Measuring the Heterogeneous Effects of a Cash Windfall on Women's Empowerment: A Machine Learning and Regression Discontinuity Design Based Approach

A thesis submitted by

Fatimah Faisal

in partial fulfillment of the requirements for the degree of

Master of Science

in

Economics

Tufts University

May 2023

Adviser: Cynthia Kinnan

Abstract

To understand how additional resources affect women's decision-making power and wellbeing, this paper examines the heterogeneity in the impact of a cash windfall based on a woman's initial level of empowerment. By incorporating the predictions obtained through machine learning into the analysis, my paper estimates treatment effects at the individual level, providing a nuanced understanding of how the windfall may affect women based on their characteristics. Meanwhile, through the use of a regression discontinuity design, my paper provides casual estimates of receiving a large windfall. The study finds that the impact of the windfall on women's empowerment varies depending on their initial level of empowerment. While women with low initial empowerment benefit from the windfall, those with higher empowerment experience a negative impact, including an increase in intimate partner violence. This paper has consequential policy implications for women's empowerment programs, including implementing measures to prevent domestic violence.

Table of Contents

List of Tables

List of Figures

Section 1: Introduction

The COVID-19 pandemic has highlighted the importance of social protection measures, particularly in low-income countries where access to resources and opportunities for women is limited. One such measure is cash transfers made to women, which have been used to alleviate poverty and promote economic growth. However, there is mixed evidence on how much women benefit from such schemes, particularly given the concern that the resources may be appropriated by men within the household. There is also a question of whether these effects are uniform across different groups of women. This paper seeks to address these questions by examining the impact of a cash windfall on women's empowerment in southern India.

The literature on the impact of cash transfers on women's empowerment is inconclusive, with some studies finding positive effects and others finding no significant effects. One reason for this discrepancy may be that the impact of cash transfers is contingent on the initial level of empowerment of the beneficiaries. There is some evidence that interventions like cash transfers or working opportunities for women have differential effects on them depending on the characteristics they possess before start of intervention or program. One such study by Heath (2012) show that women with low bargaining power may face reduced empowerment upon entering the labor force.

One challenge in measuring women's empowerment is its latent nature, which makes it difficult to capture using traditional survey methods. In addition, traditional survey methods can be time-consuming and costly, which can limit the scope and scale of such studies. To overcome these challenges, researchers have built more direct measures of measuring empowerment (Malapit et al., 2019), and have used newer and improved data collection techniques such as satellite imagery and mobile phone data (Lobell et al., 2015; Blumenstock, Cadamuro & Onet, 2015).

My paper addresses these challenges by using a combination of machine learning (ML) and regression discontinuity design (RDD) techniques to examine the impact of a cash windfall on women's empowerment. Recent advances in machine learning and quasi-experimental techniques such as regression discontinuity design have opened up new possibilities for estimating causal effects in observational data. In this paper, I leverage these techniques to examine the impact of the cash windfall.

The use of ML allows us to accurately predict women's empowerment status using a variety of observable characteristics. By incorporating these predictions into my analysis, I can estimate treatment effects at the individual level rather than relying on group-level averages. This provides a more nuanced understanding of how the impact of the windfall may vary based on individual characteristics such as initial level of education, a couple’s marriage age gap, access to sanitation and healthcare, or level of economic well-being.

Meanwhile, RDD provides a natural experiment that allows me to estimate the causal effect of the windfall on women's empowerment. By comparing the outcomes of those who received a large cash windfall to *ex ante* similar women who did not, I can isolate the effect of the intervention from other confounding factors. This helps me overcome some of the limitations of traditional observational studies and provides a stronger basis for causal inference.

The combined use of ML and RDD in my paper provides a powerful approach to estimating the impact of a cash windfall on women's empowerment. By leveraging these techniques, I am able to obtain more accurate and precise estimates of treatment effects, while also ensuring that these estimates are causally interpretable. This can have important implications for policymakers and practitioners seeking to design effective social protection programs for women in low-income settings.

The research question of this study is twofold: first, what precise features of a household enable a woman to gain from a sudden cash windfall, and second, does the windfall's effect on women's empowerment depend on varying levels of pre-treatment empowerment? To answer these questions, the study analyzes the impact of a cash windfall on five different categories of outcomes: access to resources, agency, achievements, intimate partner violence, and women's overall empowerment. By answering these questions, I hope to provide insights into the effectiveness of cash transfer programs in improving women's empowerment and inform the design of such programs in the future.

The rest of the paper is organized as follows: Section 2 provides a literature review on the impact of cash transfers on women's empowerment, Section 3 describes the data sources used in the analysis, Section 4 describes the methodology, Section 5 presents the results, Section 6 provides an analysis of the results, and Section 7 concludes with policy implications and recommendations for future research.

Section 2: Literature Review

By increasing decision-making and involvement towards income generating activities, financial access programs such as social protection aim to raise women's empowerment (Chughtai et al, 2015). In Egypt, a 14% increase in women employment has been noticed where women started opening up their own businesses due to a conditional cash grant (Zaky, 2014). Globally, there is evidence from Brazil, Mexico, South Africa, and Bangladesh that social protection programs increase labor market participation, self-employment, and intra-household decision making among women after taking income-generating grants (Bobonis et al, 2013).

In the context of South Asia, the government of Pakistan started the Benazir Income Support Program (BISP) as a means of social protection for women. Poor households were identified after the nationwide "Poverty Score Card Survey" and the proxy means test approach, where people below a certain threshold were targeted. Most studies found that consumption expenditures were positively affected by this grant (Nayab and Shujaat, 2014). Building on past evaluations done in South Asia, my research paper focuses on evaluating the impact of a household receiving extra cash on women's empowerment in the context of Andhra Pradesh, India.

Many financial inclusion programs have been seen as successful, especially during the COVID era, by providing immediate short-term relief to beneficiaries. However, some financial products like microfinance have also been condemned for not meeting the goal of reduced poverty and increased women's empowerment as compared to men. Zinman and Karlan (2010), in their study on impact of microcredit in Philippines, found no evidence that microloans given to women had any larger impact than with loans given to men. A meta-analysis done by Haberland et al. (2021) in their "Review of reviews" discovered that from the 8 reviews included in reviewing the impact of economic interventions such as microfinance or social protection on young girls' and women's empowerment, there is no strong evidence of such programs being effective because of small effect sizes, but those interventions which were combined with business and vocational training saw an increased effect.

Given the mixed results of the impact of these economic interventions, there is a need to conduct more quantitative research to objectively measure the impact of these services on women in particular. Amongst different financial inclusion services, microfinance has played a central role in employing and encouraging the use of quantitative analysis for its impact evaluation, especially through RCTs. My paper moves beyond the current evaluation techniques and makes use of a regression discontinuity design as an identification strategy to study the casual impact of a cash windfall on women's empowerment.

Women's empowerment is difficult to measure due to its latent nature. Most indices on women empowerment such as the Gender Gap Index (World Economic Forum [2018] and prior years), Gender Development Index (GDI), and Gender Inequality Index (GII) (UNDP, 2018), measure gender inequalities in a broad set of categories on an average level. However, they rely on only indirect proxies, such as women's age, schooling attainment, and share of parliamentary seats.

Filling a niche unaddressed by existing metrics, efforts have been made to directly measure women's agency, in more recent years, which is one measure of women's empowerment. Malapit et al (2019) have developed a "Project level Women's Empowerment in Agriculture Index" (PRO-WEAI), which measures women's empowerment in the agricultural sector directly through a focus on women's agency using individual-level data. It focuses on three domains: intrinsic agency (power within), instrumental agency (power to), and collective agency (power with). Another measure developed by Ewerling et al (2017), is the Survey-based women's empowerment Index (SWPER), that represents three dimensions of empowerment: attitudes toward violence, social independence, and decision making. They develop this by analyzing Demographic and Health Survey questions

Most relevant to my research is the paper by Seema Jayachandran et al. (2021), which uses machine learning methods and semi-structured interviews to select the best predictors of women's agency. The paper determines the benchmark level of agency from the semi-structured interviews. The authors have used three types of data to select five survey questions to measure agency of women from Northern India, whereas my paper would use a similar methodology for selecting the best predictors of women's empowerment, but for Southern India. This effort will shed light on differences in women's agency across India and the importance of local context.

A different segment of literature focuses on this aspect of local context and how there is a need to reassess current practices for measuring agency. Donald et al. (2017) highlight conceptual challenges and provides frameworks to guide measurement and insights of adapting this framework to Sub-Saharan African contexts. For the context of India, my paper will make use of the guide "Evaluating women empowerment in impact evaluations," designed by J-PAL (Glennerster et al), predominantly working with India, and will follow the definition stated by Naila Kabeer on women empowerment. She defines women empowerment as "the process by which those who have been denied the ability to make strategic life choices acquire such an ability."

