Do Conditional Cash Transfers Create Resilience Against Poverty? Long-run Evidence From Jamaica

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Abstract

Conditional Cash Transfer programs (CCT) have become the prominent component of social assistance programs in many developing countries. A major objective of CCT programs is breaking the cycle of intergenerational poverty and building a population resilient to adverse shocks that may push a person into poverty. The literature to date has not provided conclusive evidence for the long-run impact of CCT programs on beneficiaries' resilience against poverty. To fill this gap, I exploit the age-based eligibility thresholds and regional variation in exposure to the Jamaican CCT program to identify its long-run impact on resilience against poverty. I find that child beneficiaries of the program are 11.5 percentage points more resilient against poverty when they become adults than they would have been in the absence of the program. Moreover, these benefits are realized after the beneficiary is in their early 20's, when they have become more integrated into the labor market. Overall, this study provides further justification for the expansion of CCTs or similar programs targeting children living in less-developed countries.

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1 Introduction

Conditional Cash Transfer programs (CCT) have become a prominent component of social assistance programs in many developing countries. These programs include PROSPERA in Mexico, Familias en Acción in Columbia, Bolsa Família in Brazil, Program Keluarga Harapan in Indonesia, and the Programme of Advancement Through Health and Education (PATH) in Jamaica. The PATH program, for example, provides benefits to a third of all children in Jamaica, which highlights the potential prominence of CCTs amongst national populations. These programs are conditional because beneficiaries must meet certain conditions, often satisfactory school attendance, to continue to receive benefits. The goal of CCT programs is not only ex-post poverty alleviation, but also the ex-ante prevention of future poverty. The latter goal is important for breaking the cycle of intergenerational poverty in the long-run and building a population resilient against adverse health, weather and economic shocks. Most of the existing studies that have examined the long-run impact of CCT programs have analyzed whether people who receive benefits when they were children attend college or have higher incomes when they are older (see Millán et al. (2019) for a review). However, the answer to these questions goes only part-way in determining whether CCTs can help build a resilient population. Showing that a CCT program increases the adult income of child beneficiaries does not necessarily imply long-run resilience against poverty since resilience is more concerned with the volatility of income than the average observed income. Furthermore, focusing on the effect of programs on the first moment of income (or consumption) distribution ignores the potential for future shocks to push households back into poverty. Yet, the literature to date has not provided conclusive evidence for the long-run impact of CCT programs on beneficiaries' resilience against poverty.

This paper uses the Jamaican CCT program, PATH, as a case study to answer the question of whether (and to what extent) CCT programs make beneficiaries more resilient against poverty, where a person's resilience against poverty is the probability that their welfare (measured as adult equivalent consumption in the present paper) will be above some minimum threshold. Answering this question will allow us to evaluate the potential for CCTs to break the cycle of intergenerational poverty and build a resilient population. Using individual level data from the 2017 Jamaica Survey of Living Conditions (JSLC), this paper answers this question by exploiting the age-based eligibility thresholds and regional variation of Jamaica's PATH in a difference-in-differences (DiD) framework inspired by the DiD designs of Duflo (2001), Havnes and Mogstad (2015), and Parker and Vogl (2018). Variation in the age-based eligibility thresholds stems from the fact that PATH was rolled out nationally in Jamaica in 2002 and only children younger than 18 years old at that time were able to participate in the program. Regional variation stems from variation in the saturation of PATH beneficiaries across geographic regions.[1] This DiD strategy uses the age of the individual as the time variable and uses regions with high levels of individuals exposed to PATH (due to high saturation) as exposed regions. Since the "non-exposed" regions would still have some treated individuals, this paper identifies the differential effect of treatment and estimates the intent-to-treat (ITT) impact of PATH on resilience. To provide confidence that this empirical strategy does indeed identify the effect of PATH, I conduct a battery of falsification tests and robustness checks.

Since resilience is defined as the probability that an individual's welfare will be above some minimum threshold, it is tied directly to the conditional (individual specific) distribution of the welfare measure.[2] This measure of resilience is similar to the standard approach in the vulnerability literature of measuring vulnerability to poverty, where resilience and vul-

[1]The geographic regions are called constituencies, each of which is a collection of electoral districts represented by a political representative voted in by the constituents. It is similar to congressional districts in the United States.

[2]The distribution of welfare can also be considered in an unconditional sense, and there have been a few papers that examined the effect of CCT programs on the unconditional distribution of outcome variables such as high school completion, tertiary enrollment and completion, cognitive ability, income and consumption (e.g. Djebbari and Smith, 2008; Galiani and McEwan, 2013; Barrientos et al., 2016; Dammert, 2009; and Figueroa, 2014).

nerability are considered two sides of the same coin (Jorgensen and Siege, 2019). It is also related to the measure of resilience proposed by Barrett and Constas (2014) and Cissé and Barrett (2018). See Ansah et al. (2019) for a review of other methods of measuring resilience.

In addition to identifying the long-run effects of CCTs on resilience, this paper is also the first to identify any long-run effect of CCTs in the context of a Small Island Developing State (SIDS). It is important to analyze resilience in SIDS because, due to their size, they are very susceptible to internal and external shocks (Encontre, 1999; Guillaumont, 2010). Furthermore, I examine the source of resilience; is it manifested through better educational attainment and/or higher probability of employment? The results show that people exposed to PATH as children are 11.5 percentage points more resilient against poverty, 7.4 percentage points more resilient against food poverty, and are more likely to obtain a college level education and be employed than they would have been in the absence of the program. Moreover, the long-run benefits of the program are strongest after the child reaches their early 20's. These results are important insofar as they provide important evidence of the potential of CCT programs to break intergenerational poverty by directly looking at how CCTs mitigate the risk of poverty.

There is some previous evidence that children exposed to CCT programs attain positive long-run outcomes when they are adults. For example, Millán et al. (2020) found positive impacts of the Honduras CCT program on secondary school completion and tertiary school enrollment for adults who were exposed to the program as children. Kugler and Rojas (2018), and Parker and Vogl (2018) found positive effects of the Mexican CCT program on educational and labor market outcomes. Barrera-Osorio et al. (2019) found that the Colombian CCT program leads to increased secondary and tertiary enrollment and completion. Finally, Cahyadi et al. (2020) and Barham et al. (2018) found positive educational and labor market outcomes for the Indonesian and Nicaraguan CCT programs, respectively.

While the long-run evidence as outlined above shows some effect on average educational and labor market outcomes, the literature is sparse when it comes to looking at the question of resilience (and vulnerability) in the context of CCT or Unconditional Cash Transfer (UCT) programs. To the best of my knowledge, there are 4 studies that have examined this previously: Premand and Stoeffler (2020), d'Errico et al (2020), Uchiyama (2019) and de Janvry et al. (2006). First, Premand and Stoeffler (2020) studied the impact of the Niger UCT program on resilience. They identify resilience by looking at specific shocks and by using a composite measure of resilience that represents the probability of future poverty. They found that cash transfer programs can foster resilience by facilitating savings and income smoothing. Second, d'Errico et al (2020) studied the impact of Lesotho's UCT program on a multidimensional measure of resilience and found a positive impact on resilience due to increases in expenditure and improvements in food security indicators. Third, Uchiyama (2019) studied the impact of Mexico's CCT program on a household's ability to maintain smooth consumption, where a lower ability to maintain smooth consumption corresponds to greater vulnerability. Results showed that the CCT program played a role in reducing household vulnerability in the early 2000's. Finally, de Janvry et al. (2006) studied the effectiveness of the Mexican CCT program in helping to protect against shocks to school enrollment and shocks that induce child work. They found that the CCT program protected enrollment, but did not stop parents from increasing child work in response to shocks.

This paper improves upon the related literature mentioned above in three main ways. First, none of these studies explicitly examined the long-run effect of CCT programs on resilience to poverty, where the long-run effects are defined as the impact on the adult outcomes of child beneficiaries. Rather, they conduct short or medium-term analysis, which are periods before the child turns an adult, and infer possible long-run effects. It may be best to limit projections like this since there is no guarantee that these effects will persist into adulthood (long-run) to break intergenerational poverty.[3] The present paper directly examines the long-run effect of a CCT program on resilience.

Second, the main analysis of these papers examined resilience by i) considering only specific shocks, or ii) by using a definition of resilience/vulnerability that is not indexed to a minimum welfare measure such as the poverty line. Therefore, they do not specifically inform on protection against downside risk that will send the person into poverty, or iii) by using a subjective resilience measure computed by constructing a multidimensional index using "pillars" (d'Errico et al, 2020) conjectured to be important for determining resilience. The present paper refines these by i) using a probabilistic measure of resilience which considers resilience against any shock; ii) considering resilience in a manner which specifically demonstrates some protection from poverty/downside risks; and iii) using an objective measure by indexing the resilience measure to the poverty line. Premand and Stoeffler (2020) does conduct complimentary analysis using a measure of resilience similar to the one used in this paper. However, their analysis is conducted in the short term and was done by examining an unconditional cash transfer program which is not a program specifically designed to target children and break intergenerational poverty. In fact, only Uchiyama (2019) examined resilience in the context of a CCT program; the others used the context of an UCT program. Third, these studies focused on large countries, mostly in Latin America. This study will be the first to examine the effect of CCTs on resilience, or any long-run impacts of CCTs, in the context of a Small Island Developing State. As mentioned earlier, the focus on a Small Island Developing State is important since they are especially susceptible to internal and external shocks due to their size.

