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HOW PRO-POOR GROWTH AFFECTS THE DEMAND FOR ENERGY

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ABSTRACT

Most of the future growth in energy use is forecast to come from the developing world. Understanding the likely pace and specific location of this growth is essential to inform decisions about energy infrastructure investments and to improve greenhouse gas emissions forecasts. We argue that countries with pro-poor economic growth will experience larger increases in energy demand than countries where growth is more regressive. When poor households' incomes go up, their energy demand increases along the extensive margin as they buy energy-using assets for the first time. We also argue that the speed at which households come out of poverty affects their asset purchase decisions.

We provide empirical support for these hypotheses by examining the causal impact of increases in household income on asset accumulation and energy use in the context of Mexico's conditional cash transfer program. We find that transfers had a large effect on asset accumulation among the low-income program beneficiaries, and the effect is greater when the cash is transferred over a shorter time period. We apply lessons from the household analysis to aggregate energy forecast models using country-level panel data. Our results suggest that existing forecasts could grossly underestimate future energy use in the developing world.

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Understanding the likely growth in the demand for energy is critical for several reasons. First, energy use is a key contributor to climate change as energy-related emissions account for three-quarters of worldwide anthropogenic greenhouse gas emissions.[1] Forecasting the likely path of greenhouse gas emissions is essential to understanding the range of possible effects of climate change. And, expected country-level emissions are critical inputs to any international climate agreement. Negotiations that aim to include developing countries can break down if the parties have different expectations about emissions paths. Second, investments in energy infrastructure require long lead times, and most governments and energy companies base their investment decisions on demand projections. Incorrect forecasts can lead to energy shortages that affect both productivity and welfare. On a global scale, faster than anticipated growth in energy demand can lead to significant increases in energy prices.

Aggregate forecasts of energy use and greenhouse gas emissions suggest that the developing world will contribute to most of the growth over the next several decades (see, e.g., EIA, 2011). These forecasts rely on assumptions on the form of the relationship between GDP growth and energy use. In this paper, we argue that energy use may rise faster in response to GDP growth when the growth is pro-poor. Forecasts that ignore this may significantly underestimate the effect of GDP growth on energy use.[2]

Today nearly 1.5 billion people live without electricity in their home, most of them in developing countries. This is likely to change in the near future as wide-scale poverty alleviation programs as well as continued economic growth lift the incomes of many of the world's poor. As incomes rise and electricity coverage expands, families formerly living in poverty will for the first time purchase refrigerators, water pumps, air conditioners, washing machines, and other household electrical appliances, as well light the rooms in their houses. In this paper, we argue that if the reduction in poverty is rapid, there could be a surge in the demand for energy. Such a large increase in energy consumption would have broad implications both for energy markets and for greenhouse gas emissions.

Importantly, increasing the income of the poor moves their demand for energy along the extensive margin as they buy energy-using assets for the first time. When a household acquires an energy-using asset, like a refrigerator or car, its energy use increases substantially. While income growth will also affect energy consumption on the intensive margin (i.e., holding asset ownership fixed), the effect is small compared to the effect of accumulating more energy-using

[1] See, for example, http://www.epa.gov/climatechange/science/indicators/ghg/global-ghg-emissions.html.
[2] In Wolfram, Shelef and Gertler (2012) we elaborate on the potential underestimates in some of the most prominent energy forecasts.

assets (i.e. the extensive margin). As households come out of poverty, their demand moves mostly along the extensive margin leading to large discrete jumps in energy consumption.

The discrete jump is suggested by the well-documented S-shaped relationship between income and asset ownership (Koptis and Cropper, 2005; Dargay, Dermot and Sommer, 2007; Letschert and McNeil, 2007). Figure 1 uses household data from several of the most populous developing countries to plot the share of households that own refrigerators against per-person household expenditures in logs. While the cross-sectional relationships in Figure 1 are not necessarily causal, they do show that at a particular income level, which varies country by country, there is rapid growth in refrigerator ownership with income implying rapid growth in the demand for energy.