In conclusion, my paper contributes to the literature on the impact of cash transfers on women's empowerment by examining the heterogeneous treatment effects of a cash windfall on women with varying levels of baseline empowerment. By using ML and RDD techniques, and a more direct measure of empowerment, this paper provides a more nuanced understanding of the impact of cash transfers on women's empowerment in southern India.

Section 3: Data Description

3.1 Data source

This paper uses panel data collected by Banerjee et al. (2015), which includes three rounds of survey data. As discussed in earlier papers, a randomized control trial was rolled out in 104 slums in Hyderabad India, starting in early 2006, where initially 52 slums received credit from a Microfinance lender, Spandana. The first round of data collection was completed in late 2007 and the second round was completed in mid-2010. This second round was completed right before a microfinance crisis occurred, abruptly changing the landscape. A third round of data collection was completed in mid-2012, two years after the microfinance crisis.

On 15th October 2010, the government of Andhra Pradesh unexpectedly released an emergency ordinance to regulate microfinance institutions (MFIs) operating in the state. This was due to concerns about over-borrowing by citizens and alleged abuses by microfinance collection agents. The provisions of the ordinance brought the activities of the MFIs to a halt, as they were not allowed to seek loan repayments or disburse any new loans. In mid-2012, the third round of the survey was completed, capturing the direct consequences of the AP ordinance. About one-third of the respondents had an outstanding loan at the time of the second survey in mid-2010, and almost half had taken at least one microloan from any lender between 2004 and 2010. The AP ordinance had two effects on the borrowers in the study: borrowers had their loans waived off and therefore experienced a cash windfall equal to the amount they would have to pay, and secondly, the borrowers would see a reduction in future credit.

This paper will focus on the windfall effect of the crisis by focusing on households who had a maturity date within 10 weeks before or after the crisis, thus estimating a local average treatment effect of receiving a windfall. For this, data on outstanding loan installments was used from the endline 3 dataset where households reported the size of their loans and how many installments they had not paid as of October 2010. This results in the comparison of otherwise similar households who receive different windfalls depending on where they are in the loan repayment cycle. As illustrated in Appendix Figure 1, households borrow similar size loans in late 2009, but at different times. A household which has borrowed a loan earlier would have finished repaying that loan and would have gotten a new loan just before the crisis, and therefore would have many installments remaining which got written-off, resulting in a large windfall. On the other hand, a household which had taken out a loan slightly later, would be close to fully repaying the current loan at the time of crisis and therefore would have few installments left. They would not have started a fresh loan and so would have a smaller windfall. This exogeneous variation in windfall, resulting from small differences in timing of the initial loan disbursement, allows for a regression discontinuity (RD) design to estimate casual effects of receiving a larger windfall[1].

In particular, out of the total sample, the local average treatment effect is estimated for households within +/- 10 weeks of the loan maturity date at the time of crisis, restricting the sample to only 542 households which are within this bandwidth. The methodology section expands on this RD design and the bandwidth selection. Since I am considering this short-term period of only +/- 10 weeks, those who do receive a large windfall are *ex ante* similar to those who do not. For instance, it is unlikely that the effect of reduction in future credit is differential, and so will not bias the estimated effect of the immediate windfall on empowerment.

[1] This exogenous variation is different from the treatment-control variation in the RCT done in the original study by Banerjee et al (2015), where the treatment was the microfinance loan. In this paper, the treatment-control variation comes from the windfall effect of the AP Ordinance crisis, where the treatment is a large windfall defined as more than 80% of installments outstanding. In the rest of the paper treatment refers to receiving a large windfall.

3.2 Outcome measures

All in all, the data contains 6,864 observations from 104 slums, surveyed over three rounds. To measure the outcome variables on women's empowerment, my paper will focus on the endline three (EL3) survey data, from the year 2012 — which was 2 years after the AP ordinance — to analyze the windfall effect. Out of the total sample, the selected bandwidth of +/- 10 weeks restricts the sample to only 542 observations to estimate the effects of the windfall.

I make use of data available on households and women to measure the extent to which the windfall had an empowering effect on them. For this, I create a comprehensive index of women's empowerment using variables from endline three, closely following the framework on measuring women's empowerment designed by Naila Kabeer (1999) where the overall index of empowerment has three subindices measuring access to resources, agency, and women's achievements. Where resources are defined as "gaining access to material, human, and social resources that enhance people's ability to exercise choice, including knowledge, attitudes, and preferences"; agency is defined as "increasing participation, voice, negotiation, and influence in decision-making about strategic life choices"; and achievements is defined as "the meaningful improvements in well-being and life outcomes that result from increasing agency, including health, education, earning opportunities, rights, and political participation, among others". Using this intuitive guide, I construct indices capturing the elements of resources, agency, and achievements, from the data available to me at EL3 (see Table 1). For instances, to capture social capital, data on households borrowing or lending items (including financial items) and taking or giving advice is used as proxy. To measure decision-making of women, data on women taking decisions on household expenditures such as food, education, and health, is used. To measure income generating achievements of women, data on their business activity is used. Table 1 shows the summary statistics of all the variables used to construct the overall index of empowerment, indicating the composition of the subindices as well. The three subindices are constructed following the methodology of Kling, Liebman, and Katz (2007), by constructing an equally weighted average of z-scores for the variables in each category of access to resources, agency, and achievements. Finally, for the overall measure on women's empowerment, all the variables in the three indices are included to construct an equally weighed average of the z-scores of all the variables. In the analysis of my results, apart from the three subindices discussed, I show the results for Intimate partner violence (IPV) as a separate outcome variable to facilitate discussion of those results. For any missing data, I generate flags and include the missingness indicators as controls in the regressions in case they have a statistically significant effect on empowerment.

3.3 Explanatory variables

Additionally, I measure heterogeneity in treatment effect at EL3, given a women's empowerment at the endline two (EL2), just before they got exposed to the windfall effect. For this, I consider a range of time-invariant and time-variant features capturing women's empowerment. This measure of EL2 women's empowerment is different from the EL3 measures of empowerment used as outcome, for the following two reasons.

One caveat of the three round panel data is the change in survey questionnaire throughout the years. Endline 1 and 2 questionnaires are quite similar in construction and do not pose a problem for my research paper. However, for the endline 3 questionnaire, certain questions measuring women's decision-making were removed and an additional module on well-being and social network was included, along with questions on intimate partner violence (IPV). Therefore, it is impossible to construct comparable measures on women's empowerment at EL2 and EL3.

Another reason for using a range of time-invariant and time-variant features is to use machine learning to select the best predictors of empowerment and then use those predictors of pre-treatment empowerment to evaluate the heterogeneity in treatment effect at EL3. Such an exercise can be helpful in contexts where researchers might have constraints on data collection and can only observe either time invariant features or variant features. Table 2 shows the summary statistics of the variables used by machine learning to select the best predictors. Time invariant features include variables such as those on expenditures of education and health, housing material or access to tap water. Instead, time-variant features include variables likely to vary over time and especially be impacted by the treatment, such as the earning gap between the couple or the business profits generated by a woman. This process of feature selection will be explained further in Section 4.

3.4 Balance check

Lastly, one of the most important falsification tests for a regression discontinuity design involves examining whether, near the cutoff, treated units are similar to control units in terms of observable characteristics. These variables can be divided into two groups: variables that are determined before the treatment is assigned — such as those at EL2 — and variables that are determined after the treatment is assigned, but, according to substantive knowledge about the treatment's causal mechanism, could not possibly have been affected by the treatment — such as those at EL3. Table 3 shows that for most covariates, the effect of being in the treatment group is not statistically different from the effect of being in the control group, hence showing that the data is balanced. I control statistically different variables in my regression models.

Section 4: Methodology

4.1 Machine learning to predict pre-treatment level of women's empowerment

This research paper pertains to the growing body of literature on machine learning (ML). While econometric methods aim to provide unbiased estimates of the effect of a variable on an outcome, ML is better suited for maximizing accurate predictions. Despite many policy issues that only require accurate predictions rather than causal inference, the use of ML in such applications has been limited. At the survey design stage, ML can help researchers develop a more effective tool for measuring outcomes by identifying the most relevant and meaningful questions to ask. This can enhance the accuracy and reliability of survey data, which is crucial for policy decisions and understanding complex indicators like women's empowerment. Moreover, it can be a cost-effective way to obtain a good measure of empowerment without conducting long surveys or when resources are limited. On the other hand, once data has been collected, ML has the advantage of selecting the most important predictors from a set of inputs, which is especially useful when the predictors could be many, but observations are limited.