[3] For example, Barrera-Osorio et al. (2019) finds that some educational outcomes such as high school enrollment are positive in the near term but not in the long-term, which points to the need to explicitly look at long-run effects rather than infer long-run effects from short-term analysis.

The rest of the paper is structured as follows: section 2 gives an overview of PATH and section 3 provides a conceptual description of the resilience measure used in this paper. Section 4 describes the data and specifies how the resilience variable is constructed. Section 5 outlines the identification strategy and estimation models. Section 6 presents the results of the main analysis along with some auxiliary results, along with a battery of robustness checks and falsification tests. Section 7 concludes.

2 The Jamaican CCT Program

At the turn of the millennia, Jamaica's social safety net (SSN) constituted a broad spectrum of programs designed to provide welfare benefits to the needy and assist the vulnerable. In 2000, the government of Jamaica, with technical assistance of the World Bank, undertook an evaluation of the SSN. This evaluation was aimed at improving both the identification of the poor and the delivery of state-funded assistance to the poor and vulnerable (Planning Institute of Jamaica, 2002). The reforms coming from the evaluation led to the consolidation of overlapping programs and improved service delivery, increased benefits given to beneficiaries, and led to the introduction of conditional transfers.

The nucleus of the SSN reform was the introduction of the *Programme of Advancement Through Health and Education (PATH)* which consolidated three other SSN programs. Moreover, the program incorporated all elements from the SSN reform, which included the targeting of children by using conditional cash transfers. A pilot for PATH commenced in October 2001 with full national rollout beginning by the end of 2002. About 72% of all PATH beneficiaries in 2015 were children who receive benefits from birth until the completion of secondary school.[4] The objectives of PATH include poverty alleviation, breaking

[4] Author calculation from the Economic and Social Survey Jamaica (ESSJ) 2015.

intergenerational poverty, and to prevent families from falling further below the poverty line in the event of an adverse shock (Overseas Development Institute, 2006). Technical and budgetary support comes from a combination of both the government of Jamaica and the World Bank. PATH provides two types of benefits for child beneficiaries; 1) a health benefit which is conditional on children attending regularly scheduled health clinics, and 2) an education grant which is conditional on children 6-17 years old attending school regularly (minimum 85% attendance). In 2017 the education benefit was $600 Jamaican dollars (JMD) (approximately PPP USD8.9) per child per month. In 2007 approximately 16% of all children in Jamaica were beneficiaries, and by 2017 about a third of all children were beneficiaries. For a child to become a beneficiary of the program, the household she belongs to must pass a "proxy means test". This is implemented by collecting data on household and individual characteristics which is then used in an econometric model by the program administrators to estimate a value representing the welfare level of the household. If this value is below some minimum threshold then the household is determined as eligible to receive benefits.

There have been some evaluations of the effectiveness of PATH. Levy and Ohls (2010) found that PATH is generally implemented as intended with better targeting of the poor than other social security programs in Jamaica. Moreover, they found that the program had positive and statistically significant impacts on school attendance, but no impact on other school outcomes such as marks and grade progression. On the other hand, a later study by Stampini et al. (2018) found that PATH improved the test scores of urban male beneficiaries who were also more likely to be placed in higher ranked secondary schools. Those two previous studies provided short term insight of the impact of PATH, but longer term studies examining the impact of any early childhood development (ECD) intervention implemented in a less-developed country are rare. One example of this is a recent study by Gertler et al (2021), who examined the impact of another early childhood intervention on long-run (adulthood) outcomes of child beneficiaries in the Jamaican context. Longer-term studies are relevant in "providing justification for expanding similar ECD interventions targeting disadvantaged children living in poor countries around the world" (Gertler et al, 2021).

3 Measuring Resilience Against Poverty

While a person's consumption, income and poverty status are realized every year and can be observed, resilience when measured as the capacity of individuals to avoid poverty, is a latent variable. Barrett et al. (2021) refers to this as "resilience as capacity". This resilience measure is never directly observed and thus can only be inferred using observable information on individual, household and community characteristics. There is an important distinction between "resilience as capacity" and "resilience capacities". The latter corresponds to independent variables that are thought to explain the variation in observed welfare and explain a person's resilience, and the former corresponds to the latent unobserved overall capacity of individuals to avoid poverty.

The measure of resilience used in this paper as the main outcome variable is in the spirit of "resilience as capacity", and measures resilience as the probability that welfare will be above some minimum threshold; that is $P(y_{it} > \underline{y}|X_{it})$, where y_{it} is the welfare variable for person i in time t (such as income or consumption), y is a minimum threshold value of the welfare variable above which the individual is not deprived, and X_{it} is a vector of variables which includes individual and/or household characteristics. A key advantage of this approach to measuring resiliency is that it directly incorporates the poverty line into its calculation, instead of subjective deprivation approaches used in multidimensional measures. This approach is also consistent with the World Bank's conceptualization of resilience described in their Social Risk Management conceptual framework (SRM 2.0) (Jorgenson and Siegel, 2019).

This measure of resilience is similar to the standard approach in the vulnerability literature of measuring vulnerability to poverty, where resilience and vulnerability are considered two sides of the same coin; that is, $vulnerability = 1 - resilience$ (Jorgensen and Siege, 2019). In the vulnerability literature, the typical way the conditional distribution of welfare is characterized is by assuming a two-parameter distribution of consumption and estimating its mean and variance via OLS or maximum likelihood as $\hat{E}(y_{it}|x_{it}) = \hat{\beta}_E x_{it}$ and $\hat{\sigma}_{it} = \hat{\beta}_V x_{it}$. This paper improves on this approach by using non-crossing quantile functions to characterize the conditional distribution of the welfare measure and estimate the required probability. Quantile functions are more accurate in measuring vulnerability relative to making assumptions about the underlying distribution of consumption, and will therefore be more accurate in measuring resilience (Oconnor, 2021).[5]

There are two steps needed to construct the measure of resilience. First, each individual's welfare distribution needs to be estimated. Then second, the resiliency score is estimated as the probability that a person's welfare is above a certain cutoff. The first step in generating conditional welfare distributions is to run the following quantile regression:

$$Q_\tau(y_{it}) = x_{it}\beta(\tau) + \epsilon_{it} \tag{1}$$

This formulation gives the τ^{th} quantile estimate of y_{it}, with $\tau \in (0, 1)$. After estimating many quantile functions for values of τ between 0 and 1, the sorting procedure of Chernozhukov et al. (2020) is used to fully characterize the conditional distribution of y_{it}, $F(y_{it}|x_{it})$. With the distribution then known, it can be evaluated at $y_{it} = \underline{y}$, where $\underline{y}$ is the poverty line, and then resilience scores ($\hat{\rho}_{it}$) can be estimated as $\hat{\rho}_{it} = P(y_{it} > \underline{y}|x_{it}) = 1 - F(\underline{y})$. These estimated resilience scores will then be used as the outcome variable in a

[5]Accuracy here refers to how well the resilience measure identifies an individual's or household's true vulnerability to poverty.

difference-in-differences regression framework.

This paper joins a short list of recent papers that have used this conceptualization of resilience as a probability in a difference-in-differences framework with estimated resilience scores as the outcome variable. To the best of my knowledge, the only other examples are Phadera et al. (2019) and Premand and Stoeffler (2020). Phadera et al. (2019) estimates the impact of an asset transfer program on household resilience, not the effect of a social safety net program like this paper. Also, as mentioned in the introduction, Premand and Stoeffler (2020) conducted complimentary analysis of the short-run impact of an UCT program on household resilience, which is not a program mainly targeted to children with the objective of breaking intergenerational poverty like CCTs.

Educational and labor market covariates, which are important for characterizing a person's resilience, will be used as outcome variables in other DiD regressions in section 6.4. This will help to evaluate some of the mechanisms through which the PATH program affects a person's resilience.

The measure of resilience used in this paper is similar to the Cissé and Barrett (2018) measure of resilience.[6] Cissé and Barrett (2018) estimates resilience using the dynamic welfare probability $\hat{\rho}_{it} \equiv \mathrm{P}(\mathrm{y}_{it} > \underline{y} | X_{is} = x_{it}, y_{it-1})$, where $\hat{\rho}_{it}$ is the resilience level (or resilience score) for person i in time t, y_{it} and $\underline{y}$ are as previously defined, and X_{is} is a vector of covariates in time period $s = \{t, t-1\}$ specifically shown here to include individual and/or household characteristics (x_{it}) and previous values of the welfare measure (y_{it-1}). This formulation considers potentially non-linear path dynamics of the welfare variable by conditioning on y_{it-1}. The only difference between the measure of resilience used in this paper and Cissé

[6] Which is based on the conceptualization outlined in Barrett and Constas (2014).

and Barrett (2018) is the exclusion of the additional covariate y_{it-1} in this paper. Directly adopting the Cissé and Barrett (2018) measure necessarily requires panel data due to the inclusion of y_{it-1}. However, household level panel data is not available for most developing countries, and it is not available for any Small Island Developing State that has a conditional cash transfer program. Nevertheless, it is possible to use JSLC data from before 2009 to compare the resilience measure used in this paper with Cissé and Barrett (2018).[7] The result of this check, which is in the appendix, shows that for 93.7% of households the calculated resilience scores were statistically equal across the two resilience measures. However, the Cissé and Barrett formulation shifts the upper portions of the conditional distribution of adult equivalent consumption to the left relative to the distribution estimated using the formulation adopted by this paper (see appendix). Notwithstanding this caveat, both methods still provide a useful summary measure of someone's resilience.