The dashed lines in Figure 1 show the density of households by expenditure level. The three plots in the top row depict regions that have experienced income growth among the poor, largely driven by poverty alleviation programs in Mexico and Brazil, and economic growth in urban China. As a result, a substantial share of the population in these regions has already moved through the income level associated with the increase in refrigerator ownership. Income growth beyond this point has less of an effect on energy demand as more of it occurs on the intensive as opposed to extensive margin. The plots in the bottom row, however, indicate that there are significant populations poised to buy refrigerators in India, Indonesia and rural China, which together represent more than two billion people.

We also show that the speed at which poor households come out of poverty affects their energy demand. In Section 1, we present a simple two-period model of asset accumulation in the presence of liquidity constraints such as those faced by most families living in poverty. In this case, the intertemporal dynamics become important. We show that both income and savings accumulated from past income drive acquisition. As a result, both income levels and income growth impact the decision to purchase an energy-using good such as a refrigerator. In fact, with growing incomes, we show that it can be in a family's interest to reduce current consumption and save in order to acquire the asset sooner.

Our model has important implications for understanding the rate of lumpy asset acquisition in different countries. For example, it predicts that two countries that are at the same current level of income per capita may have different asset ownership rates because the country where recent growth was fast will have a higher ownership rate than the country where recent growth was slower. Our model also predicts that the design of poverty alleviation policies such as cash transfer programs will affect asset accumulation. Specifically, we show that the timing of payments should matter for asset acquisition rates. For instance, a program that distributes transfers on a quarterly basis may lead to more refrigerator acquisition than a program that distributes transfers bi-weekly.

In the empirical section of the paper, we examine the causal impact of different income streams on asset accumulation and energy use in the context of Mexico's conditional cash transfer program, Oportunidades. Oportunidades is one of the largest and most generous programs in the world, covering some five million Mexican families and providing benefits on the order of a 20 percent increase in income on average. The program provides a unique empirical setting to examine the relationship between income and asset acquisition both given the size of the cash transfers and given the heterogeneity in transfer amounts across households and over time. We exploit several sources of variation in cash transfer amounts, including the fact that the program was rolled out randomly across villages.

Our results are consistent with the theoretical predictions of the model presented in Section 1. First, we find that the increase in income through the transfers had a large effect on asset accumulation. Specifically, we estimate that the median transfer amount led to a seven percentage point increase in refrigerator ownership over a six-year period off a four percent base level of ownership. Second, we show that the effect on asset accumulation is substantially greater when the cash is transferred over a shorter time period. Specifically, we estimate that there would have been nearly a 13-percentage point increase in refrigerator ownership if the same benefits were delivered in four years instead of six.

We also use data from Oportunidades to estimate a model of electricity demand, separately identifying the intensive and extensive margins. We find that most of the income effect is driven by asset ownership as opposed to the income effect on electricity use conditional on asset ownership. This result is consistent with our hypothesis that a fast reduction in poverty that leads to massive asset accumulation will have a greater effect on energy demand than a similar-sized increase in income for households that already own the assets.

Finally, we return to the aggregate energy forecast models that motivated this analysis, now incorporating the lessons learned from the causal, household-level data analysis. We use country-level panel data to describe the relationship between GDP and energy consumption. We show that if a country's growth has been pro-poor, the income elasticity of energy is nearly double that of a country with GDP growth that has been less favorable to the poor. This implies that not accounting for pro-poor growth would grossly underestimate future energy use.

The next section presents a simple two-period model of asset acquisition in the presence of borrowing constraints and varying rates of income growth. Section 2 describes the

Oportunidades program, which we use to test the predictions of our model. Section 3 describes our data. We present results on asset acquisition by Oportunidades households in Section 4, and results on energy use, conditional on asset ownership in Section 5. Section 6 explores the implications of our model for cross-country estimates of the relationship between GDP and energy consumption. Finally, Section 7 concludes.

1. Conceptual Framework

Changes in income affect energy consumption through several channels. In their influential paper, Dubin and McFadden (1984) emphasized that energy consumption depends not only on the usual utility-maximization problem as a function of income and energy prices, but also on the household's current appliance holdings. A number of subsequent papers have analyzed appliance acquisitions, however, few researchers have analyzed the intertemporal dynamics that may influence these decisions. In fact, most researchers make assumptions that preclude intertemporal considerations, such as perfectly efficient capital markets.[3] While such assumptions may or may not be appropriate in the developed world, it is clear that capital constraints are significant among the poor in the developing world.[4]

To illustrate the impact of capital constraints and to motivate our empirical specification we develop a simple dynamic model of savings and durable good acquisition. We show that both current income as well as savings, accumulated from past income, drive acquisition. This implies that both current income and the speed at which income grows impact acquisition.