I draw inspiration from the work done by Jayachandran et al. (2021) and follow the methodology, adapted to my dataset and limitations. The paper outlines a methodology for designing a short survey module to measure women's agency using both machine learning and qualitative interviews. The process involves selecting a set of potential questions based on previous literature and then using ML algorithms to identify the most predictive questions. These questions are then refined through qualitative interviews with women to ensure that they capture the intended meaning and are culturally appropriate.

In the case of my paper, in the place of qualitative data, I use the list of variables in Table 2 to predict a "Ground truth" level of EL2 empowerment created by Banerjee et al. (2015), for the previous study. This ground truth measure comprises of variables on the share of children in school, hours worked by children, the share of teenagers in school, female businesses and newly set up businesses by women. My model prediction technique uses LASSO linear regression, where the penalizing parameter is selected through cross-validation since that reports the lowest mean-squared-error in out of sample prediction. I run three LASSO linear regressions to create three sets of predictors: time-invariant predictors, time-variant predictors and a set containing both time-invariant and variant predictors. The purpose for this categorization is to facilitate research in settings where there is no panel data or data on pre-treatment time varying characteristics, in which case, a researcher would use time-invariant features. The purpose of using time varying features is to then see how the addition of each variable could explain the outcome of interest. Table 4 shows the list of predictors selected by ML in each of the three sets.

Once I have my three sets of selected predictors, I predict the EL2 level of empowerment. Lastly, I split that distribution into three equal parts to get variables on low level of predicted EL2 empowerment (LEW), intermediate level of predicted EL2 empowerment (IEW) and high level of predicted EL2 empowerment (HEW) to measure the heterogeneity in treatment effects given one's pre-treatment level of empowerment. I use these predicted variables in my RD design to get casual estimates of the effect of the windfall on EL3 outcomes.

4.2 Identification strategy: Regression Discontinuity Design

The quasi-experimental technique this paper makes use of is regression discontinuity. Due to the AP ordinance crisis households were no longer required to repay their microfinance loans. This meant that households that had more installments left had a large cash windfall as compared to households which had fewer installments left. The loans were very similar in size and so the proportion of installments left to repay was consequential for a household. Another feature of the borrowing process was that fresh loans were often acquired on the same day a loan was paid off, and so the borrowing was cyclical in nature.

For this paper, the identification assumption will be that the variation in size of the "windfall", depending on the timing of withdrawal from the microfinance grant, is exogenous. Therefore, the running variable here will be the percentage of installments outstanding, referred to as the windfall each household gains. The treatment is defined as the households that had just received a new loan and therefore had a large windfall; these households avoided paying 40–50 weekly installment payments and had 80% or more amount of outstanding loan. As for the control group, these households were very close to repaying their current loan and therefore had a small windfall; they avoided paying 0–10 weekly installment payments. The control group also includes some households that were in the control group for the original study done by Banerjee et al., and therefore had never received a microfinance loan. If X is the running variable called windfall percentage, then it takes the following definition:

$$Treatment = \begin{cases} 0 \; if \; X < 0.20 \\ 1 \; if \; X \geq 0.80 \end{cases}$$

(Households with a windfall percentage greater than 0.20 and less than 0.80 are not included in the RDD sample.)

By making use of data on both treatment-control variation in how much of a windfall a household received, and variation based on a regression discontinuity in where a household was in their loan repayment cycle when the crisis occurred, the local average treatment effect will be measured around the cutoff value. Broadly, the equation given below shows how the average treatment effect is calculated. Such an approach measures the difference in means for those just below and above the cutoff and is advantageous as it does not depend on the correct specification of the functional form.

$$\tau_{RD} = E[Y(1) - Y(0) | X = c] = Local\ average\ treatment\ effect$$

Where *X* is the running variable and *c* is the cutoff value. It is expected that the sign of the effect τ will be positive, indicating that an unexpected inflow of cash improves measures of women's empowerment and reduces IPV. However, typically there are not enough data points close to the cutoff value of the discontinuity, resulting in biased estimates. Therefore, my paper will estimate the effect using local linear regression.

I evaluate five categories of outcomes: access to resources, agency, achievements, IPV and women's overall empowerment. For each of these categories, I consider five different models, which are discussed below. Lastly, I also consider the windfall effect on well-being related outcomes and business-related outcomes for women with low levels of L2 empowerment with time-invariant features.

Average Treatment Effects

First, I consider a basic model, where I regress the outcome on the running variable, windfall percentage, and the treatment assignment, large windfall.

$$Y = \alpha + \tau Large\ Windfall + \gamma Windfall\ Percentage + \varepsilon \quad (\mathbf{1})$$

Where Y is the outcome, τ is the causal treatment effect. This model has the advantage of controlling for the nonlinear and discontinuous jump from the smooth linear function of the running variable. Although, the linear specification of the running variable in the OLS model is seldom used due to issues of bias caused by functional form assumption that both potential functions are parallel. Therefore, generally, a more localized linear regression is used where the effect of the running variable is allowed to vary, *h* points below and above the cutoff, and that value *h* is determined in an optimal manner. For the purposes of this paper, this optimal bandwidth is of +/-10 weeks near the cutoff (corresponding to +/- 20 percent of the 50 total weekly payments), considering the limitations of not having enough data points for the running variable, and therefore choosing a bandwidth that has enough power to detect significant effects.

Heterogeneous Treatment Effects

It is interesting to study the average treatment effects of a windfall on outcomes related to women's empowerment post treatment. However, I am especially interested in studying the heterogeneous effects of the windfall for those women with pre-treatment empowerment. For this, I consider a model with an interaction term between the predicted level of EL2 empowerment, with both time-variant and invariant features, and the large windfall term.

$$Y = \alpha + \tau Large\ Windfall + \beta_1 Predicted\ empowerment * Large\ Windfall + \beta_2 Predicted\ empowerment + \gamma Windfall\ Percentage + \varepsilon \quad (\mathbf{2})$$

I refer to this as the Linear model, where τ is the causal treatment effect. I control for the predicted empowerment and the running variable, windfall percentage.

Additionally, I am interested in studying the varying treatment effect for women who had low level of pre-treatment empowerment (Endline 2), in comparison to intermediate and high level of empowerment. This will allow me to study whether anti-poverty programs such as unconditional cash transfers have varying effects for women in improving their level of empowerment, depending on how empowered they are at the start of the program. I use machine learning to predict the level of EL2 empowerment, and then split that predicted value into three equal parts of the distribution, to create indicators for low (LEW), intermediate (IEW), and high level of empowerment (HEW). I then add those indicators as interactions with the treatment in my model. As discussed earlier, for my predicted empowerment I consider three sets of predictors (See Table 4); time-invariant features, time-variant features and both types of features. I run three separate regressions for each set of predictors. Equations 3–5, in tables 5-9, show these results.

First, I consider only the time-invariant features:

$$\begin{aligned} Y = \alpha + \tau Large\ Windfall\ &+ \beta_1 Time\ invariant\ LEW * Large\ Windfall \\ &+ \beta_2 Time\ invariant\ IEW * Large\ Windfall + \beta_3 Time\ invariant\ LEW \\ &+ \beta_4 Time\ invariant\ IEW + \gamma Windfall\ Percentage + \varepsilon \quad (\mathbf{3}) \end{aligned}$$

Here τ can be interpreted as the treatment effect of the large windfall on those with high level of empowerment at Endline 2, β_1 and β_2 are the differential treatment effects for women with low and intermediate levels of empowerment. The total treatment effect for the women with low level of initial empowerment is $\tau + \beta_1$, whereas the effect for the women with intermediate level of initial empowerment is $\tau + \beta_3$.

Next, I consider a model with only time-variant features:

$$\begin{aligned} Y = \alpha + \tau Large\ Windfall\ &+ \beta_1 Time\ variant\ LEW * Large\ Windfall \\ &+ \beta_2 Time\ variant\ IEW * Large\ Windfall + \beta_3 Time\ variant\ LEW \\ &+ \beta_4 Time\ variant\ IEW + \gamma Windfall\ Percentage + \varepsilon \quad (\mathbf{4}) \end{aligned}$$

Where the coefficients follow a similar interpretation.

Lastly, I consider a model with both time-invariant and variant features:

$$Y = \alpha + \tau Large\ Windfall + \beta_1 Predicted\ LEW * Large\ Windfall + \beta_2 Predicted\ IEW * Large\ Windfall + \beta_3 Predicted\ LEW + \beta_4 Predicted\ IEW + \gamma Windfall\ Percentage + \varepsilon \quad (\mathbf{5})$$

All models have standard errors clustered at the slums level and all coefficients reported have been standardized.

