Job 2	Hours Job 1	Hours Job 2
	(1)	(2)	(3)	(4)
	(FRD)	(IV)	(FRD)	(IV)
BLSM receipt	-0.557	-0.060	0.0735	0.155
	(0.484)	(0.769)	(0.106)	(0.265)
Pr(BLSM)	1.789		0.177	
	(1.261)		(1.284)	
Observations	3,324	12,397	777	2,755
Province FE	Yes	Yes	Yes	Yes
Controls	No	YES	No	YES

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

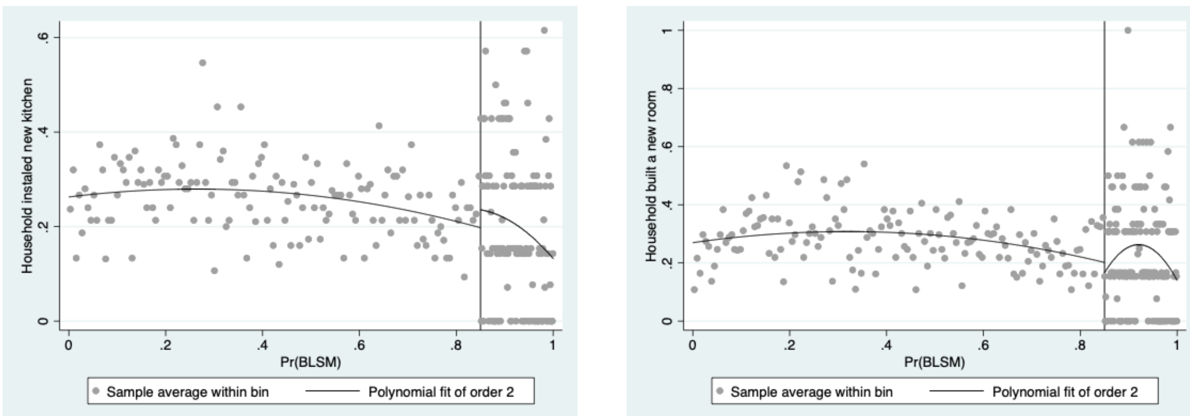
Notes: The table reports Fuzzy RD and IV estimates. The dependent variable in columns 1-4 is the log of weekly hours worked in main and secondary (if applicable) job. Robust standard errors, in parentheses, are clustered by province.

I do not present first stages - one being the effect of the threshold dummy variable on program receipt and the other being the effect of having a KPS card on program receipt - as they were already reported in Table 5. The coefficients for hours worked are consistently insignificant across both job dimensions and models. I therefore conclude that the effect of program participation does not significantly affect working hours in general, thus confirming the findings from Banerjee et al. (2017) that neither the income nor the substitution effects dominates. The findings from the Fuzzy RD analysis performed in Table 7 are also graphically represented in Figure 5 in the Appendix, which is insightful as it shows the lack of a particular pattern in the hours worked for households receiving the benefit.

8 Robustness of Results

8.1 Robustness of Fuzzy RD analysis

The first robustness check performed tests for the continuity of covariates around the threshold. I perform this test graphically for two covariates: (i) renovation of kitchen since 2007 and (ii) expansion of the house since 2007. The balance checks reported in Figure 3 show that there is no clear jump at the threshold level for the two covariates, reassuring me of the validity of the Fuzzy RD and of the construction of the PMT score.



(a) New Kitchen

(b) House Enlargement

Figure 3: Balance checks

The second test performed considers fictitious cutoffs as placebo tests for the Fuzzy RD analyses. These are reported in Table 8, where Panels A, B, C and D present the results for the 0.75, 0.3, 0.55 and 0.9 cutoffs, respectively. A graphical analysis of the first stage is reported in Figures 8-10 in the Appendix. As expected, the effect of receiving the transfer is insignificant for all cutoffs; perhaps surprisingly, however, the interaction term between receiving the cash transfer and the mother being in charge of consumption decision is significant at the 10% level for the original 0.75 cutoff, while the interaction term between receiving the transfer and the mother being in charge of food expenditures is significant at the 5% level for the 0.55 cutoff. I argue that this effect might stem from the fact that the allocation of cash transfers still suffers from far-from-perfect targeting accuracy, which could have plausibly led to few households around other cutoffs to have benefited from the transfer and therefore increasing their food and consumption expenditures. Indeed, this also explains the positive signs of the coefficients. Figures 9 and 7 in the Appendix, which show the first stages for the 75% and 55% cutoffs, support the hypothesis that, even if some households