Our model has two periods. Consumption is composed of two goods: a non-durable good, "food," that gives per-period utility $u_f(\cdot)$ with decreasing marginal utility, and a lumpy durable good, "refrigerator," that gives static per-period utility R if owned. A consumer has per period income Y, no access to credit, and the ability to save an amount $S \in [0, Y]$ from the first period to the second. For simplicity, there is no discounting, no interest, no complementarity between

[3] For example, Dubin and McFadden (1984) and, more recently, Bento, Goulder, Jacobsen and von Haefen (2009) assume a perfectly competitive rental market for durables. This could exist in the presence of efficient capital markets and an efficient resale market. In recent work, Rapson (2011) and Schiraldi (2011) model dynamic considerations focusing on, respectively, consumer expectations about future energy (i.e., usage) prices and heterogeneous consumer transaction costs. No papers, of which we are aware, explicitly model credit constraints or analyze durable good acquisition in the developing world.

[4] Liquidity constraints and poverty has been explored in Banerjee and Newman (1993), Aghion and Bolton (1997), Lindh and Ohlsson (1998), Lloyd-Ellis and Bernhardt (2000), Banerjee (2004), and de Mel, McKenzie, and Woodruff (2008) amongst others.

the two assets, and no on-going energy costs associated with owning the refrigerator.[5] We normalize the price of food to 1, and let the price of the refrigerator be P. In our context refrigerators are large purchases not easily made in one period. In fact, Gertler et al. (2012) show that low-income Mexican participants in the Oportunidades program allocate 76% of transfers towards time-specific consumption. Reflecting that, we assume that the refrigerator is too expensive to be purchased in one period: $Y < P$.[6]

Consumers vary in their valuations of the durable good R and their incomes Y. From decreasing marginal utility of food, it follows that for valuations of the durable good (income) below a threshold $\underline{R}$ ($\underline{Y}$) households do not purchase it. For valuations above that threshold, households save an amount $\frac{P}{2}$ in the first period and purchase the durable in the second period. Because of the credit constraints, households cannot borrow to purchase the durable in the first period. Under reasonable assumptions on the functional form of u_f and the distribution of R then the share of households with a given income who own a durable at the end of the second period is S-shaped.[7] Our assumptions thus far are consistent with Farrell (1954) and Bonus (1973) who assumed distributions of valuation parameters and income thresholds, respectively, and showed that these lead to S-shaped logit or probit curves for appliance ownership.

Figure 2 Panel A illustrates the threshold $\underline{R}$ ($\underline{Y}$) graphically. The figure plots a household's per-period marginal utility as a function of *Y*, so the area of the figure represents utility. As there is no discounting and no other changes to the household across periods, Figure 2 Panel A applies to both periods 1 and 2. The area under the rectangle with height $\frac{R}{P}$ and base $\frac{P}{2}$ will reflect the per-period utility the household receives if it saves $\frac{P}{2}$ in period 1 and purchases the refrigerator in period 2. The red (dark) shaded area reflects the lost utility of food from purchasing the refrigerator. As this is exactly equal to the green (light) shaded area, which captures additional utility from the refrigerator, this household will be just indifferent between saving to acquire the refrigerator and consuming only food. Households with higher valuations of the refrigerator (higher R, i.e., taller rectangles) or higher incomes (higher Y, i.e. rectangles shifted to the right) and therefore lower marginal utility of food, will strictly prefer to purchase the refrigerator.

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[5] We show below that our main results are accentuated or unchanged if the two goods are complementary. Also, for simplicity, we abstract from the energy use by the appliance. One can consider R as the net benefit from using the asset including energy costs. Our main results are robust to this extension.

[6] This simplifies the analysis because no household can purchase the good in one period. Our results are robust to relaxing this assumption. Alternatively, we can impose restrictions on $u_f(\cdot)$ such that even if a consumer was able to purchase the refrigerator in one period he or she would choose not to (e.g., by imposing that the marginal utility from subsistence food levels are sufficiently high). Those restrictions yield similar results.