Section 5: Results

5.1 Machine learning: Pivotal features

Table 4 shows the EL2 empowerment variables selected by LASSO. The table is divided into three categories: time-invariant predictors, time-variant predictors, and predictors that are both time-invariant and time-variant. The variables selected by LASSO indicate that both stable household characteristics and changing circumstances can affect women's empowerment.

The first column in Table 4 includes time-invariant predictors that are associated with women's empowerment. These variables, which are stable household characteristics, include house roof made of thatch, mother-in-law living in the household, receiving other financial support, female education, monthly medical expenditures, and house has access to own latrine. The fact that these variables are significant predictors suggests that stable household characteristics can have a long-lasting impact on women's empowerment.

The second column includes time-variant predictors that are associated with women's empowerment. These variables, which are changing circumstances, include couple's earning gap (female minus male earning), female owning a bank account, female owning/has primary responsibility of the business, percent of loans taken out by females, female deciding any food or non-food expenditures, monthly profits of female-owned businesses. These variables suggest that changes in a woman's circumstances can also have an impact on her empowerment.

The third column in Table 4 includes predictors that are selected regardless of the time dimension. These variables include couple's marriage age gap, or the medium of instruction being English in the household. This suggests that both stable household characteristics and changing circumstances are important in promoting women's empowerment.

5.2 Casual treatment effects of a large windfall

Moving beyond the prediction exercise, I use my regression discontinuity design to evaluate the impact of receiving a large windfall on five categories of outcomes related to women: Access to resources, agency, achievements, IPV and women's overall empowerment, shown in Tables 5–9. For each of these categories, I consider five different models, discussed under the methodology section. Lastly, I also consider the windfall effect on well-being related outcomes and business-related outcomes for LEW with time-invariant features, shown in Tables 10–11.

Effect on women's access to resources:

The results in Table 5 show that all specifications of the models show a negative but statistically insignificant effect on access to resources, on average, as well as for those women who have a high level of EL2 empowerment (HEW). For the HEW, a one standard deviation increase in treatment results in a 10.4%, standard deviations (s.d) reduction in the EL3 access to resources, for the linear model.

Models 3–5 zoom in on the effect of treatment on LEW vs IEW vs HEW, and interestingly, for the women with low level of predicted empowerment, for all models 3–5, there is a positive, although insignificant, impact of the windfall on their access to resources, with an increase of 3% s.d, 6.5% s.d and 9.5% s.d, all else constant. In this case, the relationship between women with low EL2 empowerment and their EL3 access to resources is negative, so although in general these women have decreased access to resources at EL3, the group of women who received a large windfall had a positive effect. This positive impact in LEW seems to be driven by the time varying features of EL2 empowerment such as women deciding any non-food and food expenditures, percent of loans taken out by women, women earning more monthly income than their husbands, women having primary responsibility of the business, women owning businesses and starting new businesses in last year, and women owning a bank account and earning profits from their businesses.

Conversely, for IEW, the windfall has a negative but insignificant effect on women's access to resources and stays negative considering time- invariant, time-variant or both types of features. For model 5, which includes both types of features, there is a reduction by 8% standard deviations in their access to resources at EL3. In this case, the relationship between women with intermediate EL2 empowerment and their EL3 access to resources is positive. So, although in general these women have increased access to resources at EL3, those group of women who received a large windfall had a negative effect on access to resources.

Overall, the results suggest that a large windfall has a negative impact on women's access to resources for women with a high or an intermediate level of initial empowerment. However, women with a low level of initial empowerment seem to be less affected by the negative impact of the windfall. In particular, a focus on time-variant features as such decision making and women's business activity for low empowered women can help them improve their access to resources after a cash windfall.

Effect on women's agency:

The results in Table 6 show that all specifications of the models show a positive but statistically insignificant effect on agency, on average, as well as for those women who have a high level of EL2 empowerment (HEW). For the HEW, a one standard deviation increase in treatment results in a 1.2% s.d increase in the EL3 agency, for the linear model. In the rest of the models, the trend is the same, except in model 3, where HEW with time-invariant features have a negative effect of windfall on agency.

For women with intermediate empowerment, there is a positive but insignificant effect on their EL3 agency for all models. Column 5 in Table 6 shows that for such women, an increase of 5.2% standard deviation in their post treatment agency can be seen. This positive impact seems to be driven primarily by the time-invariant features of EL2 empowerment.

The gains in EL3 agency are highest for LEW, most evident in model 5. There is a positive impact of the windfall on their agency, with an increase of 5.4% standard deviations. This positive impact seems to be driven by the time-invariant features of EL2 empowerment such as reduced education gap and age gap between couples, households with expenditures in health and education, and households which have basic amenities (see Table 4 for full list of features). Table 6, col 3, shows that for such women, an increase of 4.8% standard deviation in their post treatment agency can be seen.

It is also interesting to note that for women with low and intermediate empowerment, the relationship between their EL2 empowerment and their EL3 agency is negative and statistically significant. This implies that although in general these women have decreased agency at EL3, amongst them, those who received a large windfall had a positive effect on their EL3 outcomes.

These results suggest that a large windfall can have a negative impact on women's agency for women with a high level of initial empowerment. However, women with a low level of initial empowerment seem to have a positive impact of the windfall and gain agency at EL3. In particular, a focus on time-invariant features as such housing material and availability of amenities for low empowered women can help them improve their agency after a cash windfall.

Effect on women's achievements:

The effect on women's level EL3 achievements is similar in nature to the effect on access to resources. The results in Table 7 show that a large windfall has a negative but insignificant effect on women's achievements, on average, as well as for HEW in all models, except for model 3. Model 2 reports that for HEW, a one standard deviation increase in treatment results in a 4.4% s.d reduction in the EL3 achievements.

For women with intermediate level of predicted empowerment, which includes both time-variant and invariant features, they have a positive but smaller and insignificant impact of the windfall on women's achievements. The impact is 0.5% less for IEW as compared to LEW, when considering all features, as shown in columns 5, 3, and 4 of Table 7.

In model 5, for LEW, there is a positive impact of the windfall on their achievements, with an increase of 0.9% standard deviations. This positive impact in LEW seems to be driven by the time varying features of EL2 empowerment such as women deciding any non-food and food expenditures (see Table 4 for full list of features). Table 7, column 4, shows that for such low empowered women, given their time varying features, an increase of 1.7% standard deviation in their post treatment level of achievements can be seen. On the other hand, variation driven by invariant features of empowerment is associated with a decrease in achievements at EL3.

Similar to the previous results is also the finding that for LEW, the relationship between their EL2 empowerment and their EL3 achievements is negative. This implies that although in general these women have decreased level of achievements at EL3, amongst them those who received a large windfall had a positive effect on their EL3 outcomes.

These results suggest that a large windfall has a negative impact on women's achievements for women with a high level of initial empowerment and a less positive impact on women with intermediate empowerment. However, women with a low level of initial empowerment have a positive impact of the windfall and see improvement in their achievements at EL3. In particular, a focus on time-variant features as such decision making and women's business activity for low empowered women can help them improve their achievements after a cash windfall.

Effect on Intimate Partner Violence:

The results in Table 8 show that the ATE or the HTE in the linear model have a positive but statistically insignificant impact of windfall on IPV. However, in models 3–5, which zoom in on the differences between LEW, IEW, HEW, all specifications of the models show a positive and statistically significant effect on IPV.

In models 3–5, in the case of HEW, the results show that the large windfall leads to an increased significant effect on cases of IPV. For HEW, a one standard deviation increase in treatment results in a 10.3%, 11.8% and 11.0% increase in IPV for all three specifications, respectively. These results are significant at the 10% level and raise a cause for concern.

On the other hand, for models 3–5, I observe that for low and intermediate empowered women, there is a negative but insignificant effect of the large windfall on domestic violence. Overall, the results from column 5 in Table 8 suggest that intermediate empowered women see most reduction in domestic violence, followed by low empowered women. This effect is especially driven by time varying features of empowerment, as shown in Table 8, where the estimate for IEW in reducing violence is 9.2% and for LEW is 6.6%. Interestingly, it is also for these set of time-variant features that high empowered women see the highest increase in cases of violence, amongst all three specifications.

Additionally, for women with low and intermediate empowerment, the relationship between their EL2 empowerment and their EL3 level of violence is positive. This implies that although in general these women have increased level of violence at EL3, amongst them those women who received a large windfall had a positive effect in terms of reducing domestic violence.