Table 8: Placebo test for Fuzzy RD analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	Cons	Food	Job 1	Job 2	*First Stages*	
Panel A: 0.75 cutoff						
BLSM receipt	-0.749	-0.999	1.196	1.178	-0.856	-0.887
	(0.766)	(0.761)	(0.738)	(6.438)	(0.717)	(0.724)
BLSM receipt					0.459*	
x cons. mother					(0.270)	
BLSM receipt						0.165
x food mother						(0.161)
Panel B: 0.3 cutoff						
BLSM receipt	10.13	-2.805	0.379	-2.978	38.43	-2.163
	(26.29)	(17.11)	(19.11)	(45.42)	(254.4)	(45.70)
BLSM receipt					21.14	
x cons. mother					(74.41)	
BLSM receipt						6.307
x food mother						(10.44)
Panel C: 0.55 cutoff						
BLSM receipt	5.336	4.795	2.055	-7.641	5.859	1.353
	(5.460)	(5.134)	(3.734)	(7.842)	(5.059)	(4.077)
BLSM receipt					-0.868	
x cons. mother					(2.617)	
BLSM receipt						3.016**
x food mother						(1.242)
Panel D: 0.9 cutoff						
BLSM receipt	4.351	8.637	-5.851	-1.589	57.14	-20.91
	(26.32)	(45.59)	(22.81)	(1.487)	(2,104)	(177.9)
BLSM receipt					5.726	
x cons. mother					(198.4)	
BLSM receipt						3.044
x food mother						(25.50)
Province FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Notes: The table reports Fuzzy RD estimates. The dependent variable in columns 1-4 are: log of per capita household consumption and food expenditure and log of hours worked (primary and secondary job) by household head. Robust standard errors, in parentheses, are clustered by province.

received the transfer around other cutoff points, such cutoff are not matched by a significant jump in the number of households actually receiving the benefits, thereby invalidating the significance of any second stage results reported in Table 8.

Lastly, I perform a McCrary density test to ensure the number of households varies smoothly around the threshold. The graphical representation of this test is represented in Figure 4, which hints that the density of households does not vary particularly around the threshold.

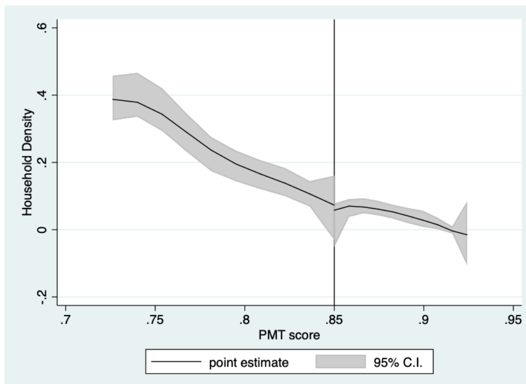


Figure 4: McCrary density test

This visual representation is supported by an econometric test, reported in Table 9, in which the null hypothesis of densities not differing around the threshold is not rejected. Though not rejecting the null hypothesis is not enough to prove that it is true, combining the test with the graphical representation reassures me that density changes at the threshold are unlikely.

Table 9: McCrary Density test

Test description	T	P > | T |
H_0 : density is continuous	-0.869	0.385

8.2 Robustness of Intent to Treat analysis

Table 10 reports the results from the Plausibly Exogenous method. Columns 1 and 3 of Table 10 report, respectively, negative and positive values of σ for each range $[\sigma_{min}, \sigma_{max}]$, under the assumption that the true value of σ is at the mean of the interval. Since the objective of this test is to assess if the significance of a coefficient is carried for cases in which the exogeneity restriction is slightly violated, I only perform this robustness check for significant coefficients in the IV model, that is, only for the coefficient of the interaction effect between mother being responsible for food consumption and program receipt, reported in Table 6. For reference, I report the 2SLS coefficient of the interaction effect in the row below.