Another difference is that Cissé and Barrett (2018) assumes that the conditional distribution of welfare is Gamma and then estimates its mean and variance. Upton et al. (2020) shows that the Cissé and Barrett (2018) probabilistic measure of resilience suffers from high rates of false positives and negatives. It is possible that the reliance on the assumption of the distribution of the welfare measure is a major contributor to these inaccuracies. As mentioned earlier, this paper uses non-crossing quantile functions to characterize the conditional distribution of the welfare measure and estimate the required probability. This improves on Cissé and Barrett (2018) by allowing the full shape of the distribution to be unrestricted and specific to the individual.

[7] Before 2009, it was possible to create a two-period household panel using cross sectional data across two different years. This is due to the how households were sampled in that time; a sample of 'electoral districts' were selected in a first stage, and these comprised the Primary Sampling Units (PSU). These PSUs were kept for 2-4 years, and households were randomly sampled from the PSUs every year. As a result, within the 2-4 years period, a household may be visited more than once, and those households could be used to construct a panel. Since the panels were created at the household level, the checks were conducted at this level of aggregation.

4 Data and Resilience Score Construction

4.1 Data

The main analysis is conducted using the 2017 JSLC, with auxiliary analysis conducted using the 2008 and 2002 JSLC. The JSLC is a Living Standards Measurement Survey and has been fielded in Jamaica since 1988. The sample is based on a cross-section of households chosen every year and follows a two-stage cluster random sampling framework: administrative regions called 'electoral districts' were selected in a first stage and these comprise the Primary Sampling Units (PSU). In the second stage, households were randomly sampled from each PSU. Normally, the JSLC sample covers a third of 1.0% of all households in Jamaica, which is the case with the 2017 sample when over 2000 households were surveyed (over 1000 in rural areas).[8] In some years, however, the data covers around 1.0% of all households in Jamaica, which is the case with the 2008 and 2002 samples when over 6000 households were surveyed (over 3000 households in rural areas).

Table 1 provides some descriptive statistics of the variables used in the analysis in this paper. In this table, the *young* are individuals 19-28 years old in 2017 and thus they were potentially exposed to PATH as children when the program began in 2002. The *old* are individuals 33-39 years old in 2017 and thus were not children (under 18 years old) when PATH began. Furthermore, high exposed regions are those with a relatively high proportion of households receiving PATH benefits.[9] The welfare variable used to characterize resilience is an individual's adult equivalent consumption. Information on consumption expenditure in the JSLC is collected at the household level, and in this study adult equivalence scales are used to obtain individual specific consumption expenditure values.[10] Average annual adult

[8]Specifically, the sample is designed to be nationally representative by region, which allows representative analysis for each region. Therefore, the sample will cover a third of all households in rural and urban areas.
[9]High exposed regions will be more precisely defined in section 5
[10]Adult equivalent scales are calculated by the Jamaican authorities and provided with the JSLC dataset.

equivalent consumption expenditure in 2017 was \$280,834.2 JMD for the young cohort in high exposed regions, and \$370,119.2 JMD for the old cohort across high and low exposed regions, which is approximately PPP USD3,989.6 and PPP USD5,258.0, respectively (Table 1).

Households with older people are more likely to be single person or small, and so these households are likely to have a smaller household size on average than households with children or young adults. This dynamic is evident in the summary statistics as the *young* cohort in high exposed regions lives in statistically larger households on average than the *old* cohort (see Table 1). On the other hand, the sex of individuals is balanced across these two groups, with 46-48% of the sample being males.

The *old* cohort, being older and from a time when education was less accessible to Jamaicans, are less educated than the *young* cohort in high exposed regions. Specifically, the *young* cohort have a higher share of persons obtaining at least a secondary level education compared to the *old* cohort. In terms of employment, the old cohort is more likely to be employed (sum of occupation group means) than the young cohort in the high exposed areas, which follows the general observation in many countries of younger individuals being more likely to be without work (see Table 1). The young and old cohorts have statistically similar employment rates in formal occupation categories like legislators, professionals and service and sales. However, the groups have dissimilar rates in employment categories relating to skills and trades, such as skilled agriculture and crafts, with the old cohort relying on these skills more.

4.2 Resilience Score Construction

The main outcome variable is estimated resilience scores ($\hat{\rho}_{it}$), which is a measure of a person's resilience against poverty: $\hat{\rho}_{it} \equiv \mathrm{P}(\mathrm{y}_{it} > \underline{y} | x_{it})$. As mentioned in section 3, to estimate $\hat{\rho}_{it}$

all the possible consumption outcomes for that person need to be estimated which will allow us to characterize their conditional distribution of consumption and estimate the required probability. This is done by first estimating 99 different quantile values of the conditional distribution of consumption expenditure using a sample of working age individuals (19-59 year-olds) in rural areas (the focus on rural areas is explained in section 5.2 below). Table 2 provides the result from one of these quantile models, the median. After generating these quantile values, the sorting procedure of Chernozhukov et al (2020) is used to characterize the whole conditional distribution which is specific for each individual based on their individual, household and community characteristics. From this distribution, the latent resilience variable (resilience score) is estimated as $\hat{\rho}_{it} = \int_{\underline{y}}^{\overline{y}} f(y_{it}|x_{it})\, dy_{it}$ (the count of all the quantile values above the poverty line, $\underline{y}$), where $\overline{y}$ is the largest value from the individual's conditional distribution. The covariates in Table 1 were used to estimate each quantile of the conditional distribution of consumption.[11] The average estimated resilience level is 0.814, which also implies that the average probability of future poverty (ie., vulnerability) is 0.186.

Following Cisse and Barrett (2018), the effect of the CCT program on resilience $\left(\frac{\partial \hat{\rho}_{it}}{\partial x_{0.it}} = \hat{\beta}_0\right)$ is estimated using the estimated resilience scores. This is done with the regression $\hat{\rho}_{it} = \hat{\beta}_0 x_{0.it} + \hat{\beta}_1 x_{1,it}$, where $x_{0,it}$ is the covariate of interest from the x_{it} vector, and $x_{1,it}$ are the remaining covariates in the x_{it} vector. I exclude covariates from $x_{1,it}$ that are likely mechanisms for how PATH might affect resilience, such as education and labor market covariates; otherwise, conditioning on these covariates will control away some of the variation in $\hat{\rho}_{it}$ that is explained by PATH.

[11] Regional fixed effects were also included in the quantile models.

5 Identification Strategy and Estimation Model

5.1 Identification Strategy

This paper exploits variation that comes from a combination of 2 sources: 1) regional variation in exposure to the program and 2) individual-level variation in the age of the individual. The first source of variation stems from the fact that the program targets the children in families with low levels of welfare. Thus, poorer regions in Jamaica will have a higher concentration of PATH beneficiaries compared with richer regions. Following Duflo (2001) and Havnes and Mogstad (2015) who also used two similar sources of variation in a difference-in-differences (DiD) framework, from the first source of variation I create two supergroups of regions: high and low exposed regions. To define a high/low exposed region, I first find the percentage of all individuals in a rural region that live in a household that has ever received PATH benefits. Regions are then sorted according to this percentage. Those with values above the median are defined to be high exposed and those with values below the median are low exposed. Cross tabulation shows that 63% of all path recipients were living in the highly exposed regions. To check the sensitivity of these choices for the cut-off point for high and low exposed regions, I perform several robustness checks and falsification tests. These are explained in more detail in the next subsection.

Figure 2 plots the distribution of the proportion of the total population in each region that live in households that has ever received PATH benefits. From the figure, the distribution is shown to be unimodal and the median is closer to the inflection point than the mean.

Next, and similar to Duflo (2001) and Havnes and Mogstad (2015), for the second source of variation individuals were separated according to a *young cohort* and an *old cohort*. The *young cohort* are individuals who are adults in 2017 but were young enough to "fully" participate in the PATH program at inception in 2002 (4 to 13 years old in 2002), where full participation indicates that they were exposed for all high school years. The *old cohort* are individuals who were too old at inception of the program to participate (those 18 to 24 years old in 2002).

The "non-exposed" regions would still have some treated individuals, thus this paper identifies the differential effect of treatment and estimates the intent-to-treat (ITT) impact of PATH on resilience. The ITT effect then tells us about the casual effect of the offer of treatment (Angrist and Pischke, 2009; Havnes and Mogstad, 2011). Using T as treatment indicator (1= treated) and A as cohort indicator (1=young), the impact of the program on resilience using the difference-in-differences framework can be written as:[12]

$$ITT = E(y|T = 1, A = 1) - E(y|T = 1, A = 0) - \{E(y|T = 0, A = 1) - E(y|T = 0, A = 0)\} \tag{2}$$

If PATH increases resiliency among its recipients, this term should be positive and significant. Table 3 illustrates the identification strategy using development resilience as the outcome variable.[13] The apparent difference-in-differences using only sample means is 0.061, while for the falsification test (control comparison) it is much lower and near zero, as expected. The falsification test compares the *old* cohort with an *older* cohort and is explained in more details in the next subsection.

5.2 Threats to Identification

The DiD analysis depends on the sensitivity of the cut-off point for creating the supergroups. To assess this sensitivity, I conduct three robustness checks. First, I use a fixed

[12]The difference-in-differences effect in this paper is identified using an independent cross-section, but this identifies the treatment effects with assumptions similar to using panel data. See Lee and Kang (2006) for the full set of conditions that identifies the treatment effect in cross-sectional and panel data.