These results are interesting insomuch as they suggest that for high empowered women, a large windfall increases domestic violence especially in the case of initial level of time varying empowerment such as increased decision making and women's business activity. However, women with a low or intermediate level of initial empowerment experience a positive impact of the windfall by way of reducing domestic violence.

Effect on overall women's empowerment

Overall, the results reported in Table 9 show that for all specifications of the model, the impact on average as well as on HEW is negative, although insignificant. A one standard deviation increase in treatment results in a 6.6% s.d reduction in empowerment at EL3, as shown in column 2. This negative effect is more prominent in the case of time-variant empowerment as opposed to time-invariant empowerment.

For IEW, the impact of the windfall is negative and insignificant, but less negative as compared to high empowered women. A one standard deviation increase in treatment results in a 0.2% s.d reduction in empowerment for IEW but a 7.9% s.d reduction in empowerment for HEW, as shown in column 5 of Table 9.

The LEW seem to gain most from the windfall as they see a positive, although insignificant effect for all specifications. A one standard deviation increase in treatment results in a 6.7% s.d improvement in empowerment at EL3, as shown in column 5. Here, the effect is more positive in the case of time-variant empowerment as compared to time-invariant empowerment.

Lastly, in line with the previous results for LEW, the relationship between their EL2 empowerment and their EL3 empowerment is negative and statistically significant. This implies that although in general these women have decreased level of empowerment at EL3, amongst them those who received a large windfall had a positive effect on their EL3 outcomes.

Effects on well-being related outcomes

Table 10 shows that in the case of HEW and IEW, the large windfall leads to an increase in the happiness scale by 24.3% s.d, a null effect on financial worries, and a reduction in overall worries index by 5.2% s.d, however all these effects are statistically insignificant. However, for the LEW, the large windfall leads to a decrease in the happiness scale by 0.6% s.d, a reduction in financial worries index by 17.3% s.d, and a reduction in overall worries index by 9.6% s.d, however all these effects are statistically insignificant.

Overall, high empowered women have the largest treatment effect in improving household happiness, but it is the low empowered women’s households that see the largest treatment effect in reducing overall worries and financial worries.

Effects on business related outcomes

The effect of the large windfall in improving business related outcomes is mostly negative and insignificant for households with high empowered women, as shown in Table 11. However, households with low empowered women perform slightly better on business outcomes as compared to the other types of women. These gains are also statistically insignificant.

Section 6: Analysis

This section analyzes the heterogeneity in results in the context of economic theory and literature. The overall results presented in this paper show that a large windfall has a negative impact on women's empowerment for those women who have a high or intermediate level of initial empowerment but a positive effect for women with low initial empowerment.

These findings are consistent with the literature in microfinance that suggests that the impact of cash transfers on the welfare of the poor is contingent on the initial level of poverty (Bastagali et al. 2016). Specifically, the results of my study suggest that cash transfers may have a positive impact on the welfare of those who are most deprived but may have negative or no impact on those who are less deprived. This is consistent with the theory of diminishing marginal utility, which suggests that the impact of a given amount of money on well-being decreases as the level of initial resources increases.

The negative effect of a large windfall on high empowered women can also be explained by the "resource curse" hypothesis, which suggests that sudden wealth can have negative effects on individuals and communities (Auty, 1993). In the context of microfinance, the resource curse hypothesis has been applied to study the impact of large lump-sum payments on the borrowers' credit discipline and financial behavior.

This finding is also consistent with previous studies on the negative impact of sudden wealth on financial discipline and savings behavior (Banerjee et al., 2015). Interestingly, for the women with low level of predicted empowerment, there is a positive impact of the windfall on their access to resources, which may be attributed to the beneficiaries' improved financial behavior and habits after receiving the windfall. This positive impact on low empowered women seems to be driven by the time-varying features of EL2 empowerment such as women's decision-making power and business activity, which may enhance their ability to invest and manage the windfall effectively (Pitt et al., 2006).

The negative impact of a large windfall on women's empowerment in my study may also be due to the disruption of the beneficiaries' financial habits and routines, increased spending on luxury goods and decreased savings, which may have negative consequences on their sense of agency and control over their lives.

Another key takeaway that merits discussion is that IPV increases for women with high initial empowerment but reduces for women with low initial empowerment. The findings from my research can be understood in the context of research which suggests that when women challenge traditional gender roles and assert their autonomy and independence, they may be perceived as violating societal norms and provoking a backlash from their partners. This can manifest in the form of verbal, physical, or psychological abuse, and may be an attempt by the partner to re-establish control and dominance in the relationship.

The increase in IPV post-treatment is driven by time-variant features of EL2 empowerment possessed by a HEW, as opposed to time-invariant features. By construction, (see Table 4), time-invariant features of empowerment have mostly to do with household features of long-term stability, often provided by or facilitated by a male partner or household head, resulting in empowerment. This type of empowerment at EL2, which is regulated by a man, saw less instances of IPV at EL3. As opposed to that, time-variant features mostly had to do with the women herself and her ability to gain economic empowerment via business profits or financial inclusion. Since this type of empowerment is unlikely to be regulated by a man, the instances of IPV increased, further eluding to this "backlash effect", where the male partner feels threatened.

Ericsson (2020) provides a comprehensive review of literature on the backlash effect in developing countries. The study suggests that as women become economically empowered, they may face a backlash from their partners, families, and communities. This backlash can take several forms, including domestic violence, gender-based discrimination, and social exclusion. Macmillan and Gartner (1999) in their paper focus on the impact of women's labor force participation on domestic violence. The study finds that women who work outside of the home are at a higher risk of experiencing spousal violence compared to those who do not work outside the home. The findings suggest that men may feel emasculated or threatened by their partner's economic empowerment, leading to an increase in domestic violence.

The study by Heath (2014) examines the impact of women's access to labor market opportunities and control over household resources on domestic violence in Bangladesh. The findings suggest that women who have greater baseline bargaining power have control over household resources and are less likely to experience domestic violence, while those with less baseline bargaining power are more likely to experience violence. This is contrary to my findings which suggest that women who had high initial empowerment faced more domestic violence when exposed to the windfall, as opposed to women who had low initial empowerment.

In a study similar to mine, Ferrari, and Iyengar (2010) found that a microfinance program in Burundi led to an increase in women's reported empowerment but had no effect on domestic violence. This evidence points to the need to supplement social protection programs with training engaging men and boys in addressing harmful gender norms which could lead to IPV. Kim et al (2009) discovered that a microfinance intervention randomly assigned in South Africa had a positive impact on women's economic status but did not lead to a reduction in domestic violence. However, the group that received microfinance in conjunction with gender and HIV training experienced a decrease in domestic violence.

Overall, the literature suggests that the backlash effect is a significant issue in cases of female economic empowerment, particularly in developing countries. Women who gain access to economic resources and labor market opportunities may face backlash from their partners, families, and communities, leading to an increase in domestic violence. Therefore, when designing programs on poverty reduction or women's empowerment, it is important to recognize and address the backlash effect in efforts to promote gender equality and women's empowerment, as it can have negative consequences for women's safety, well-being, and progress towards gender equality.

However, I may also be getting these results due to a selectivity bias or reverse causality. It is possible that high empowered women in my sample differ in important ways from low empowered women that are not captured by my measures. For example, high empowered women may be more likely to leave abusive partners or report violence, while low empowered women may feel they have fewer options and are more likely to stay in abusive relationships. It is also possible that the relationship between women's empowerment and domestic violence is not causal, but rather that experiencing domestic violence can actually lead to a greater desire for empowerment and autonomy. However, the use of variation in resources arising from exogenous variation in a cash windfall (via the RD design), interacted with initial empowerment helps to mitigate these concerns.

A third key takeaway from my paper is that for low empowered women, time-variant empowerment is associated with improved achievements and access to resources after a cash windfall, while time-invariant empowerment is associated with improved agency.

For low empowered women, a cash windfall may have a significant impact on their achievements and access to resources as it provides a one-time boost to their economic status. When cash is provided to low-empowered women, they can purchase necessary resources that they were previously unable to afford, such as food, healthcare, and education. This leads to an improvement in their overall achievements and access to resources.

However, time-invariant empowerment, which indicates a long-term state of empowerment could be more important for allowing women to have control over their own lives and resources and therefore may lead to improved agency for low-empowered women, as they are able to make choices and act on them, independent of cash windfalls or other external factors. Thus, long-term state of empowerment could be an important factor for improved agency of a woman.