Table 10: Union of Confidence Intervals. Confidence Intervals are constructed with robust standard errors, clustered by province

Union of Confidence Intervals			
(1)	(2)	(3)	(4)
σ	ln(food consumption)	σ	ln(food consumption)
-0.04	[0.060 1.044]	0.04	[-0.093 1.080]
-0.03	[0.043 1.046]	0.03	[-0.072 1.073]
-0.02	[0.026 1.049]	0.02	[-0.051 1.067]
-0.01	[0.007 1.053]	0.01	[-0.031 1.062]
0	[0.007 1.035]	0	[0.007 1.035]
BLSM receipt			
x food mother	0.521		0.521

First of all, I am reassured by the fact that the value of the 2SLS coefficient is significantly different from zero in the case for which I impose σ to be 0. As I start analysing the confidence intervals for values that are slightly different than zero, I observe that the coefficient of the interaction effect on food expenditure is still significant for negative violations of the exclusion restriction, but loses its significance for any positive violation. This implies that, if the ownership of a KPS card were to have a positive effect on consumption other than its effect through the BLSM program, the significance of the 2SLS coefficient would be threatened; while the coefficient is more robust to violations of the exclusion restriction such that the instrument has a negative effect on food expenditure other than its effect through receiving the transfer. Therefore, if households increase their food expenditures when they receive the KPS card, perhaps because they anticipate that they will receive their transfer and therefore their precautionary savings motives are lower, the significance of the interaction effect in the 2SLS might no longer hold.

9 Conclusion

In this paper, I have analysed the effect of a single Unconditional Cash Transfer Program, on various household variables such as overall per capita consumption levels, per capita food consumption, and average hours worked.

It is important to mention that my results are limited in the sense that they only provide a local estimation of the Treatment Effect. Firstly, estimates from both econometric models are local because they only estimate the effect on compliers. In the Fuzzy RD model, this means leaving out of the analysis individuals above the estimated threshold who do not receive the transfer (never-takers), nor individuals below the threshold who did receive the transfer (always-takers). In the Instrumental Variable model, this means not considering individuals who own a KPS card and do not receive the transfer (never-takers), nor individuals who do not own a KPS card but receive the transfer (always-takers). Additionally, the Fuzzy RD model is local also in that it restricts the number of households included in the analysis to a narrow range around the defined threshold.

My findings suggest that relatively poor households who do not receive the cash transfer suffer greatly from liquidity constraints as a result of the increase in fuel prices, demonstrating that fuel prices have a significant repercussion on food prices and that the BLSM cash transfer was effective in shielding poor households. Interestingly, when mothers are in charge of food expenditures, the liquidity constraints effect from not receiving the transfer is lower, suggesting that they prioritize food expenditures to other determinants of consumption. This result is further supported by the fact that, when mothers are in charge of overall consumption expenditures, they react more strongly to liquidity constraints, possibly to devote more money to food expenditure. From this perspective, my findings support previous studies on the importance of mothers' empowerment for household nutrition when financing cash transfers (Duflo, 2003; Thomas, 1990).
My findings also support (Banerjee et al., 2017), in that I disprove theories that hold welfare recipients accountable for reacting to cash disbursements by decreasing their hours worked.

I therefore encourage the Indonesian government either to complement UCTs with programs that empower women's power over household expenditure decisions, or to consider a broader coverage of welfare recipients when implementing such drastic fuel subsidy cuts, so to lower the amount of households suffering from liquidity constraints.