[13]The model and procedure used for computing the resilience variable is outlined in section 4.2 above

effects specification which exploits the program intensity in each region rather than defining a region as high or low exposed based on the researcher defined cut-off point. This would address the question of whether the results will hold if all the observed variation in the intensity of program exposure by region were utilized, rather than collapsing the variation into a dichotomous variable. Second, I find the percentage of all individuals in a region that live in a household that has ever received PATH benefits, then I calculate the average of this number across all these regions and any region above this average is considered a high exposed region. This would examine the question of whether the results are sensitive to the measure of central tendency, which would imply that there is some ambiguity about whether dividing regions into supergroups using measures of central tendency is appropriate. Third, I again find the percentage of all individuals in a rural region that live in a household that has ever received PATH benefits. Regions were then ordered according to this percentage and the distribution of this ordering was divided into terciles. The first and third tercile were then used to define the low and high exposed regions. If there is a true DiD effect, the results of the main analysis should be robust and the estimated effect should be stronger when comparing the third and first terciles due to a reduction in attenuation.

There are two other potential problems with this identification strategy. First, if PATH recipients migrate to different regions where there are higher paying jobs or other factors that affect adult equivalent consumption, then this migration effect might confound with the DiD estimates. I check this concern by analyzing migration patterns in Jamaica. While rural to urban migration is nontrivial, urban to rural migration is low. Population census data in 2001 showed that for parishes that are predominantly rural, about 85% of individuals still live in the parish in which they were born.[14] This also implies that even migration from one rural parish to another is low. It is therefore likely that a person who lives in a rural

[14] Parishes are considered "predominantly rural" if more than half the population live in a rural part of the parish.

area as an adult was born in that same rural area. Thus, to mitigate the potential effects of migration, the analysis in this paper focuses on rural areas. The second potential problem is that the estimated treatment effects may be biased upwards (or downwards) due to the simultaneous impacts of other programs that are benefiting the young (or old) cohort in the high exposed regions. The identification assumption from this second issue is that there is no program, independent of PATH, that affects the younger cohort differently than the old cohort in terms of development resilience. For example, I must rule out programs like an extensive job training program that is given to the young specifically in high exposed regions but is not accessible to those in low exposed regions nor is it available to the old. If this identification assumption is implausible, then one should expect that the difference in resilience in high and low exposed regions for the old cohort, those 18 to 24 y/o in 2002, will be different than the same difference for an older cohort, like those 25 to 30 y/o in 2002. I therefore investigate this second potential concern using a falsification test that compares the old with an older cohort (this is the control comparison in Table 3). Two other falsification tests to address the second issue is to analyze the DiD using data from 2008 and 2002. In these years, most of the young cohort in 2017 (19-28 years old) were not yet adults. If there is a positive DiD effect in 2017, this effect should disappear using 2008 and 2002 data if the identification assumption is true.

Finally, there is a need to ensure I am not comparing fundamentally different people which would violate the parallel trends assumption necessary for identification. If this is the case, I will be comparing resilience between individuals whose resilience scores may be different in more ways than the treatment. In the DiD regression, I therefore condition on some of the covariates that were used in the starting process of generating the resilience scores, such as a person's age and sex. The conditioning covariates must not include ones that PATH feeds through to affect resilience, such as education and labor market covariates. The resulting analysis is therefore similar to a matched DiD.

5.3 Estimation Model

The identification strategy is implemented in a regression DiD framework. The basic setup of this model is that the treatment effect is identified by the difference in resilience between the young and old cohorts in the high exposed regions compared to the similar difference in the low exposed regions. Let y_{ikj} be the outcome variable of interest (estimated resilience scores) for individual i from cohort k living in region j, A_k be a dummy variable for the young-age cohort, and T_j be a dummy variable for those living in high exposed regions. Parameterization of the identification strategy then implies the following regression model (with added individual level covariates, X_i):[15]

$$y_{ikj} = \alpha_0 + \alpha_1 A_k + \alpha_2 T_j + \alpha_3 T_j A_k + \alpha_4 X_i + \epsilon_{ikj} \tag{3}$$

where α_3 is the parameter of interest for identifying the treatment effects under the assumption of parallel trends (conditional on covariates). If the program has a positive effect on resilience, then α_3 will be greater than zero and significant. Equation 3 can also be adjusted to consider the intensity of the program by region rather than the researcher defined characterization of areas as high and low exposed. The treatment effect can then be identified by simultaneously adjusting for unobserved age-cohort and region specific confounders in the following fixed effects equation:

$$y_{ikj} = \alpha_0 + \alpha_1 age_i + \alpha_2 R_j + \alpha_3 A_k I_j + \alpha_4 X_i + \epsilon_{ikj} \tag{4}$$

where I_j is the intensity of the program in region j, age_i is age effect and R_j is regional fixed-effect. Other variables are as defined previously.

[15] As noted earlier, these covariates must not include ones that PATH feeds through to affect resilience, such as education and labor market covariates.

To econometrically assess the control comparison (falsification test of the old vs older cohorts), a separate regression will be run with the old cohort (those 18 to 24 y/o in 2002) and the older cohort (those 25 to 30 y/o in 2002) using models 3 and 4 above.

Since the dependent variable is a generated regressand, the errors from the first stage of estimation will carry over to the second stage, thereby complicating the standard errors in the second stage (Dumont et al., 2005). Therefore, following Phadera et al. (2019) which also used generated resilience scores in a DiD setup, the standard errors are computed using a clustered bootstrap.[16] While the DiD estimator in this paper is technically not a matched estimator in the truest sense, because of the conditioning variables the regression estimator can be viewed as a sort of weighted matching estimator (Angrist and Pischke, 2009). Computing standard errors with the nonparametric bootstrap is generally not valid for matching estimators. An alternative strategy for inference in the situation of a matching estimator is the wild bootstrap of Hardle and Mammen (1993) (Abadie and Imbens, 2008), which is implemented in this paper.[17] When the sampling procedure used to collect data follows a two-stage process with clusters selected from a first stage (as is done in the JSLC), Abadie et al (2017) recommends clustering at the first stage randomizing level. In the JSLC, electoral districts are selected in the first stage, and standard errors are clustered at this level. The age and sex demographic identifier were used as controls in the regressions.

[16] In their paper they use the standard nonparametric bootstrap.

[17] Other ways to overcome the drawback of the nonparametric bootstrap includes the 'm-out-of-n' bootstrap and subsampling (see Abadie and Imbens, 2008).

6 Results

6.1 Main Results

As mentioned in section 5.3, since the dependent variable is a generated regressand, standard errors are computed using the wild bootstrap. Moreover, because the sampling design of the JSLC is two-stage, standard errors are clustered at the first stage level (PSU), which follows the recommendation of Abadie et al (2017). The age and sex demographic identifier were used as controls in the DiD regression. Table 4 presents the first set of results for the DiD estimates of the effect of PATH on resilience. Columns 1 through 4 present the results using four different age categories for the potentially exposed group (the young); those 19-28 (overall young-age cohort), 19-20 (lower young-age cohort), 22-25 (middle young-age cohort) and 26-28 (upper young-age cohort). This was done because for the oldest individuals in the young-age cohort (those over 25 years old), they were exposed to the program for a relatively short period of time (at most 6 years). Moreover, they likely completed almost all their primary education and higher outcomes in primary education translate to better placements in secondary schools.[18] For those in the middle-age group of the young-age cohort (22-25), they were on PATH for up 10-11 years. For the youngest individuals in the young-age cohort (those 19-20 years old), they are maybe still too young to realize all the long-run benefits of PATH exposure since they have only recently finished their schooling, may be still enrolled in post-secondary institutions and may not have yet been fully assimilated into the labor market.

The most preferred model corresponds to column 3 in Table 4 as this includes the age group (22-25 years old) from the full young-age category that are relatively more exposed to PATH while at the same time being old enough to accrue all the long-run benefits of

[18] Students who perform well in primary schools in Jamaica get generally placed in secondary schools that are at the higher end of the distribution of schools in terms of academic performance of the student body.

PATH exposure. In the preferred model, the intent-to-treat (ITT) DiD estimate was positive and significant, indicating two key findings: 1) people exposed to PATH when they were children had significantly increased resilience against poverty, and 2) on average, in the long-run PATH significantly improved the lower end of the conditional distribution of consumption of treated individuals. This result indicates that individuals exposed to PATH were less susceptible to random shocks that caused lower welfare outcomes below the minimum threshold. The results can be interpreted as, on average, being 'highly exposed' to PATH increased resilience by 11.5 percentage points. Since resilience is measured as the opposite of vulnerability, the results also indicate that high exposure to PATH makes children 11.5 percentage points less vulnerable to downward shocks that could send them into poverty.

For the models that include those 19-20 and 26-28 years old, the DiD coefficients were positive but small and insignificant. For the model which includes all the young-age individuals (model 1), the treatment effect coefficient was higher than models 2 and 4 (although still insignificant), pointing again to the effect being strongest for the middle young-age group. This is not surprising since those too young are likely not old enough to fully accrue the long-run benefits of PATH, such as labor market benefits, and those too old were likely not exposed long enough. This validates the choice of disaggregating the results by different young-age groups since the potential effect of PATH would have otherwise been masked.