Section 7: Conclusion

In conclusion, this paper highlights the heterogeneity in the impact of a large windfall on women's empowerment, which varies depending on their initial level of empowerment. While the windfall has a positive impact on women with low initial empowerment, it has a negative effect on women with high or intermediate initial empowerment. Furthermore, the study highlights the increase in intimate partner violence (IPV) for women with high initial empowerment, which suggests the existence of a backlash effect against female economic empowerment.

The findings of this study have important policy implications for poverty reduction and women's empowerment programs. Firstly, policymakers and practitioners should recognize the heterogeneity in the impact of cash transfers on women's empowerment and tailor their interventions accordingly. Programs should be designed to target women with low initial empowerment and focus on providing them with the necessary resources and training to build their capacity and enhance their financial behavior and habits.

Secondly, policymakers should recognize the potential for backlash against female economic empowerment and implement measures to prevent and respond to domestic violence. This could include initiatives that promote gender equality, protect women's rights, and provide support to women who experience domestic violence. In addition, programs that engage men and boys in promoting gender equality and addressing harmful gender norms could be effective in reducing the prevalence of intimate partner violence.

Finally, future research should focus on identifying the mechanisms through which a large windfall affects women's empowerment and how to mitigate the negative consequences for women with high initial empowerment. Additionally, more research is needed on the link between economic empowerment and intimate partner violence, particularly in different cultural and socioeconomic contexts.

Overall, this study highlights the importance of addressing the heterogeneity in the impact of cash transfers on women's empowerment and the need for policies and programs that promote gender equality and prevent intimate partner violence. By doing so, we can promote women's empowerment and reduce poverty in a sustainable and equitable manner.

Tables

Table 1 – Summary statistics for EL3 Women's empowerment index

	Mean	SD	Min	Max	Observations
Access to resources:					
Female owning a bank account	0.75	0.44	0	2	542
Female-owned businesses	0.21	0.45	0	2	542
New business in last year * female most knowledgeable	0.02	0.16	0	2	542
HH borrowed items/advice from social network	10	3.7	0	19	542
HH borrowed financial items/advice from social network	6.3	2.04	0	11	542
HH borrowed non-financial items/advice from social network	3.7	2.35	0	9	542
HH lent items/advice to social network	7.99	3.07	0	17	542
HH lent financial items/advice to social network	4.99	1.76	0	9	542
HH lent non-financial items/advice to social network	2.99	1.9	0	8	542
Agency:					
Pro-woman attitudes index	0.29	0.21	0	1	542
Percent of loans taken out by females	1.8	2	0	10	542
Female takes most decisions about business	0.16	0.37	0	1	542
Female takes most decisions about Profit	0.03	0.16	0	1	542
Cases when beating wife not justified	0.16	0.3	0	1	542
Not Beaten in last month	0.94	0.25	0	1	542
Achievements:					
Log monthly inputs, female-owned businesses	1.3	2.98	0	13.59	542
Log monthly revenue, female-owned businesses	1.53	3.3	0	13.71	542
Log monthly profits, female-owned businesses	1.35	2.93	0	11.51	542
Total weekly labor hours, female-owned businesses	7.54	23.91	0	280	542
Value of assets mostly owned by Females	170000	130000	2000	830000	542
Monthly earning gap - Female minus male earning	-1222.08	3610.34	-28000	27000	542

Table 2: Summary statistics for EL2 variables used for model prediction

	Mean	SD	Min	Max	Observations
Complete list of Time-invariant features					
Ratio of pucca rooms in the house	0.36	0.47	0	1	542
House roof made of thatch	0.02	0.15	0	1	542
House has access to own latrine	0.62	0.49	0	1	542
Couple's Marriage gap: Female minus male age	-5.01	3.86	-20	12	542
Mother-in-law lives in HH	0.18	0.38	0	1	542
Couple's Education gap: Female minus male education	-1.46	4.18	-15	10	542
Female working amongst all women	0.57	0.49	0	1	542
Education from a government institution	0.89	0.31	0	1	542
Education from a private institution	0.74	0.44	0	1	542
Medium of instruction is English	0.74	0.44	0	1	542
Worked at a business owned by neighbor	0	0	0	0	542
Received other financial support	0.24	0.43	0	1	542
HH uses tap water	0.89	0.31	0	1	542
HH lives in own house	0.58	0.49	0	1	542
HH has rooms that are totally waterproof	0.44	0.5	0	1	542
Female being educated	3.46	3.81	0	15	542
Monthly education expenditures	919.67	1734.12	0	18394.95	542
Monthly medical expenditures	813.75	2224.87	0	37178.63	542
Complete list of Time-variant features					
Female owning a bank account	0.79	0.42	0	2	542
Female owns/has primary responsibility of the business	0.21	0.41	0	1	542
Female-owned businesses	0.34	0.63	0	5	542
Monthly earning gap: Female minus male earning	-3018.36	4886.88	-49000	24525	542
Percent of loans taken out by females	1.89	2.49	0	14	542
New business in last year * female most knowledgeable	0.06	0.28	0	2	542
Female deciding any non-food expenditures	0.51	0.5	0	1	542
Female deciding any food expenditures	0.64	0.48	0	1	542
Log monthly profits, female-owned businesses	3.34	4.11	0	11.32	542

Table 3 – EL2 and EL3 Balance check

	EL2			EL3		
	Control Mean	Treatment Mean	Coefficient on treatment	Control Mean	Treatment Mean	Coefficient on treatment
Household Composition						
Number members	6.25	6.46	-0.711	5.86	5.79	-0.980*
Number adults	3.45	3.36	-0.125	3.55	3.34	-0.504
Male head	0.81	0.88	0.0346	0.77	0.79	0.0426
Female Head	0.23	0.22	0.0513	0.23	0.21	-0.0426
Access to credit						
Loan from Spandana	0.15	0.37	-0.183*	0.07	0.36	-0.149
Loan from other MFI	0.03	0.04	-0.0742	0.00	0.01	0.0179**
Loan from a bank	0.07	0.09	0.168***	0.05	0.05	-0.0213
Informal loan	0.60	0.67	-0.0337	0.62	0.78	0.125
Amount borrowed from (in INR)						
Spandana	1425.55	3305.39	-979.8	1448.19	3325.30	-976.7
Other MFI	1722.58	3488.02	553.0	1739.17	3509.04	545.9
Bank	5657.12	6613.65	9,241**	9780.43	3595.92	2,363
Informal loan	32324.66	36865.01	10,263	56774.92	68607.10	23,338
Business Activity						
Businesses in total	0.58	0.75	0.167	0.40	0.46	-0.118
Revenue	6023.11	5635.80	645.8	7923.90	6692.43	-4,164
Hours worked per week	14.88	18.78	-2.774	14.88	18.78	-2.774
Consumption						
Total monthly nondurables expenditure	9553.10	9972.03	798.2	11912.65	12187.19	-1,995
Total monthly expenditure	10429.35	11156.02	992.5	13004.67	13785.59	-2,252
Total monthly durables expenditure	8659.92	11834.82	1,941	13103.07	19180.76	-3,081
Temptation goods expenditure per capita	110.54	173.40	-70.94*	131.35	244.12	30.18
Annual festival expenditure	6134.77	6426.81	-1,951	9099.25	9720.12	-1,631

Table 4: EL2 empowerment variables selected by LASSO

	Variables selected by LASSO		
Predictors	*Time-invariant*	*Time-variant*	*Time-variant & invariant*
House roof made of thatch (EL2)	✓		✓
Couple's Marriage gap: Female minus male age (EL2)	✓		✓
Mother-in-law lives in HH (EL2)	✓		✓
Received other financial support (EL2)	✓		✓
Female being educated (EL2)	✓		✓
Monthly medical expenditures (EL2)	✓		✓
Female owning a bank account (EL2)		✓	✓
Female owns/has primary responsibility of the business (EL2)		✓	✓
Monthly earning gap: Female minus male earning (EL2)		✓	✓
Percent of loans taken out by females (EL2)		✓	✓
Female deciding any non-food expenditures (EL2)		✓	✓
Female deciding any food expenditures (EL2)		✓	✓
Log monthly profits, female-owned businesses (EL2)		✓	✓
House has access to own latrine (EL2)	✓		
Couple's Education gap: Female minus male education (EL2)	✓		
Female working amongst all women (EL2)	✓		
Education from a government institution (EL2)	✓		
HH uses tap water (EL2)	✓		
HH has rooms that are totally waterproof (EL2)	✓		
Monthly education expenditures (EL2)	✓		
New business in last year * female most knowledgeable (EL2)		✓	
Medium of instruction is English (EL2)			✓
HH lives in own house (EL2)			✓