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Appendix

A Tables

Table 11: Summary Statistics of PMT score variables

Variable	Mean	SD	Min	Max	Variable	Mean	SD	Min	Max
Head of HH characteristics					**Household characteristics**				
Male	0.82	0.38	0.00	1.00	Size	5.55	3.20	1.00	40.00
Age	44.00	14.74	15.00	101.00	Dep.rat.	0.58	0.52	0.00	5.00
Married	0.80	0.41	0.00	6.00	Age 0-4	0.39	0.58	0.00	4.00
Education					*N of children in:*				
Elementary	0.34	0.47	0.00	1.00	Elementary	0.52	0.72	0.00	7.00
Junior High	0.17	0.37	0.00	1.00	Junior High	0.26	0.50	0.00	4.00
Senior High+	0.40	0.49	0.00	1.00	Senior High	0.26	0.51	0.00	4.00
Employed	0.59	0.49	0.00	1.00	*Assets:*				
Self-employed	0.17	0.37	0.00	1.00	Appl.	0.05	0.23	0.00	1.00
S.e. nonperm	0.16	0.36	0.00	1.00	Vehic	0.07	0.26	0.00	1.00
S.e. perm	0.02	0.14	0.00	1.00	Wall	0.80	0.40	0.00	1.00
Employment sector:					Roof	0.02	0.13	0.00	1.00
Agriculture	0.23	0.42	0.00	1.00	Toilet	0.83	0.38	0.00	1.00
Mining	0.01	0.12	0.00	1.00	Water	1.91	1.17	0.00	4.00
Manuf.	0.12	0.32	0.00	1.00	House	0.69	0.46	0.00	1.00
Electr.	0.01	0.07	0.00	1.00	Floor	0.51	0.50	0.00	1.00
Constr.	0.05	0.22	0.00	1.00	Gas cook	0.70	0.46	0.00	1.00
Retail	0.22	0.42	0.00	1.00	*Other*				
Transp.	0.02	0.15	0.00	1.00	Doctor	0.77	0.42	0.00	1.00
Finance	0.04	0.21	0.00	1.00	Urban	0.60	0.49	0.00	1.00
Soc. serv.	0.19	0.40	0.00	1.00	BLT card	0.17	0.38	0.00	1.00

Table 12: Summary statistics of variables representing weekly hours worked

Variable	Mean	St. Dev.	Min	Max	N
Panel A: work outcomes					
Avg hrs worked (primary job)	41.02	18.30	7.00	84.00	11,691.00
Avg hrs worked (secondary job)	18.99	15.69	2.00	63.00	2,629.00
Panel B: work outcomes for Men					
Avg hrs worked (primary job)	41.38	18.11	7.00	84.00	10,147.00
Avg hrs worked (secondary job)	19.09	15.76	2.00	63.00	2,371.00
Panel C: work outcomes for Women					
Avg hrs worked (primary job)	38.62	19.31	7.00	84.00	1,544.00
Avg hrs worked (secondary job)	18.07	14.98	2.00	63.00	258.00

Table 13: Control variables of IV regression in Column 2 of Table 5. Dependent variable is log of per capita household consumption expenditure, instrument is KPS card ownership. Robust standard errors, in parentheses, are clustered by province.

Control	Coefficient	St. Error
Head of HH characteristics		
Age	-0.00318	(0.002)
Married	0.105	(0.110)
Male	0.155	(0.159)
Education		
Elementary	-0.266**	(0.123)
Junior High	-0.146	(0.163)
Senior High +	0.192	(0.123)
Employment type:		
Self-Employed	-0.0199	(0.091)
S.e. non-permanent	0.107	(0.103)
S.e. permanent	0.809***	(0.173)
Employment sector		
Agriculture	-0.942***	(0.241)
Mining	-0.288	(0.358)
Manufacturing	-0.739**	(0.314)
Electrical	-1.333**	(0.540)
Construction	-1.002***	(0.287)
Retail	-0.804***	(0.259)
Transport	-0.859***	(0.318)
Finance	-0.665**	(0.259)
Social services	-0.681***	(0.261)

Control	Coefficient	St. Error
Household characteristics		
Size	-0.0785***	(0.012)
Dependency Ratio	-0.0275	(0.059)
Age 0-4	-0.0307	(0.044)
N children in:		
Elementary	0.0783	(0.208)
Junior High	0.273*	(0.146)
Senior High +	0.322**	(0.144)
House:		
Wall	0.0466	(0.100)
Roof	0.412	(0.277)
Toilet	0.291**	(0.136)
Water	-0.0754***	(0.018)
Own house	0.0586	(0.134)
Gas cook	-0.386***	(0.099)
Floor	0.246***	(0.070)
Assets:		
Vehic.	-0.116	(0.0912)
Appl.	-0.160	(0.178)
Other		
Doctor	-0.105	(0.099)
Urban	-0.0491	(0.131)
BLT card	0.0231	(0.236)

Table 14: Control variables in IV regression. Dependent variable is log of per capita household food expenditure, instrument is KPS card ownership. Robust standard errors, in parentheses, are clustered by province.