I can also estimate the effect of PATH on resilience on a more extreme form of deprivation: food poverty. This can be done by looking at a different point of the conditional distribution corresponding to the food poverty line rather than the main poverty line. The overall poverty line is \$177,025.3 JMD (PPP USD 2,625.9) while the food poverty line is 68.5% of this value at \$121,274.7 JMD (PPP USD 1,798.9).[19] Table 5 presents the results

[19] Poverty line numbers are per-person adult equivalent values for the year.

of this analysis, focusing on the middle young-age cohort (22-25 years old). While the treatment effect coefficient was positive and significant for the model with the middle young-age group, it was insignificant for the model with the full young-age cohort (column 1 in Table 5). The same intuition for the main analysis holds; the insignificance of model 1 is likely rooted in the fact that some individuals were not on PATH long enough, while for other individuals they were not old enough yet to accrue all the long-run benefits of PATH. The ITT coefficients were smaller in the models looking at resilience to food poverty compared to the models looking at resilience to overall poverty. Intuitively, this is likely because average resilience against this extreme form of poverty (food poverty) was already high in the sample of young-age individuals, at 0.894, so there is less room for PATH to impact resilience at this level.

6.2 Robustness Checks

To corroborate the main results, four robustness checks were conducted. The first addresses the question of the sensitivity of the results to the researcher defined cut-off point for high/low exposed regions. In particular, there may be a question of whether the results will hold if all the observed variation in the intensity of program exposure by region were utilized. This check is done by using a two-way fixed effects specification which simultaneously adjusts for unobserved age-cohort and region-specific confounders. Under this setup, regions are not defined as high or low exposed, but rather the intensity of the program by region is used to identify the differential effect of increased exposure. Panel A of Table 6 presents these findings.[20] The results show that the effect of PATH on resilience was significant for the middle young-age group and for the overall young-age cohort. This indicates that the

[20] Results of the fixed effects control comparison between the "old" and "older" cohort are presented in section 6.4: Falsification tests.

average resilience against poverty for young persons was higher the more intensely the area was exposed. These results are similar to main result of the DiD analysis, but with two notable differences. First, the treatment effect coefficients were larger under the fixed effects specification compared with the DiD model. This is likely because the fixed effects model exploited more variation in regional exposure compared to the DiD results. Secondly, the overall young-age cohort was significant in the fixed effects model compared to the main DiD results where it was not. This is likely because of the strength of the estimated effect in the middle young-age cohort for the fixed effects model increasing the overall significance for the entire young-age cohort.

While the DiD coefficient can be interpreted as the effect of 'high exposure' relative to 'low exposure' (ITT effects), the treatment effect coefficient in the fixed effect model can provide an estimate closer to the average-treatment-effect (ATE). Using the coefficient from Table 6 panel A column 2, the interpretation is that full/complete exposure to PATH increased resilience against poverty by 25.1 percentage points compared with no exposure (never being exposed by PATH).

The second robustness check, like the first, also examines the question of the sensitivity of the results to the researcher defined cut-off point. Specifically, I examine the robustness of the results when the mean intensity of PATH across all regions is used to determine the cut-off point for high/low exposed regions instead of the median as done in the main analysis. If the results are sensitive to this measure of central tendency, then this would imply that there is some ambiguity about whether dividing regions into supergroups using measures of central tendency was appropriate. The results of this check, presented in panel B of Table 6, are very similar to the main results.

For a third robustness check, regions were then ordered according to the distribution of the intensity of PATH within the region, and this ordering was then separated into terciles. Regions in the first and third tercile were then used to define the low and high exposed regions, respectively. The idea is that if the program really worked and the identification strategy identifies the ITT effect of PATH due to high exposure, then focusing on the first and third terciles should produce larger estimates due to a reduction in attenuation caused by many households in high exposed regions that did not receive PATH, and many households in low exposed regions that did. Panel C of Table 6 presents the result of this analysis, As expected, the estimated DiD coefficient from the main model (from Table 4) became larger when exposed regions were defined using terciles due to a reduction in attenuation. Moreover, the overall young age category became statistically significant due to the strength of the estimated DiD effect on those 22-25 years old.

There may also be a question as to whether the results are sensitive to the choice of the poverty line. If it is, then it might imply that the main results were obtained by chance and not due to true resilience against poverty. The fourth and final robustness check determines whether the results are robust around a neighborhood of the poverty line, both up and down. To do this, two new poverty lines are defined, such that $\underline{y}_{new} = \underline{y} \pm \Delta$, where Δ is a marginal deviation from the main poverty line. The robustness of the main results were checked using these new lines. If Δ is set too large, then this would be identifying a completely different type of resilience/vulnerability rather than checking for the robustness of the current measure of resilience. For example, if Δ is large enough this may be identifying the effect of PATH on more extreme deprivation (such as food poverty) rather than normal poverty. An appropriate value of Δ must therefore be chosen. In Jamaica, a person is identified as vulnerable by arbitrarily scaling up the poverty line and comparing it to the person's adult equivalent consumption. The scaling factor is 10%; therefore, a policy relevant value of Δ could be a value such that the new poverty lines are 10% above and 10% below the current poverty lines.[21] The main analysis from Table 4 was redone using these new poverty lines to determine if the choice of poverty line influenced the results. Panels D1 and D2 of Table 6 presents the result of this analysis; the overall conclusion is that the impact of PATH does not change even when other poverty lines around the neighborhood of the old poverty lines were chosen. The DiD effect was significant for the same young-age cohorts as in the main analysis. Furthermore, the results appear to be stronger when using the poverty line 10% above the original line for the middle young-age cohort, which resulted in the overall young-age cohort becoming significant.

6.3 Falsification Tests

In addition to the robustness checks, four different falsification tests were carried out. One of the implied assumptions of the identification strategy is that there is no program or secular trend, independent of PATH, that affects the young cohort in high exposed regions differently than the old cohort in terms of resilience. If there were and it affected the old cohort differently, then this might bias the estimated treatment effects. The first three falsification tests checked the validity of this identification assumption using both the DiD and fixed effects specifications. The first check is an analysis between the 'old' cohort and an 'older' cohort. If there is a cohort difference between these two cohorts, then those same differences (possibly caused by some independent program specifically in regions highly exposed to PATH) may likely be what is being identified (and not the effect of PATH) in the comparison between the 'young' and 'old' cohorts. The second falsification test involves conducting the same DiD regression analysis between the 'young' and 'old' cohort as in Table 4, but using data from the 2008 JSLC. In 2008 most of the 'young' cohort (specifically, 20 to 28 years old) would not have been fully exposed to the PATH program since they had already begun high school at the inception of the program in 2002. The idea is that if there were

[21] In comparison, the food poverty line is 31.5% below the main/overall poverty line.

some time-invariant differences between the 'young' and 'old' cohorts (across high and low exposed regions) caused by some program that is independent of PATH, and those were the differences being picked up using the 2017 JSLC data, then those differences should also be picked up using the 2008 JSLC data. The third falsification test does the same thing with the 2002 JSLC data as with the 2008 data.

Panel A of Table 7 presents the results of the first falsification test. Since here the comparison is between the old cohort with an older cohort, panel A is not completed for column 1 which compares the middle young-age cohort to the old cohort. As expected, the DiD estimator of this falsification test is insignificant for the old and older cohort comparison, with the coefficient close to zero. The treatment effect coefficient on the fixed effects estimator presents the same picture. This result indicates that there are no cohort specific differences across these cohorts, thus it is unlikely there would be differences across the main cohorts. Panels B and C bolster this analysis with the results of the second and third falsification tests comparing the 'young' and 'old' cohorts using 2008 and 2002 data, respectively. The same high and low exposed regions from 2017 were used in the 2008 and 2002 comparison with a minor alteration; three additional constituencies/regions in two parishes were introduced between 2008 and 2017, making analysis using regions from those parishes problematic. To address this, I excluded the rural regions from these parishes in the analysis, affecting only 3 regions of 38 regions from the 2017 analysis, leaving 35 regions for the analysis using 2008 and 2002 data. While it is unlikely the exclusion of individuals from these 3 regions across the 2 parishes would affect the analysis, for reassurance additional analysis was carried out by counting all rural area individuals in each of the 2 parishes as one "region". Also, the JSLC data from 2008 and 2002 does not include labor market variables. The results from panels B and C for the 2008 and 2002 data, respectively, show that the positive DiD effect comparing the young and old cohorts from 2017 disappears. All the coefficients are close to zero and statistically insignificant. The results from these panels provide corroborative evidence that there are no time invariant differences between the 'young' and the 'old' cohort that would have held independent of PATH, just as there is none between the "old" and "older" cohorts (Panel A). The results from Panels B and C were consistent whether the two parishes affected by the changes in regions were included or excluded from the analysis. The differences that are picked up in 2017 are then because of the effect of PATH on the young cohorts who were exposed to the program due to their age.

The fourth and final falsification test checks whether there is any real information to be gathered when regions are grouped into high or low exposed according to the intensity of PATH. If there is none, then the estimated effects will hold true after random assignment of regions into these categories, and it is likely the difference observed is due to some a-priori difference between young and old age cohorts that is independent of PATH exposure in a region. The main analysis was then rerun with this new regional distinction created by random assignment. Panel D of Table 7 presents the results of this falsification test. The results show the DiD coefficient of the comparison between the middle young-age cohorts and the old cohort becomes insignificant when randomized regions are used. This reassures that the separation of regions according to PATH intensity does help to identify the effect of exposure to treatment and is not identifying some other factor that is independent of PATH exposure.