[7] For example, if u_f is log, and R is distributed log normally.

We next extend this framework to consider changes in income period-to-period. Since our empirical setting involves a conditional cash transfer program, we describe the model in terms of transfer payments, although those could equally be interpreted as expected changes in income. Consider an increase in household income by a per-period transfer, T, such that the refrigerator is still unaffordable in one period ($Y + T < P$). This increase will cause more households to acquire the refrigerator. Specifically, all households with purchasing thresholds between $\underline{Y} - T$ and $\underline{Y}$ now purchase. This leads to our first empirical prediction:

Prediction 1: The larger the increase in income, the more likely the household is to purchase a durable.

We next consider differences in the rates of change in income. For example, in our empirical setting, not all households receive transfers at the same rate. Consider a household that receives the same transfers in total ($2T$), but receives transfer $\mathrm{L} < T$ in the first period and $\mathrm{H} = 2\mathrm{T} - \mathrm{L}$ in the second period. Suppose that $\mathrm{H} - \mathrm{L} < P$. Observe that if the household saves and purchases the durable, the path of consumption is exactly as it was for the household with even transfers (*T*), but savings are lower. However, the utility from not purchasing is reduced because consumption is uneven. The household would prefer to shift consumption from period 2 to period 1 but cannot because of the credit constraints.[8] Instead, additional households find it preferable to save and purchase the durable good. If $\mathrm{H} - \mathrm{L} \geq \mathrm{P}$, households do not save and the credit constraint prevents consumption smoothing. Some households who would prefer to consume more than $Y + L$ and not purchase the asset in the case of even transfers now find it optimal to purchase the durable in the second period.

This effect is represented in Panels B and C of Figure 2. Panel B is similar to Panel A, except that total income is equal to *Y + T* instead of *Y*. Panel B establishes that for a low enough valuation of the refrigerator (R^L), the household will not purchase the refrigerator in the even transfer case. Compare this to the case where transfers are uneven, as depicted in Panel C. In order to purchase the refrigerator, the household now must save only amount S in period 1. The lost utility from forgoing food consumption in order to save (net of the gain from the refrigerator in period 2) is indicated by the red (dark) shaded area. In period 2, the household also forgoes the wedge under the marginal utility of food curve (red/dark shaded area plus dotted area), but gains the green (light) shaded area. As drawn, the green (light) shaded areas is larger, suggesting that the household with refrigerator valuation R^L will purchase the refrigerator in

[8] While optimal transfer design is not the focus of this simplified model, it is clear that front loading all transfers in the first period is first best in this simplified context. However, we restrict attention to higher second period transfers consistent with real world transfer programs and the effects of growth.

the increasing transfer case, whereas it would not have purchased the refrigerator in the even transfer case.

This result combines a "forced savings" and a "complementary savings" effect. A household whose transfers are delayed has the same income in each period as a household with even transfers that was forced to save $T - L$. Expecting that it will receive these forced savings in the second period, it may be willing to complement the forced savings and save an additional amount (S in Panel C) in order to purchase the lumpy asset in period 2. These two effects cause some households who would not have purchased the refrigerator with evenly spaced transfers to buy the asset if transfers are delayed. This provides a second empirical prediction.

Prediction 2: Holding cumulative income fixed, households who gain more income in the second period (i.e., for whom income growth is faster) will be more likely to acquire assets.

Finally, the model predicts that there will be an interaction effect between the size of cumulative transfers (T) and the timing of transfers. Specifically, hold the ratio of first to second period transfers, α, constant (the ratio, α, is 1 in the even-transfers case, and between 0 and 1 in the delay case). Consider an increase of total transfers from $2T$ to $2(T + T')$. As long as delayed households still save to purchase $(H + (1 - \alpha)2T' - L - \alpha 2T' < P$ is a sufficient condition) and the ratio of transfers is small enough, then the increase in total transfers by $2T'$ decreases the valuation threshold $\underline{R}$ for delayed households more than households with constant transfers.

To understand this mechanism, first note that if the household saves and purchases the durable good it has the same consumption pattern regardless of the pattern of transfers. So we only need to show that the delayed transfers receive a smaller increase in utility than the even transfers group from the increase in transfers. This follows from decreasing marginal utility if α is sufficiently small.[9] This leads our third empirical prediction:

Prediction 3: The effect of additional income on asset acquisition will be larger for households whose income is growing quickly.