Table 5: Effect on measures of Access to resources at EL3

	Access to resources (EL3)				
	ATE	Linear Model	Time-invariant HTE	Time-variant HTE	Time-variant & invariant HTE
	(1)	(2)	(3)	(4)	(5)
Large windfall	-0.076	-0.104	-0.091	-0.111	-0.106
	(0.102)	(0.105)	(0.124)	(0.118)	(0.121)
Predicted empowerment * Large Windfall		0.003			
		(0.107)			
Predicted empowerment		0.042			
		(0.057)			
Time-invariant LEW * Large Windfall			0.003		
			(0.079)		
Time-invariant IEW * Large Windfall			-0.006		
			(0.069)		
Time-invariant LEW			-0.083**		
			(0.041)		
Time-invariant IEW			-0.052		
			(0.033)		
Time-variant LEW * Large Windfall				0.067	
				(0.126)	
Time-variant IEW * Large Windfall				-0.023	
				(0.102)	
Time-variant LEW				-0.080	
				(0.065)	
Time-variant IEW				-0.001	
				(0.056)	
Predicted LEW * Large Windfall					0.095
					(0.122)
Predicted IEW * Large Windfall					-0.080
					(0.106)
Predicted LEW					-0.093
					(0.072)
Predicted IEW					0.057
					(0.056)
Windfall Percentage	-0.250	-0.386	-0.370	-0.363	-0.393
	(0.459)	(0.469)	(0.480)	(0.468)	(0.475)
Observations	542	542	542	542	542
Low-windfall Mean			0.000		

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Effect on measures of Agency at EL3

	Agency (EL3)				
	ATE	Linear Model	Time-invariant HTE	Time-variant HTE	Time-variant & invariant HTE
	(1)	(2)	(3)	(4)	(5)
Large windfall	0.036	0.012	-0.016	0.015	0.002
	(0.081)	(0.083)	(0.106)	(0.100)	(0.101)
Predicted empowerment * Large Windfall		0.042			
		(0.119)			
Predicted empowerment		0.259***			
		(0.060)			
Time-invariant LEW * Large Windfall			0.048		
			(0.119)		
Time-invariant IEW * Large Windfall			0.096		
			(0.134)		
Time-invariant LEW			-0.239***		
			(0.061)		
Time-invariant IEW			-0.209***		
			(0.063)		
Time-variant LEW * Large Windfall				-0.000	
				(0.127)	
Time-variant IEW * Large Windfall				0.007	
				(0.112)	
Time-variant LEW				-0.230***	
				(0.066)	
Time-variant IEW				-0.171***	
				(0.065)	
Predicted LEW * Large Windfall					0.054
					(0.119)
Predicted IEW * Large Windfall					0.052
					(0.115)
Predicted LEW					-0.263***
					(0.060)
Predicted IEW					-0.235***
					(0.060)
Windfall Percentage	0.226	0.046	0.197	0.152	0.230
	(0.351)	(0.343)	(0.354)	(0.355)	(0.351)
Observations	542	542	542	542	542
Low-windfall Mean	0.000				

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Effect on measures of Achievement at EL3

	Achievements (EL3)				
	ATE	Linear Model	Time-invariant HTE	Time-variant HTE	Time-variant & invariant HTE
	(1)	(2)	(3)	(4)	(5)
Large windfall	-0.044	-0.025	0.027	-0.019	-0.027
	(0.057)	(0.058)	(0.058)	(0.063)	(0.062)
Predicted empowerment * Large Windfall		0.010			
		(0.065)			
Predicted empowerment		0.008			
		(0.033)			
Time-invariant LEW * Large Windfall			-0.041		
			(0.065)		
Time-invariant IEW * Large Windfall			-0.116		
			(0.072)		
Time-invariant LEW			-0.010		
			(0.044)		
Time-invariant IEW			0.062*		
			(0.037)		
Time-variant LEW * Large Windfall				0.017	
				(0.071)	
Time-variant IEW * Large Windfall				-0.030	
				(0.071)	
Time-variant LEW				-0.035	
				(0.042)	
Time-variant IEW				0.038	
				(0.038)	
Predicted LEW * Large Windfall					0.009
					(0.072)
Predicted IEW * Large Windfall					0.004
					(0.074)
Predicted LEW					-0.035
					(0.044)
Predicted IEW					-0.009
					(0.035)
Windfall Percentage	-0.133	-0.087	-0.112	-0.092	-0.084
	(0.270)	(0.271)	(0.285)	(0.277)	(0.272)
Observations	542	542	542	542	542
Low-windfall Mean	0.000				

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Effect on Intimate Partner Violence at EL3

	Beaten in last month (EL3)				
	ATE	Linear Model	Time-invariant HTE	Time-variant HTE	Time-variant & invariant HTE
	(1)	(2)	(3)	(4)	(5)
Large windfall	0.062	0.073	0.103*	0.118*	0.110*
	(0.054)	(0.053)	(0.056)	(0.064)	(0.062)
Predicted empowerment * Large Windfall		0.035			
		(0.060)			
Predicted empowerment		-0.025			
		(0.017)			
Time-invariant LEW * Large Windfall			-0.065		
			(0.066)		
Time-invariant IEW * Large Windfall			-0.022		
			(0.063)		
Time-invariant LEW			0.006		
			(0.021)		
Time-invariant IEW			0.011		
			(0.025)		
Time-variant LEW * Large Windfall				-0.066	
				(0.076)	
Time-variant IEW * Large Windfall				-0.092	
				(0.059)	
Time-variant LEW				0.020	
				(0.027)	
Time-variant IEW				0.004	
				(0.019)	
Predicted LEW * Large Windfall					-0.047
					(0.074)
Predicted IEW * Large Windfall					-0.081
					(0.062)
Predicted LEW					0.027
					(0.025)
Predicted IEW					0.022
					(0.020)
Windfall Percentage	-0.035	0.016	0.022	-0.015	-0.003
	(0.259)	(0.254)	(0.258)	(0.249)	(0.253)
Observations	542	542	542	542	542
Low-windfall Mean	0.042				

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Effect on Overall Women's empowerment at EL3

	Women's empowerment (EL3)				
	ATE	Linear Model	Time-invariant HTE	Time-variant HTE	Time-variant & invariant HTE
	(1)	(2)	(3)	(4)	(5)
Large windfall	-0.051	-0.066	-0.059	-0.077	-0.079
	(0.055)	(0.055)	(0.068)	(0.061)	(0.064)
Predicted empowerment * Large Windfall		0.006			
		(0.066)			
Predicted empowerment		0.088***			
		(0.033)			
Time-invariant LEW * Large Windfall			0.003		
			(0.079)		
Time-invariant IEW * Large Windfall			-0.006		
			(0.069)		
Time-invariant LEW			-0.083**		
			(0.041)		
Time-invariant IEW			-0.052		
			(0.033)		
Time-variant LEW * Large Windfall				0.049	
				(0.072)	
Time-variant IEW * Large Windfall				0.005	
				(0.057)	
Time-variant LEW				-0.104***	
				(0.037)	
Time-variant IEW				-0.031	
				(0.031)	
Predicted LEW * Large Windfall					0.067
					(0.069)
Predicted IEW * Large Windfall					-0.002
					(0.060)
Predicted LEW					-0.119***
					(0.040)
Predicted IEW					-0.039
					(0.030)
Windfall Percentage	-0.083	-0.183	-0.149	-0.142	-0.137
	(0.257)	(0.256)	(0.266)	(0.255)	(0.259)
Observations	542	542	542	542	542
Low-windfall Mean	0.000				

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Effect on Well-being related outcomes at EL3

	Overall worries index (EL3)	*Finance worries index (EL3)*	*Happiness scale (EL3)*
	(1)	(2)	(3)
Large windfall	-0.052	0.000	0.243
	(0.141)	(0.149)	(0.202)
Time-invariant LEW * Large Windfall	-0.096	-0.173	-0.006
	(0.126)	(0.125)	(0.204)
Time-invariant LEW	0.010	-0.000	-0.038
	(0.082)	(0.085)	(0.123)
Windfall Percentage	-0.183	-0.051	0.274
	(0.612)	(0.605)	(0.763)
Observations	522	522	521
Low-windfall Mean	-0.0280	-0.0224	-0.0337