6.4 Source of Resilience

The ultimate goal of CCT programs is to break the cycle of intergenerational poverty, which can be achieved if program beneficiaries are made to have a lower risk of exposure to poverty in the future. The main mechanism through which PATH and most other CCT programs aim to accomplish this goal is through educational conditionalities. Other studies, as outlined in the introduction, have already presented evidence of the positive long-run impact of CCT programs on the educational and labor market outcome (see Millán et al. (2019)

for a review). The objective of this section is to briefly show that those features are also present in the Jamaican CCT program. Moreover, since the educational and labor market variables examined here were used to generate the resilience score, the coefficients will show how PATH affects these variables directly in impacting resilience against poverty. Specifically, I will examine whether PATH increases the likelihood that beneficiaries will complete primary and secondary level education, and transition to a tertiary institution. Moreover, in this section I will examine whether PATH results in more youth employment.

Table 9 presents the results for the effect of PATH on the probability of completing primary school, completing secondary school, obtaining a tertiary level education and being employed. Each model was estimated using a linear probability regression, using the same model specification on the right-hand-side like the models used to generate the main results. The young-age cohort used in this analysis are those 22-25 years old since they were shown to have the strongest impact from PATH. The results show that the DiD coefficients for all the dependent variables were positive and implies that exposure to PATH increase the probability of beneficiaries completing primary, secondary and tertiary education, as well as being employed. However, only the coefficient on the tertiary variable was significant. This result is consistent with another recent study evaluating the effectiveness of PATH, Stampini et al. (2018). Specifically, they found that PATH improved the test scores of urban male beneficiaries and they were more likely to be placed in higher ranked secondary schools. Consequently, it may be the case that PATH recipients were more likely to attend and graduate from tertiary level institutions, which is what the present study identifies by showing that PATH increases the probability of graduating from tertiary level institution by 10.5 percentage points.

7 Conclusion

Conditional Cash Transfer Programs (CCT) are the leading source of social assistance in many developing countries and can be found in many Latin-American and Caribbean countries. One such program is the Programme of Advancement Through Health and Education (PATH) in Jamaica, which provides benefits to a third of all children in Jamaica and highlights the potential reach of these programs. PATH is conditional since beneficiaries must meet educational and health conditions to receive benefits. A common goal of CCT programs, including PATH, includes the ex-ante prevention of poverty which can be achieved if beneficiaries are made more resilient against poverty. While there have been numerous evaluations of the impact of CCT programs on various outcomes, there is no rigorous evidence available to guide whether or how agencies might build resilience among target populations in the long-run. This paper uses PATH as a case study, by exploiting its age-based eligibility thresholds and its regional variation, to answer the question of whether (and to what extent) CCT programs can make beneficiaries more resilient against poverty in the long-run, where a person's resilience is the probability of not being poor in any time period.

This paper uses quantile regression models to estimate a person's resilience, and difference-in-differences (DiD) and fixed effects models to identify the intent-to-treat (ITT) effect of exposure to PATH. The results show that persons exposed to PATH when they were children have a higher level of resilience against poverty than they would have had in the absence of the program. However, the long-run (adulthood) program benefits do not materialize until after the child becomes 22 years old, which is after they have become more integrated into the labor market. Specific point estimates reveal that 'high exposure' to PATH makes beneficiaries 11.5 percentage points more resilient against poverty when a dichotomous treatment distinction is used. When a continuous treatment variable is used, the exposure to treatment effects were large: full/complete exposure to PATH increased resilience against poverty by 25.1 percentage points compared with no exposure. PATH was also shown to have a significant effect on resilience against food poverty (the probability that a person will not be 'food poor' in any time period). Other results showed that PATH also increased the likelihood of attaining a college level education.

A battery of robustness checks and falsification tests were carried out to provide confidence about the results. The results were shown to be robust when resilience was estimated using other values of the poverty line in the neighborhood of the original poverty line, or if the treated areas were defined based on the mean level of exposure to PATH rather than the median level of exposure. Moreover, the falsification tests did not show any results that were contradictory to the main results which would have disproved identification. Overall, these results rigorously illustrate whether and how agencies might build resilience among target populations in the long-run and provide further justification for the expansion of CCTs or similar programs targeting children living in less-developed countries. This makes CCTs a valuable tool for governments in places like Small Island Developing States (SIDS) such as Jamaica, which due to their size are very susceptible to internal and external shocks which can drive an individual into poverty.

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Tables

Table 1: Summary Statistics of Variables for Main Analysis

	Young in H/E (1)		Old (2)		
	Mean	Std. Err.	Mean	Std. Err.	Test: (1)= (2) [p-value]
Adult equivalent consumption expenditure ($), '000	370.1	18.9	280.8	12.97	0.000
Individual is HH head	0.198	0.028	0.483	0.031	0.000
Sex of individual (1=male)	0.475	0.035	0.457	0.030	0.694
Age of individual	22.75	0.174	35.96	0.122	0.000
HH size	4.797	0.211	4.169	0.140	0.010
Highest education of individual (=1 if true)					
Some primary	0.045	0.015	0.240	0.026	0.000
Some secondary	0.658	0.033	0.506	0.031	0.001
Technical/vocational	0.139	0.024	0.154	0.022	0.651
Tertiary	0.054	0.016	0.041	0.012	0.501
Occupation of individual (=1 if true)					
Legislator	0.020	0.010	0.034	0.011	0.364
Managers and Professional	0.015	0.009	0.011	0.006	0.730
Technicians	0.000	0.000	0.015	0.007	0.081
Clerical support	0.069	0.018	0.086	0.017	0.503
Service and sales	0.233	0.030	0.225	0.026	0.839
Skilled agriculture and elementary work	0.074	0.018	0.131	0.021	0.048
Crafts and similar trade	0.030	0.012	0.064	0.015	0.092
Plant and Machine	0.020	0.010	0.079	0.016	0.005
Armed forces	0.069	0.018	0.142	0.021	0.013
Type of employment of individual (=1 if true)					
Central government employee	0.010	0.007	0.090	0.018	0.000
Other government employee	0.010	0.007	0.019	0.008	0.435
Private sector employee	0.371	0.034	0.390	0.030	0.687
Unpaid family worker	0.010	0.022	0.022	0.009	0.298
Employer	0.005	0.005	0.004	0.004	0.843
Own account worker	0.129	0.024	0.270	0.027	0.000

Note: Author calculation using 2017 JSLC. Dollar values are in 2017 local currency unit (Jamaican dollars). H/E=High exposed regions. Old=Old cohort (33-39 years old in 2017), Young=Young cohort (19-28 years old in 2017).

Table 2: Quantile regression results for the conditional median of adult equivalent expenditure

Dependent variable: Adult equivalent consumption expenditure			
Covariate	Coefficient ('000)	Covariate	Coefficient ('000)
Individual is HH head	14.4	**Type of employment of individual (=1 if true)**	
	(10.6)	Central government employee	90.4
Sex of individual (1=male)	51.1***		(65.4)
	(9.76)	Other government employee	-24.0
Age of individual	-0.247		(76.4)
	(2.54)	Private sector employee	30.1
Age of individual squared	0.0058		(70.1)
	(0.033)	Unpaid family worker	29.2
HH size	-18.5***		(75.8)
	(1.28)	Employer	189**
Occupation of individual (=1 if true)			(81.6)
Legislator	3.46	Own account worker	58.5
	(74.9)		(71.1)
Managers and Professional	51.3	**Highest education of individual (=1 if true)**	
	(81.1)	Some primary	-39.1**
Technicians	1.20		(19.5)
	(76.0)	Some secondary	-1.04
Clerical support	9.91		(17.6)
	(73.3)	Technical/vocational	32.0
Service and sales	3.22		(26.9)
	(70.1)	Tertiary	104.9
Skilled agriculture and elementary work	12.8		(23.3)
	(71.2)		
Crafts and similar trade	91.3		
	(70.4)		
Plant and Machine	13.1		
	(67.2)		
Armed forces	-41.5		
	(70.7)		

Note: Standard errors (in parenthesis) are computed using a kernel estimate of the VCE proposed by Powell (1991). Coefficients are monetary values in local currency unit (Jamaican dollars).

Table 3: Mean of resilience to poverty by cohort and region

	Estimated resilience score		
Comparison of interest (2017 data)	Treated area	Untreated area	DIFF
4 to 13 y/o in 2002 (19 to 28 y/o in 2017)	0.760	0.717	0.042
	(0.23)	(0.25)	(0.551)
18 to 24 y/o in 2002 (33 to 39 y/o in 2017)	0.841	0.860	-0.018
	(0.017)	(0.015)	(0.468)
DIFF	-0.082	-0.142	0.061
	(0.482)	(0.531)	(0.708)
Control Comparison (2017 data)			
18 to 24 y/o in 2002	0.841	0.859	-0.018
	(0.205)	(0.164)	(0.454)
25 to 30 y/o in 2002	0.840	0.855	-0.015
	(0.177)	(0.147)	(0.446)
DIFF	0.001	0.005	-0.003
	(0.435)	(0.442)	(0.627)

Note: Author calculation using 2017 JSLC. Standard errors of differences (in parenthesis) are computed by bootstrap.