[9] Formally, we prove this as follows: The increase in utility from not purchasing in the even case is $2\left(u_f(T + T') - u_f(T)\right)$. For the uneven case it is $u_f(L + \alpha 2T') - u_f(L) + u_f(H + (1 - \alpha)2T') - u_f(H)$. As $\alpha \to 0$, $u_f(L + \alpha 2T') - u_f(L) \to 0$ and, from decreasing marginal utility $2\left(u_f(T + T') - u_f(T)\right) > u_f(H + 2T') - u_f(H) > u_f(H + (1 - \alpha)2T') - u_f(H)$. So, by continuity, for a sufficiently small α: $2\left(u_f(T + T') - u_f(T)\right) > u_f(L + \alpha 2T') - u_f(L) + u_f(H + (1 - \alpha)2T') - u_f(H)$.

While the model and these three predictions are described in terms of transfers expected by the households, it could easily be interpreted as additional income expected from economic growth.[10] The model predicts that holding constant total increases in income over some time period, asset acquisition will depend on the pattern of growth. For example, in Figure 3 at point t^*, the integral under the green (light) line is equal to the integral under the red (dark) line, so the cumulative income of two sets of households facing these income trajectories would be the same. Our model suggests that households whose income followed the green line may be more likely to acquire a refrigerator in period t^* because of the forced and complementary savings effects. While the incomes of households facing the green line are growing slowly, income levels may be so low that very few are willing to purchase a refrigerator. Fast income growth at the higher income levels may lead to more asset acquisition following prediction 2 above.

Also, while the model has two periods, the underlying mechanisms are quite general.[11] Any multiple period model of asset acquisition with increasing income has three phases: a savings phase in which the asset is not owned and weakly positive amounts are saved, an endogenously determined purchase period when the asset is purchased, and a utilization phase in which the asset is enjoyed. Our model represents the first two phases, with the final phase held constant. With more periods, the comparative statics remain: The wealthier is the household, the more likely they are to purchase (and sooner). The more uneven is income in the savings and purchase period, the more likely the consumer is to purchase. Similarly, the higher future income is, the more likely the consumer is to delay purchasing. Finally, holding fixed the purchase period, the income increases lead to more acquisition the more the savings phase and purchase period are uneven.

A multi-period model also suggests interesting conclusions about the shape of the S-curve. For instance, if households are credit constrained and incomes are growing, the range of incomes where asset ownership is increasing narrows. Thus, the S-curve is steeper than it would be with either no income growth or no credit constraints. This is because expected income growth leads some poor households to delay asset purchases while richer households will not be constrained. As a result, in intermediate periods, there are poor households who are delaying their purchases because of growth in future incomes.

[10] All of the comparative statics hold if households are uncertain about second period income, but the predictions are in terms of first-order stochastically dominated distributions of future income instead of higher income.

[11] Complementarity between the two goods – food and refrigerators – will amplify the results of prediction 1 and leaves unchanged predictions 2 and 3. Prediction 1 is magnified because the benefit from the refrigerator then rises with income. Predictions 2 and 3 are unchanged because households who acquire and have the same total income have the same consumption path regardless of the path of their income. So complementarity changes the benefit of acquisition in the same way for all acquirers and does not affect the benefit of not purchasing the refrigerator.

Our model has important implications for thinking about the rate of lumpy asset acquisition in different countries. Cross-sectionally, it predicts that two countries that are at the same current level of income per capita may have very different refrigerator ownership rates because of the timing and distribution of income growth. In terms of conditional cash transfer programs, our model also suggests that the rate of the payments may matter for asset acquisition rates. For instance, a program that distributes transfers on a quarterly basis may lead to more refrigerator acquisition than a program that distributes transfers bi-weekly.

2. Empirical Context

Over the last 15 years, living standards for poor Mexicans have improved substantially in large part due to the country's aggressive antipoverty programs. As their incomes have gone up, many low-income Mexican households acquired energy-using assets.