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

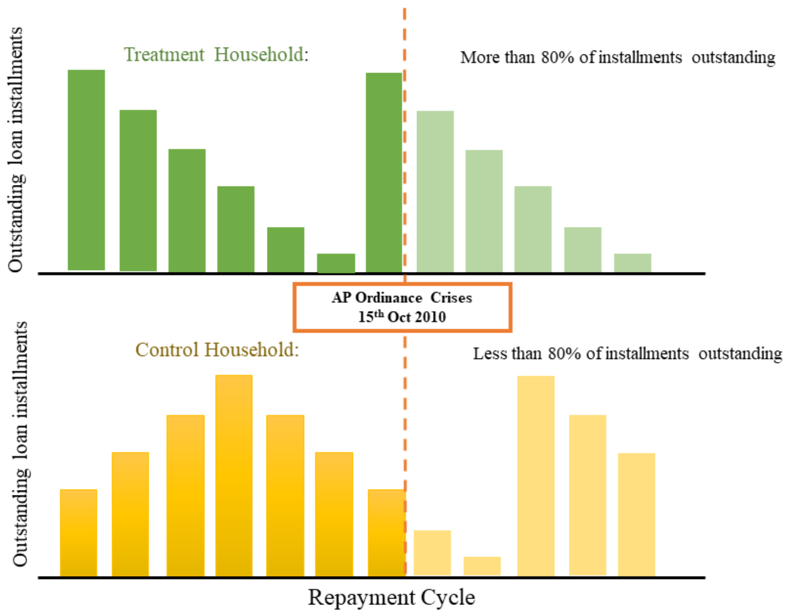
Table 11: Effect on Businesses related outcomes at EL3

	Any businesses (EL3)	*Any new business started in last year (EL3)*	*Total businesses stopped in last year (EL3)*	*Value of all business assets (EL3)*	*Log monthly business inputs (EL3)*	*Log monthly business revenue (EL3)*
	(1)	(2)	(3)	(4)	(5)	(6)
Large windfall	-0.093	-0.045	0.044	-3,924.484	-0.507	-0.693
	(0.088)	(0.044)	(0.037)	(3,151.304)	(0.811)	(0.874)
Time-invariant LEW * Large Windfall	-0.062	0.003	0.043	7,172.764	-0.617	-0.738
	(0.102)	(0.037)	(0.027)	(6,907.607)	(0.913)	(1.017)
Time-invariant LEW	0.008	-0.022	-0.063***	5,912.593*	0.254	0.241
	(0.066)	(0.018)	(0.016)	(2,981.350)	(0.508)	(0.579)
Windfall Percentage	-0.517	-0.240	0.328	-15,633.527	-2.517	-3.818
	(0.378)	(0.176)	(0.203)	(15,869.988)	(3.244)	(3.529)
Observations	524	524	524	524	522	510
Low-windfall Mean	0.326	0.0368	0.0307	7297	2.416	2.769

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix

Figure 1: Identification strategy



Bibliography

Auty, R. (1993). Sustaining Development in Mineral Economies: The Resource Curse Thesis (1st ed.). Routledge. https://doi.org/10.4324/9780203422595

Banerjee, Abhijit, Esther Duflo, Rachel Glennerster, and Cynthia Kinnan. 2015. "The Miracle of Microfinance? Evidence from a Randomized Evaluation." American Economic Journal: Applied Economics, 7 (1): 22–53.

Bastagli, F. (2016, July 25). Cash transfers: what does the evidence say? ODI: Think Change. https://odi.org/en/publications/cash-transfers-what-does-the-evidence-say-a-rigorous-review-of-impacts-and-the-role-of-design-and-implementation-features/

Blumenstock J, Cadamuro G, On R. Predicting poverty and wealth from mobile phone metadata. Science. 2015 Nov 27;350(6264):1073-6. doi: 10.1126/science.aac4420. PMID: 26612950.

Bobonis, Gustavo, et al. “Public Transfers and Domestic Violence: The Roles of Private Information and Spousal Control.” American Economic Journal: Economic Policy, vol. 5, 2013, pp. 179–205.

Chughtai, Muhammad, et al. “Estimating the Effects of Microcredit on Women’s Empowerment: An Empirical Evidence from District Attock.” Research Journal of Social Sciences and Management, vol. 04, 2015, pp. 167–76.

Donald, Aletheia; Koolwal, Gayatri; Annan, Jeannie; Falb, Kathryn; Goldstein, Markus. 2017. Measuring Women's Agency. Policy Research Working Paper;No. 8148. World Bank, Washington, DC. © World Bank. https://openknowledge.worldbank.org/handle/10986/27955 License: CC BY 3.0 IGO.

Ericsson, S. (2020). Backlash: Undesirable Effects of Female Economic Empowerment. *ideas.repec.org*. https://ideas.repec.org/p/hhs/lunewp/2019_012.html

Ewerling, F., J. W. Lynch, C. G. Victora, A. van Eerdewijk, M. Tyszler, and A. J. Barros (2017). The SWPER index for women’s empowerment in Africa: Development and validation of an index based on survey data. The Lancet Global Health 5 (9), e916–e923.

Glennerster, Rachel, and Claire Walsh. “A Practical Guide to Measuring Women's and Girls' Empowerment in Impact Evaluations.” *The Abdul Latif Jameel Poverty Action Lab (J-PAL)*, https://www.povertyactionlab.org/practical-guide-measuring-womens-and-girls-empowerment-impact-evaluations

Haberland, Nicole, Thomas de Hoop, Sapna Desai, Sarah Engebretsen, and Thoai Ngô. 2021. "Adolescent girls’ and young women’s economic empowerment programs: Emerging insights from a review of reviews," ECWG Working Paper 03. Evidence Consortium on Women's Groups.

Heath, R. (2012). Women's Access to Labor Market Opportunities, Control of Household Resources, and Domestic Violence. In *World Bank policy research working paper*. https://doi.org/10.1596/1813-9450-6149

Iyengar, G. F. &. R. (2010). Discussion Sessions Coupled with Microfinancing May Enhance the Roles of Women in Household Decision-Making in Burundi. *ideas.repec.org*. https://ideas.repec.org/p/cep/cepdps/dp1010.html

Jayachandran, Seema & Biradavolu, Monica & Cooper, Jan, 2021. "Using Machine Learning and Qualitative Interviews to Design a Five-Question Women's Agency Index," IZA Discussion Papers 14221, Institute of Labor Economics (IZA).

Kabeer, N. (1999), Resources, Agency, Achievements: Reflections on the Measurement of Women's Empowerment. Development and Change, 30: 435-464. https://doi.org/10.1111/1467-7660.00125.

Karlan D, Zinman J. Microcredit in theory and practice: using randomized credit scoring for impact evaluation. Science. 2011 Jun 10;332(6035):1278-84. doi: 10.1126/science.1200138. PMID: 21659596.

Kim, J., Ferrari, G., Abramsky, T., Watts, C., Hargreaves, J. R., Morison, L., Phetla, G., Porter, J. B., & Pronyk, P. (2009). Assessing the incremental effects of combining economic and health interventions: the IMAGE study in South Africa. *Bulletin of the World Health Organization*, *87*(11), 824–832. https://doi.org/10.2471/blt.08.056580

Kling, Jeffrey R., Jeffrey B. Liebman, and Lawrence F. Katz. 2007. "Experimental Analysis of Neighborhood Effects." Econometrica 75 (1): 83–119.

Lobell, D. B., Thau, D., Seifert, C., Engle, E., & Little, B. B. (2015). A scalable satellite-based crop yield mapper. *Remote Sensing of Environment*, *164*, 324–333. https://doi.org/10.1016/j.rse.2015.04.021

Macmillan, R., & Gartner, R. (1999). When She Brings Home the Bacon: Labor-Force Participation and the Risk of Spousal Violence against Women. Journal of Marriage and Family, 61, 947-958.
https://doi.org/10.2307/354015

Malapit, H., A. Quisumbing, R. Meinzen-Dick, G. Seymour, E. M. Martinez, J. Heckert, D. Rubin, A. Vaz, K. M. Yount, G. A. A. P. Phase, et al. "Development of the project-level Women's Empowerment in Agriculture Index (pro-WEAI)". World Development 122, 2019, pp

Nayab, Durre, and Farooq Shujaat. "Effectiveness of Cash Transfer Programmes for Household Welfare in Pakistan: The Case of the Benazir Income Support Programme." The Pakistan Development Review, vol. 53, 2014, pp. 75–104.

Pitt, M. M., Khandker, S. R., & Cartwright, J. (2006). Empowering Women with Micro Finance: Evidence from Bangladesh. *Economic Development and Cultural Change*, *54*(4), 791–831. https://doi.org/10.1086/503580

UNDP (United Nations Development Programme) (2018). Human Development Indices and Indicators: 2018 Statistical Update. New York: United Nations Development Programme.

Zaky, Hassan. “Does the Conditional Cash Transfer Program Empower Women? Evidence from Ain El-Sira, Egypt.” Social Sciences, vol. 3, 2014, pp. 132–36. doi:10.11648/j.ss.20140304.14.