Table 4: Estimated impact of PATH on resilience to poverty

	Dependent Variable: Resilience Scores			
	Models			
	(1) 19-28 years old (Y/O)	(2) 19-21 Y/O	(3) 22-25 Y/O	(4) 26-28 Y/O
Comparison of interest (2017 data)				
Young cohort X High exposed region	0.051	0.013	0.115**	0.010
	(0.041)	(0.046)	(0.047)	(0.059)
Young cohort	0.019	0.267	0.127	-0.111
	(0.044)	(0.184)	(0.123)	(0.127)
High exposed region	-0.015	-0.016	-0.016	-0.017
	(0.024)	(0.023)	(0.023)	(0.023)
Constant	0.243	-0.839	-0.782	2.810
	(0.229)	(1.000)	(0.943)	(2.102)
Sample size	719	412	457	384

Note: Author calculation using data from the 2017 JSLC. Standard errors (in parenthesis) estimated using the wild bootstrap set to 600 reps and clustered at the Primary Sampling Unit (PSU) level. ** denote significance at the 0.05 level. Models 1, 2, 3 and 4 uses those 19-28, 19-20, 22-25 and 26-28 years old as the young age-cohort. In addition to the covariates listed in the table, the models also control for the age and sex of each individual. The dependent variable in each column are resilience scores constructed from the cumulative distribution, which were characterized by quantiles estimated using the same control variables listed in Table 2 (along with region fixed effects). The "young" are defined by the age categories in the column headings, and the "old" are those 18-24 years old in 2002 (33-39 years old in 2017).

Table 5: Estimated impact of PATH on resilience against food poverty

	Dependent Variable: Resilience Scores	
	Models	
	19-28 years old (Y/O)	22-25 Y/O
Comparison of interest (2017 data)		
Young cohort X High exposed region	0.030	0.074**
	(0.030)	(0.034)
Young cohort	-0.012	0.038
	(0.035)	(0.095)
High exposed region	-0.019	-0.020
	(0.015)	(0.015)
Constant	0.597	-0.782
	(0.200)	(0.780)
Sample size	719	457

Note: Author calculation using data from the 2017 JSLC. Standard errors (in parenthesis) estimated using the wild bootstrap set to 600 reps and clustered at the Primary Sampling Unit (PSU) level. ** denote significance at the 0.05 level. Models 1 and 2 uses those 19-28 and 22-25 years old as the young age-cohort. In addition to the covariates listed in the table, the models also control for the age and sex of each individual. The dependent variable in each column are resilience scores constructed from the cumulative distribution, which were characterized by quantiles estimated using the same control variables listed in Table 2 (along with region fixed effects). The "young" are defined by the age categories in the column headings.

Table 6: Robustness Checks

	Models	
	(1) 19-28 years old (Y/O)	(2) 22-25 Y/O
Panel A: FE estimation of resilience against poverty (2017 data)		
Young cohort X PATH intensity in region	0.109**	0.251***
	(0.051)	(0.093)
Panel B: High exposed regions based on mean program intensity		
Young cohort X High exposed region	0.050	0.111**
	(0.040)	(0.046)
Panel C: High exposed regions based on terciles		
Young cohort X High exposed region	0.096*	0.169**
	(0.046)	(0.054)
Panel D1: Using poverty line 10% below original poverty line		
Young cohort X High exposed region	0.045	0.104**
	(0.039)	(0.044)
Panel D2: Using poverty line 10% above original poverty line		
Young cohort X High exposed region	0.059**	0.127**
	(0.044)	(0.052)
Sample size	719	457

Note: Author calculation using data from the 2017 JSLC. Standard errors (in parenthesis) estimated using the wild bootstrap set to 600 reps and clustered at the Primary Sampling Unit (PSU) level. ** and *** denote significance at the 0.05 and 0.01 levels. Models 1 and 2 respectively uses those 19-28 and 22-25 years old as the young age-cohort. In addition to the covariates listed in the table, the models also control for the age and sex of each individual. The dependent variable is resilience scores constructed from the cumulative distribution, which were characterized by quantiles estimated using the same control variables listed in Table 2 (along with region fixed effects). The "young" are defined by the age categories in the column headings. FE=Fixed effects. Panels A presents treatment effects based on fixed effects specification, while the other panels present treatment effects based on DiD specification.

Table 7: Falsification tests of the estimated impact of PATH on resilience to poverty

	Dependent Variable: Resilience Scores	
	Models	
	(1) 22-25 Y/O	(2) Old vs Older
Panel A: Main control comparison (2017 JSLC data)		
Falsification test A1: DiD using ”old” and ”older” with main data	-	-0.014
	-	(0.035)
Falsification test A2: FE using ”old” and ”older” with main data	-	0.016
	-	(0.041)
Sample size	-	509
Panel B: Control comparison (2008 JSLC data)		
Falsification test B: DiD using ”young” and ”old”	0.012	-0.011
	(0.020)	(0.015)
Sample size	1276	1496
Panel C: Control comparison (2002 JSLC data)		
Falsification test C: DiD using ”young” and ”old”	0.016	0.000
	(0.026)	(0.018)
Sample size	1836	1969
Panel D: Randomized treatment groups (2017 JSLC data)		
Falsification test D: DiD using ”young” and ”old”	-0.034	-
	(0.044)	-
Sample size	457	-

Note: Author calculation using data from the 2017, 2008 and 2002 JSLC. Standard errors (in parenthesis) estimated using the wild bootstrap set to 600 reps and clustered at the Primary Sampling Unit (PSU) level. FE=fixed effects. None of the DiD/FE estimators were significant in the models. Models 1 compares the middle young age-cohort (22-25 y/o in 2017) with the old age-cohort (33-39 y/o in 2017) across regions. Model 2 compares the old cohort with the ”older” age-cohort (40-45 y/o). In addition to the covariates listed in the table, the models also control for the age and sex of each individual. The dependent variable in each model are resilience scores constructed from the cumulative distribution, which were characterized by quantiles estimated using the same control variables listed in Table 2 (along with region fixed effects), except for the labor market variables in the case of panels B and C. In 2008 and 2002 there were no labor market information collected in the JSLC.

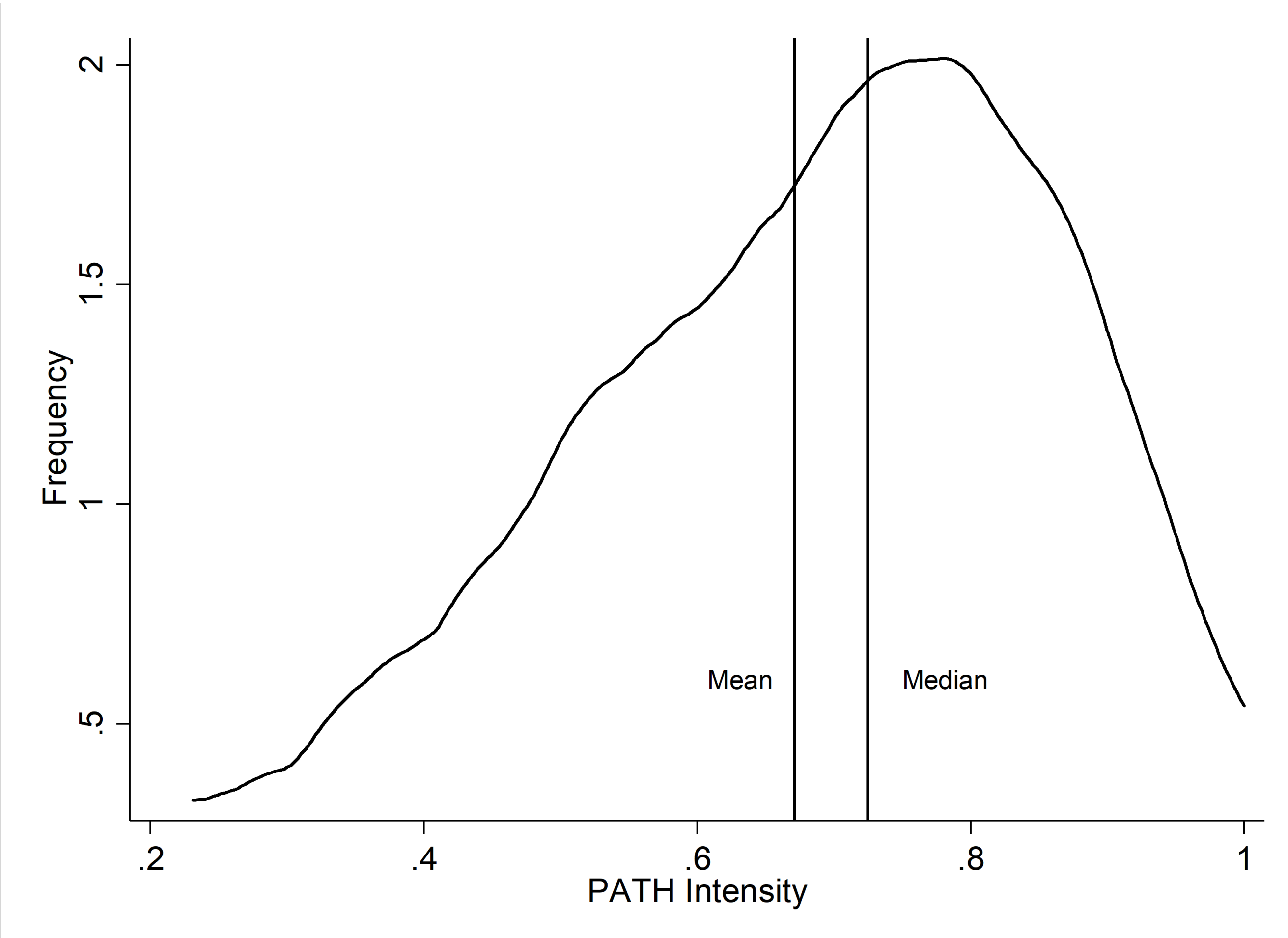
Table 8: Estimated impact of PATH on Educational and Labor Market Outcomes

Model	Dependent Variable	Sample Size	Marginal Effects
1	Primary School Completion	412	0.067
			(0.065)
2	High School Completion	416	0.061
			(0.092)
3	Tertiary Education	350	0.105*
			(0.060)
4	Employment	352	0.062
			(0.109)

Note: Author calculation using data from the 2017 JSLC. Standard errors are clustered at the Primary Sampling Unit (PSU) level. * denote significance at the 0.05 level. Each row represents a model with a different dependent variable as listed. The models are estimated using a linear probability regression. The model specification is a DiD and includes additional controls for the age and sex of each individual. The "young" are those 22-25 years old in 2017 since these individuals were shown to have the largest treatment effect coefficient from PATH. The "old" are those 18-24 years old in 2002.