Figure 4 plots the share of households that own refrigerators in Mexico over time by income decile, where the three poorest deciles are graphed separately, and the seven richest deciles are grouped together. The poor accounted for most of the asset acquisition between 1996 and 2008, as the share of households in the lowest income quartile that owned refrigerators grew from 32 percent to nearly 70 percent. Further, in the late 1990s the fastest growth was in the 3rd decile. With income growth, particularly programs targeted at the poor, this acquisition moves further down the income distribution: in the early 2000s the 2nd decile grows the fastest until eventually in the later 2000s the bottom decile grows the fastest. This pattern suggests that more and more of the population was moving through the first inflection point in the S-curve depicted in Figure 1.

The same pattern is also reflected in energy demand growth. Figure 5 plots normalized per capita electricity expenditures across all Mexican households by the same income decile groupings. Again, the poor had the highest growth rate: between 1996 and 2008, electricity expenditures nearly doubled for households in the first three income deciles and only grew by 50 percent for households with higher expenditures.[12]

[12] These trends do not appear driven by changes in relative prices. Over the early part of the sample, through 2002, prices rose more slowly for high-volume users than for low-volume users and use is correlated with income. In the later part of the sample, however, prices rose more slowly for low-volume users, and this is the period when expenditures deviated most dramatically between the two groups. This suggests that the differences across quartiles in the later part of the sample if anything understate different growth rates in consumption.

To better understand the growth in energy demand among low income households, we analyze asset acquisition in the context of Oportunidades, a conditional cash transfer program in Mexico that was designed to break the intergenerational transmission of poverty. The program, originally called PROGRESA, aims to alleviate current and future poverty by giving parents financial incentives, in cash, to invest in the human capital of their children. Oportunidades was conceived as a temporary program that would become obsolete over three to four decades as soon as the initial generation of beneficiary children reached adulthood. The program, which started in 1997, is one of the largest conditional cash transfer programs in the world distributing approximately four billion US dollars annually to some five million beneficiary households, representing approximately 20 percent of the population.[13]

a. Program Benefits

Cash transfers from Oportunidades are given to the female head of the household every two months conditional on two criteria. First, all beneficiary households receive a fixed food stipend as long as family members obtain preventive medical care and attend "pláticas" or educational talks on health-related topics. Program designers expected families to spend this stipend on more and better nutrition.

Second, households also receive educational scholarships conditional on children attending school a minimum of 85 percent of the time and not repeating a grade more than twice. The educational stipend is provided for each child less than 18 years old enrolled in school between the third grade of primary school and the third grade of high school (12th grade) and varies by grade and gender. It rises substantially after graduation from primary school and is higher for girls than boys during high school. Only children who were living in the household when the program started are eligible for the school transfers in order to prevent migration into the household. Total transfers for any given household are capped at a pre-determined upper limit.[14]

Table 1 describes the benefits to which beneficiary households were entitled in 2003. While the benefit levels and the grades covered have changed over the course of the program, its basic structure has not. In 2003, the basic (called ``alimentary'' or ``food'') support was 155 pesos every two months. The educational scholarship in 2003 ranged between 105 pesos for children in the third grade to 655 pesos for teenage girls in twelfth grade. Finally, Oportunidades also

[13] http://www.oportunidades.gob.mx/Portal/wb/Web/design_and_operation

[14] Compliance was verified through the clinics and schools, who certified whether households actually completed the required health care visits and whether kids attended schools. While full compliance varied, only about 1 percent of households were denied the cash transfer completely for non-compliance.

provides a yearly stipend to cover the costs of school supplies for children who do not get them at school.

As Table 1 documents, differently composed households are eligible to receive different transfer amounts. For example, households with more female children enrolled in higher grades are eligible for larger educational stipends than similar households with children enrolled in lower levels or with more male children. We can compute the maximum potential transfer for a family by applying the values from Table 1 to the following formula:

$$PT_{it} = \min\left(T_t^{max}, BT_t + \sum_s ST_{st} NK_{sit}\right) \quad (1)$$

where PT_{it} is the maximum potential transfer that could be received by household *i* in period *t*, T_t^{max} is the program cap on benefits, BT_t is the basic transfer amount that all households receive (the food support), ST_{st} is the educational transfer conditional on a child of type *s* (i.e. based on grade and sex) attending school, and NK_{sit} is the number of children of type *s* in household *i* at baseline aged forwarded to period *t*. Because of the cap on total benefits, potential transfers are a nonlinear function of the number of children at baseline who could attend the grades eligible for the educational scholarships in period *t*.