Control	Coefficient	St. Error
Head of HH characteristics		
Age	-0.00715***	(0.002)
Married	0.110	(0.112)
Male	0.115	(0.117)
Education:		
Elementary	-0.143	(0.105)
Junior High	0.0259	(0.150)
Senior High +	0.150*	(0.090)
Employment type:		
Self-Employed	-0.0159	(0.092)
S.e. non-perm.	0.0148	(0.091)
S.e. perm.	0.288	(0.182)
Employment sector		
Agriculture	-1.248***	(0.169)
Mining	-0.437	(0.290)
Manufacturing	-1.150***	(0.253)
Electrical	-2.108***	(0.704)
Construction	-1.260***	(0.189)
Retail	-1.211***	(0.191)
Transport	-1.265***	(0.213)
Finance	-1.093***	(0.172)
Social Services	-1.209***	(0.165)

Control	Coefficient	St. Error
Household characteristics		
Size	-0.0944***	(0.00711)
Dependency Ratio	-0.0493	(0.065)
Age 0-4	-0.0246	(0.043)
N children in:		
Elementary	0.149	(0.139)
Junior High	0.324***	(0.096)
Senior High +	0.307***	(0.079)
House:		
Concrete Wall	-0.100	(0.079)
Roof	0.695**	(0.272)
Toilet	0.196*	(0.114)
Water	-0.0311	(0.0251)
Own House	0.0968	(0.106)
Gas cook	-0.286***	(0.108)
Floor	0.270***	(0.0478)
Assets:		
Vehicle	0.0345	(0.104)
Appliance	-0.231*	(0.121)
Other:		
Doctor in village	-0.210***	(0.081)
Urban	-0.0287	(0.124)
BLT program	0.00737	(0.208)

Table 15: Control variables of IV regression in Column 2 of Table 6. Dependent variable is the log of per capita household consumption expenditure, instrument is the interaction term between KPS card and mother administering household consumption decisions.Robust standard errors, in parentheses, are clustered by province.

Control	Coefficient	St. Error
Head of HH characteristics		
Age	-0.00313	(0.00256)
Married	-0.000555	(0.049)
Male	0.216	(0.160)
Education:		
Elementary	-0.348	(0.222)
Junior High	-0.312	(0.202)
Senior High +	0.0290	(0.163)
Employment type:		
Self-Employed	0.00173	(0.139)
S.e. non permanent	0.146	(0.119)
S.e. permanent	0.731***	(0.199)
Employment sector:		
Agriculture	-0.719**	(0.295)
Mining	0.0242	(0.393)
Manufacturing	-0.450	(0.333)
Electrical	-0.599	(0.481)
Construction	-0.647**	(0.324)
Retail	-0.554*	(0.323)
Transport	-0.560	(0.385)
Finance	-0.506	(0.366)
Social services	-0.405	(0.308)

Control	Coefficient	St. Error
Household characteristics		
Size	-0.0739***	(0.0135)
Dependency ratio	-0.0529	(0.089)
Age 0-4	-0.0446	(0.059)
N children in:		
Elementary	0.119	(0.185)
Junior High	0.263**	(0.133)
Senior High +	0.324***	(0.111)
House:		
Concrete wall	0.0843	(0.137)
Roof	0.326	(0.283)
Toilet	0.337**	(0.151)
Water	-0.0783***	(0.030)
Own house	-0.00395	(0.143)
Gas cook	-0.481***	(0.102)
Floor	0.307***	(0.087)
Assets:		
Vehicle	-0.163	(0.106)
Appliance	-0.0626	(0.196)
Other village with doctor	-0.0603	(0.0833)
Urban	-0.125	(0.132)
BLT program	-0.0104	(0.236)

Table 16: Control variables of IV regression in Column 4 of Table 6. Dependent variable is the log of per capita household food expenditure, instrument is the interaction term between KPS card and mother administering household food decisions. Robust standard errors, in parentheses, are clustered by province.