Figures

Figure 1: Distribution of Program Intensity across regions



Note: Author calculation from 2017 JSLC. Kernel=epanechnikov and bandwidth=0.08. Figure illustrates the distribution of the intensity of PATH across all regions. PATH intensity is the proportion of all individuals in a region that live in a household that has ever received a PATH benefit.

Appendix

The measure of resilience used in this paper is similar to the Cissé and Barrett (2018) measure of resilience. However, this paper estimates resilience as $\hat{\rho}_{it} = f(y_{it} > \underline{y}|x_{it})$, while Cissé and Barrett (2018) uses the dynamic welfare probability $\hat{\rho}_{it} = f(y_{it} > \underline{y}|X_{is} = x_{it}, y_{it-1})$, where the parameters in these specifications are as defined in section 3. The only difference between the measure of resilience used in this paper and Cissé and Barrett (2018) is the exclusion of the additional covariate y_{it-1} in this paper. Directly adopting the Cissé and Barrett (2018) measure necessarily requires panel data, but household level panel data is not available for most developing countries, including Jamaica. This appendix provides a brief comparison between the resilience measure used in this paper and the Cissé and Barrett (2018) measure.

Two different sensitivity analysis were used to compare the two measures: the first is a Kolmogorov–Smirnov (K-S) test to determine whether the quantiles estimated across the two specifications were drawn from the same distribution. The second will directly determine whether the estimated resilience value significantly differed across specifications for each household. The comparisons are possible since, before 2009, a two-period household panel could be created using cross sectional data from the JSLC across two different years. This is because of how households were sampled in that time. A sample of 'electoral districts' were selected in a first stage, and these comprised the Primary Sampling Units (PSU). These PSUs were kept for 2-4 years, and households were randomly sampled from the PSUs every year. Thus, within the 2-4 years period, a household may be visited more than once and those households could be used to construct a panel by matching households surveyed in one year (for example 2004) with those surveyed in another year (for example 2006). Since some households are rented and the tenants may have changed between panel waves, matches were considered valid only if the gender of the household head remained the same and the household head in 2006 was 1-3 years older than they were in 2004. Since the panels were created at the household level, all the following checks were conducted at this level of aggregation. Balance tests were carried out to ensure that the covariates used balanced between the panel sample and full sample using 2006 data. These results, reported in Table A, shows that the covariates balanced for almost all the variables, which importantly includes the dependent variable.

For the first sensitivity analysis, the 99 quantiles from the distribution of consumption were estimated using the two model specifications for each household. A K-S test was then conducted to determine whether the quantiles were drawn from the same distribution. Results showed that for 73.3% of households, the quantiles were drawn from different distributions when comparing the two specifications at the 5% level of significance (panel A of Table B). This signifies that for most households, previous value of welfare does affect the overall distribution of welfare. The quantile consumption values were then averaged across households and the average distribution plotted in Figure A below. The figure illustrates how the specification with past consumption values shifts the distribution to the left. The visualization also suggests that while past consumption changes the distribution, this change is not monotonic across the whole distribution. That is, for lower quantiles of the distribution, including the parts below the poverty line, the effect of changing specification appears to be non-existent. This implies that the specification might not matter to the estimated resilience level. The second sensitivity analysis directly looks at this. The resilience measure under each specification (with and without past consumption) was first calculated for each household using the 99 quantiles. The standard error for this estimate was then estimated by bootstrap under each specification for each household. The results, in panel B of Table B, showed that for over 93% of households the 95% confidence interval for the resilience estimate under the specification without past consumption included the resilience estimate under the specification with past consumption. This corroborates the visual evidence that, generally, the specification did not significantly affect the estimated resilience score.

Overall, the evidence suggests that the calculated resilience scores are generally similar across the two resilience measures. However, there are nontrivial differences in the characteristics of the full conditional distribution as mentioned above. Nevertheless, both techniques can provide a good summary estimate of a person's resilience against poverty.

Table A: Balance test between panel and full sample using 2006 data

	Full sample		Panel Sample		Difference	
	Mean	Std. Err.	Mean	Std. Err.	Diff	Std. Err. Diff
log Adult equivalent consumption expenditure (in 2006 local currency unit)	12.045	0.016	12.008	0.020	0.037	0.025
Age of HH head	49.594	0.385	50.915	0.494	-1.322	0.627**
Sex of HH head (1=male)	0.541	0.011	0.536	0.015	0.005	0.019
HH size	3.286	0.050	3.453	0.067	-0.166	0.083**
Number of Children (0-17 years old)	1.240	0.035	1.345	0.047	-0.105	0.058
Number of elderly (¿65 years old)	0.438	0.018	0.471	0.025	-0.033	0.031
# persons per habitable rooms in home	1.458	0.026	1.487	0.034	-0.029	0.043
Rent home (=1 if true)	0.194	0.009	0.154	0.011	0.040	0.014***
Own home (=1 if true)	0.611	0.011	0.665	0.014	-0.054	0.018***
HH head is married (=1 if true)	0.303	0.010	0.316	0.014	-0.013	0.017
Highest education of HH head (=1 if true)						
Some primary	0.196	0.009	0.214	0.012	-0.018	0.015
Some secondary	0.689	0.011	0.686	0.014	0.003	0.017
Technical/vocational	0.022	0.003	0.017	0.004	0.005	0.005
Tertiary	0.063	0.006	0.057	0.007	0.006	0.009
Occupation of HH head (=1 if true)						
Legislator	0.042	0.005	0.046	0.006	-0.005	0.008
Managers and Professional	0.037	0.004	0.039	0.006	-0.003	0.007
Technicians	0.029	0.004	0.025	0.005	0.003	0.006
Clerical support	0.049	0.005	0.045	0.006	0.003	0.008
Service and sales	0.143	0.008	0.144	0.010	-0.001	.013
Skilled agriculture and elementary work	0.287	0.010	0.289	0.013	-0.001	0.017
Crafts and similar trade	0.158	0.008	0.159	0.011	-0.001	0.014
Plant and Machine	0.054	0.005	0.049	0.006	0.005	0.008
Armed forces	0.011	0.002	0.010	0.003	0.000	0.004

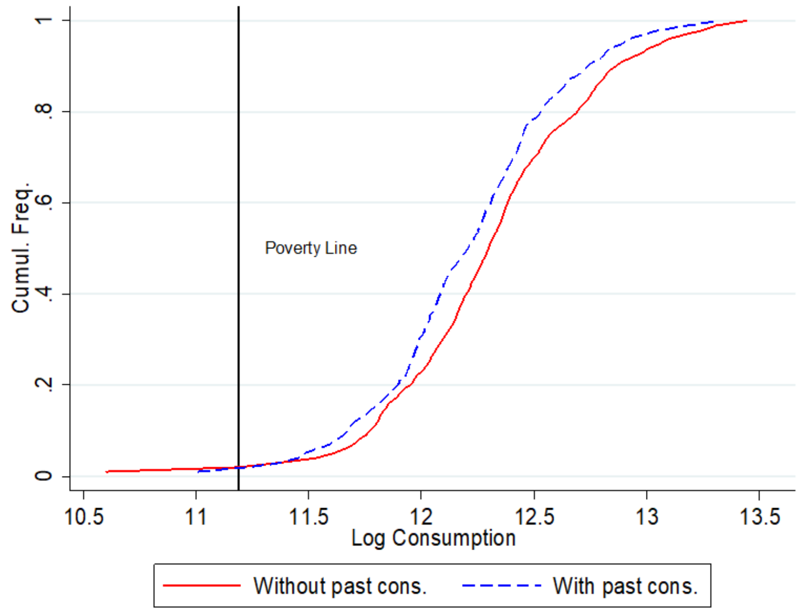
Note: Author calculation using the 2004 and 2006 JSLC. Standard error of the difference computed via bootstrap. ** and *** denote significance at the 0.05 and 0.01 levels, respectively.

Table B: Checks for differences across specifications

	Percent
Panel A: KS test for differences in conditional distribution	
% Households whose distribution were not affected by specification	26.7
% Households whose distribution were affected by specification	73.3
Panel B: Household level estimated resilience	
% Households whose measured resilience were not affected by specification	93.7
% Households whose measured resilience were affected by specification	6.3

Note: Author calculation using the 2004 and 2006 JSLC.

Figure A: Average conditional cumulative distribution



Note: Author calculation using the 2004 and 2006 JSLC. Analysis is at the household level. The cumulative distribution of consumption is estimated for each household, then is averaged and then plotted.