The actual transfers received by a household are less than the potential amount if some children do not attend school. Thus the actual bimonthly transfer amount received by household *i* at each time *t*, AT_{it}, is computed by applying the values from Table 1 to the following formula:

$$\boldsymbol{AT_{it} = min\left(T_t^{max}, BT_t + \sum_s ST_{it} K_{sit}\right)} \quad (2)$$

where K_{sit} is the number of children of type *s* in household *i actually* attending school in period *t*.[15]

b. Eligibility, Enrollment and Duration of Benefits

When Oportunidades was first rolled out in rural areas in 1997, program eligibility was determined in two stages (Skoufias et al., 2001). First, the program identified underserved or marginalized communities and then identified low-income households within those communities. Selection criteria for marginalized communities were based on the proportion of households living in very poor conditions, identified using data from the 1995 census (*Conteo de Población y Vivienda*).

[15] To simplify notation, equation (2) assumes that all households attend the health care classes and receive BT_t.

To select eligible households within marginalized communities, Oportunidades conducted a socio-economic survey of all households, the *Encuesta de Características Socioeconómicas de los Hogares* (ENCASEH). The Mexican government used the ENCASEH to construct a proxy means index and classify households as eligible for treatment ("poor") or ineligible ("non-poor"). The original classification scheme designated approximately 52 percent of households as eligible ("poor") (Hoddinott and Skoufias, 2004).

Eligible households were offered Oportunidades and a majority (90 percent) enrolled in the program (Gertler et al., 2012). Once enrolled, households received benefits for a three-year period conditional on meeting the program requirements. New households were not able to enroll until the next certification period, which prevented migration into treatment communities for Oportunidades benefits. Households in rural areas were "recertified" (re-assessed with a proxy means test) after three years on the program to determine future eligibility. If a household was recertified as eligible, it would continue receiving benefits. If not recertified, the household was guaranteed six more years of support before transitioning off the program. Thus, households could expect a minimum of nine years of benefits upon enrollment (Oportunidades, 2003).

c. Oportunidades Evaluation and Data Collection

The data used in this study were generated for program evaluation. At the outset of the program, the government randomly chose 320 early intervention and 186 late intervention communities in seven states. Eligible households in the early intervention communities received benefits starting in April 1998, while households in the late intervention communities did not receive benefits until October 1999. No sites were told in advance that they would be participating in the program, information about timing of program roll-out was not made publicly available, and there is no evidence of anticipatory behavior (Attanasio et al., 2011). Our analysis focuses on these 506 communities and the panel of approximately 10,000 households that were surveyed from 1997 through 2007.

Treatment and control households, which we will refer to as "early" and "late," were similar on a wide array of measured characteristics. Table 2 and Appendix Table 2 summarize a number of different household-level attributes separately for early and late households. For nearly all of the variables, the means are statistically indistinguishable across the two groups, suggesting that the randomization successfully created comparable groups.

The data used in this study comes from the baseline ENCASEH, described above, and the Oportunidades Evaluation Survey (ENCEL), which is a panel data set that was gathered over six rounds. The first survey was administered a year after the program started, during the fall of

1998 and the second one in 1999. Similarly, during 2000 two different surveys were conducted, one in March 2000 and the other one in November 2000. The fifth survey was done in 2003 and the last in 2007.

The evaluation surveys gather information on a number of potential metrics that the program may affect, including household and household members' characteristics, income and labor supply, expenditure, health and nutritional status, education, among others. Of particular importance for this study, the survey gathers information on energy-using household durable asset possession, such as refrigerators, gas stoves, televisions, and washing machines. For 2007, the evaluation survey also included questions on electricity expenditures, which we analyze in Section 5.

3. Empirical Specification and Identifying Assumptions

In this section, we describe an empirical model that allows us to test predictions of the conceptual framework in Section 1. Specifically, we examine the causal relationship between cash transfers, which provide an exogenous shock to income in the Oportunidades context, and asset accumulation. Durable asset purchases are discrete events that occur very infrequently. Hence, we model the decision to purchase an asset such as a refrigerator as the probability of purchase in a particular period given that the household has not purchased the asset so far. Also, consistent with the conceptual framework in Section 1, the cost of the assets we consider (e.g. refrigerators) is substantially higher than the monthly transfer amount.[16] To test predictions 1-3, we will examine the impact of cumulative transfers, the rate of change of transfer payments and their interaction on asset acquisition.