Control	Coefficient	St. Error
Head of HH characteristics		
Age	-0.00696***	(0.00218)
Married	-0.0187	(0.0449)
Male	0.144	(0.114)
Education:		
Elementary	-0.247	(0.150)
Junior High	-0.117	(0.175)
Senior High +	-0.0211	(0.142)
Employment Type:		
Self-Employed	-0.00261	(0.134)
S.e. non permanent	0.0390	(0.108)
S.e. permanent	0.278	(0.177)
Employment sector:		
Agriculture	-0.922***	(0.197)
Mining	-0.0629	(0.392)
Manufacturing	-0.752***	(0.279)
Electrical	-1.028***	(0.395)
Construction	-0.843***	(0.236)
Retail	-0.870***	(0.259)
Transport	-0.784***	(0.294)
Finance	-0.814***	(0.297)
Social Services	-0.829***	(0.233)

Control	Coefficient	St. Error
Household characteristics		
Size	-0.0920***	(0.00819)
Dependency Ratio	-0.0909	(0.0998)
Age 0-4	-0.0239	(0.0411)
N children in:		
Elementary	0.0584	(0.132)
Junior High	0.223***	(0.0836)
Senior High +	0.233***	(0.0573)
House		
Concrete Wall	-0.0728	(0.100)
Roof	0.623**	(0.270)
Toilet	0.199*	(0.119)
Water	-0.0476	(0.0307)
Own house	-0.00226	(0.107)
Gas cook	-0.286**	(0.131)
Floor	0.344***	(0.0674)
Assets:		
Vehicle	-0.0762	(0.0686)
Appliance	-0.122	(0.117)
Other:		
Village with doctor	-0.131**	(0.0563)
Urban	-0.0625	(0.101)
BLT program	-0.00901	(0.190)

Table 17: Additional First stages of Table 6. Columns 1-2 represent the additional first stage for regressions with log of consumption and food, where the dependent variable is BLSM receipt, and instruments are being above the threshold. Columns 3-4 represent the additional first stage for regressions with log of consumption and food, where the dependent variable is BLSM receipt, and instruments are owning a KPS card.

	(1)	(2)	(3)	(4)
	BLSM receipt	BLSM receipt	BLSM receipt	BLSM receipt
Pr(BLSM)	0.490***	0.424***		
	(0.0409)	(0.0405)		
Pr(BLSM)	-0.0257			
x consumption mother	(0.0285)			
Pr(BLSM)		0.0992***		
x food mother		(0.0212)		
KPS card			0.323***	0.270***
			(0.0303)	(0.0317)
KPS card			0.0329	
x consumption mother			(0.0249)	
KPS card				0.0987***
x food mother				(0.0255)
Observations	9,965	9,965	10,019	10,019
Province FE	Yes	Yes	Yes	Yes
F-stat	143.3	109.6	113.7	72.43

Robust standard errors clustered by province in parentheses

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

Table 18: Control Variables of IV regression in Column 2 of Table 7. Dependent variable is the log of hours worked in primary job by household head. Instrument is KPS card ownership.

Control	Coefficient	Standard Error
Head of HH characteristics		
Age	-0.00380***	(0.000718)
Male	0.127***	(0.0277)
Married	-0.00491	(0.0295)
Urban	0.0245	(0.0256)
Education:		
Elementary	0.0793***	(0.0272)
Junior High	0.0932***	(0.0265)
Senior High +	0.0667**	(0.0333)
Employment conditions:		
Working	0.123***	(0.0185)
Self-Employed	-0.189***	(0.0231)
S.E. non-permanent	0.0127	(0.0220)
S.e. permanent	0.0145	(0.0372)
Employment Sector		
Agriculture	-0.175**	(0.0744)
Mining	0.244***	(0.0851)
Manufacturing	0.125*	(0.0679)
Electrical	0.228**	(0.0922)
Construction	0.282***	(0.0613)
Retail	0.184***	(0.0657)
Transport	0.247***	(0.0707)
Finance	0.0751	(0.0552)
Social Services	-0.0808	(0.0698)

Table 19: Control Variables of IV regression in Column 4 of Table 7. Dependent variable is the log of hours worked in secondary job by household head. Instrument is KPS card ownership.

Control	Coefficient	Standard Error
Head of HH characteristics		
Age	-0.000188	(0.00206)
Male	0.212**	(0.0845)
Married	-0.101*	(0.0566)
Urban	-0.0470	(0.0789)
Education:		
Elementary	0.182***	(0.0522)
Junior High	0.105*	(0.0542)
Senior High +	-0.00642	(0.0646)
Employment type:		
Working	0.0528*	(0.0300)
Self-Employed	0.140***	(0.0422)
S.e. non-permanent	0.208***	(0.0561)
S.e. permanent	0.0209	(0.162)
Employment Sector:		
Agriculture	-0.0529	(0.281)
Mining	-0.260	(0.323)
Manufacturing	-0.135	(0.233)
Electrical	-0.0557	(0.341)
Construction	-0.280	(0.280)
Retail	-0.206	(0.244)
Transport	-0.231	(0.293)
Finance	-0.217	(0.276)
Social Services	-0.147	(0.251)

B Figures

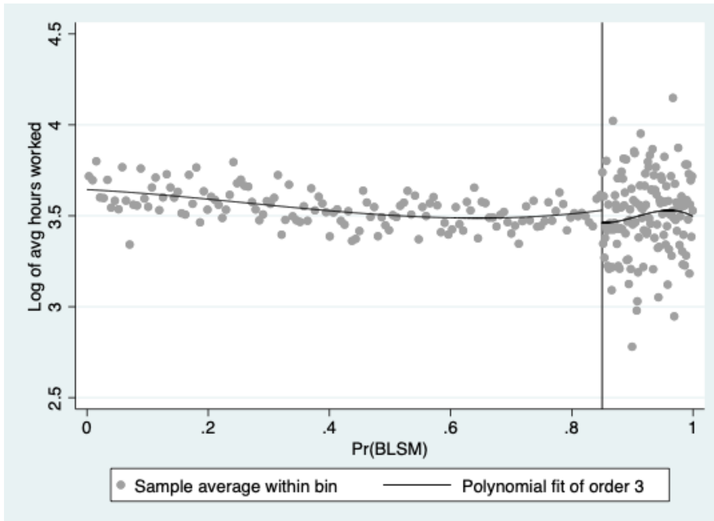

Figure 5: The effect of BLSM on hours worked in main occupation

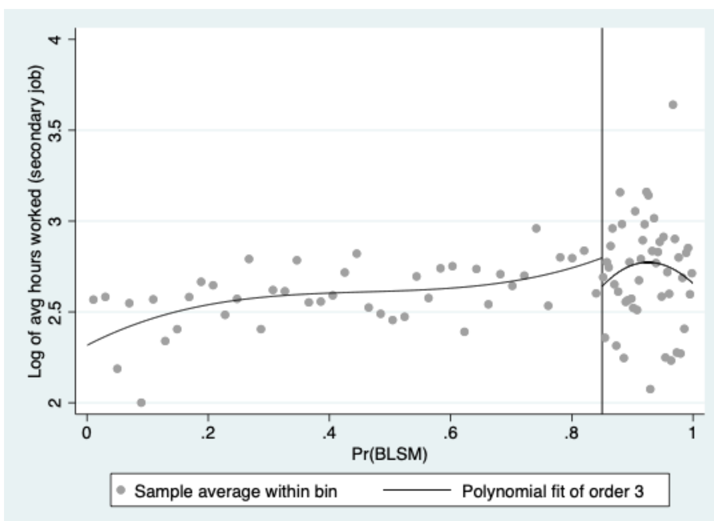

Figure 6: The effect of BLSM on hours worked in secondary occupation

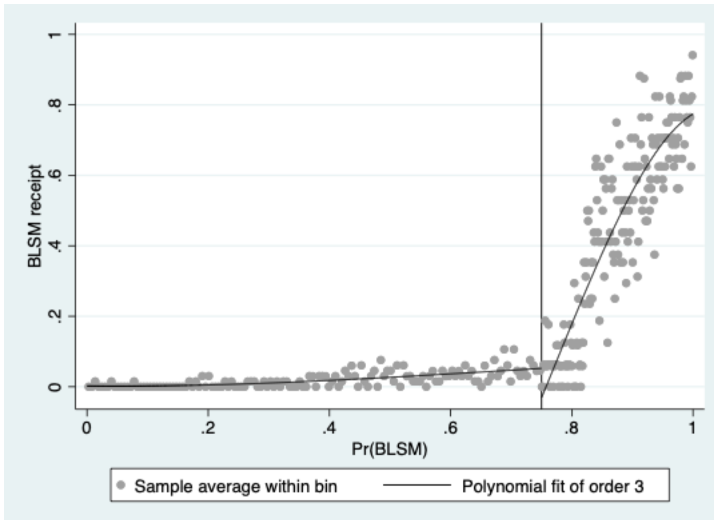

Figure 7: Placebo test for first stage of Fuzzy RD using original 0.75 cutoff

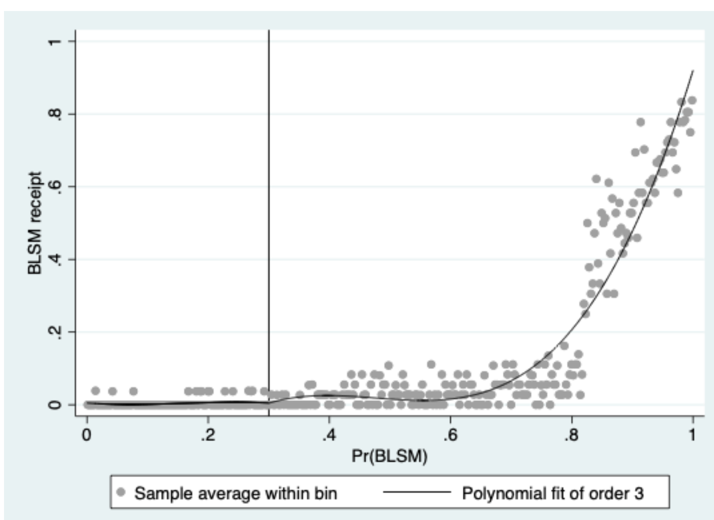

Figure 8: Placebo test for first stage of Fuzzy RD using fictitious 0.3 cutoff

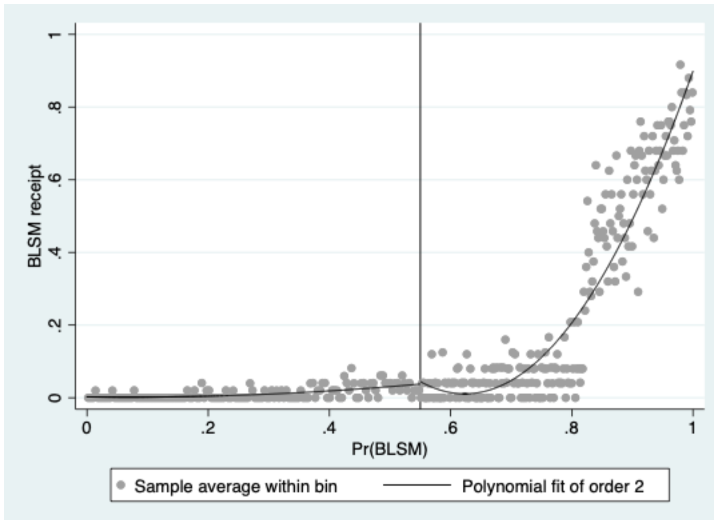

Figure 9: Placebo test for first stage of Fuzzy RD using fictitious 0.55 cutoff

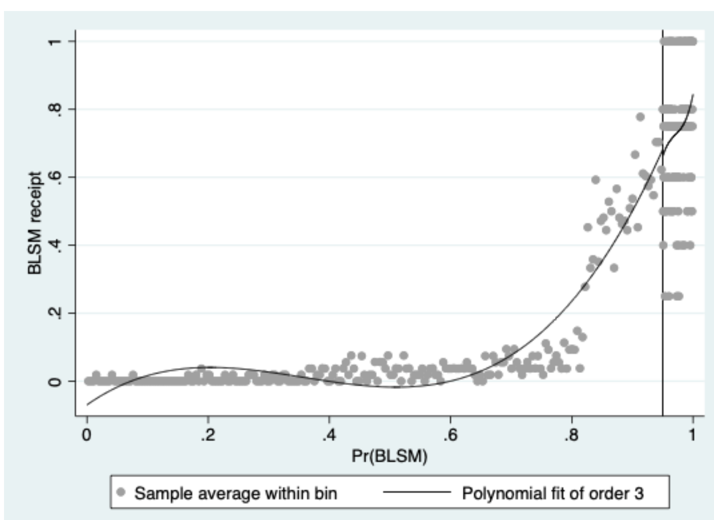

Figure 10: Placebo test for first stage of Fuzzy RD using fictitious 0.95 cutoff