We estimate a linear discrete-time hazard specification that takes advantage of the panel structure of our data. Specifically, we estimate versions of the following equation:

$$h(a_{it}) = \Pr(a_{it} = 1 | a_{it-1} = 0) = \alpha_0 + \alpha_1 cumulative\ \tau_{it} + \alpha_2 early_i + \alpha_3 early_i \times cumulative\ \tau_{it} + \beta X_i + R_{rt} + v_{it} \tag{3}$$

where $h(a_{it})$ is the probability that household *i* acquires appliance a in period t, conditional on not having it in period t-1. We specify this as a function of cumulative Oportunidades cash transfers for household i in period t, $cumulative\ \tau_{it}$, a dummy indicating that the household was in an early community, $early_i$, meaning that it began receiving transfers 18 months before

[16] We examined the prices of a set of refrigerators in Mexico from PROFECO, the Mexican Federal Bureau of Consumer Interests. The price of the cheapest refrigerator in 2003 was nearly double the bi-monthly maximum transfer amount.

the households in the late communities and the interaction between the early dummy and cumulative transfers. X_i is a vector of control variables, including household characteristics. In some specifications, we include a household fixed effect instead of the control variables. R_{rt} is a vector of region-by-period dummies, separately estimated for seven regions in all five periods. These help account for any region-specific changes in asset (for example, refrigerator) and/or electricity prices.

The model in Section 1 predicts that α_1 will be positive (prediction 1) while α_2 and α_3 will be negative (predictions 2 and 3). Early households began receiving their transfers eighteen months before late households, so, conditional on having the same level of cumulative transfers as a late household, the growth in their cumulative transfers will have been slow and steady, akin to the red line in Figure 3. It is instructive to consider the variation in our data that identifies α_1, α_2 and α_3, particularly as we are using both randomized and non-randomized variation to establish our counterfactual outcomes.

a. Sources of Variation in Key Independent Variables

The two key independent variables are $early_i$, and $cumulative\, \tau_{it}$. Variation in $early_i$, is generated by the randomization that determined which households started receiving transfers early versus late. It is important to note, however, that we are not using the randomization to evaluate the impact of Oportunidades by comparing households in treated and control villages. Instead, we are interested in how the level and timing of transfers affect asset acquisition. The randomization provides exogenous variation in the timing of transfers, which we will take advantage of, but because we also model the effect of cumulative transfers directly, we are not simply comparing treated and control households. To avoid confusion, we have relabeled treated households "early" and control households "late."

We see variation in $cumulative\, \tau_{it}$ both within a given household over time and across households. The cross-sectional variation in cumulative transfers at a point in time depends on when the family entered the program and the rate of accumulation since entry. While the time the household was incorporated into the program was randomized, the rates at which a household's cumulative transfers change over time is a nonlinear function of the grade and sex of the household's children who attend school. The nonlinearity arises from the program rules that pay nothing before grade three or after grade nine, have different rates by grade and gender, and impose a cap on total transfer payments so that after some point more children school add nothing to the payments. Rates of accumulation within a household vary with time as younger children age into the program, as they progress through school, and as children age out of the program. In addition, in 2000, Oportunidades extended the payments for grade 10-

12. So long as the variation in the transfer amounts and hence the rate of change of cumulative transfers is not correlated with the propensity to buy an appliance, our specification will yield unbiased estimates.

To better understand the extent to which different factors drives variation in $cumulative\ \tau_{it}$, we decomposed the variance as follows:

$$var(cumulative\ \tau_{it}) = var(\delta_i) + var(R_{rt}) + 2cov(\delta_i, R_{rt}) + var(\varepsilon_{it}) \quad (4)$$

where δ_i and R_{rt} represent the household and region-by-period fixed effects, respectively, and ε_{it} is a random error term. Our calculations suggest that region-by-period trends account for about 60 percent of the variation, household fixed effects account for about 20 percent of the variation and the covariance between the two terms is effectively zero. This suggests that there is substantial within household variation to help identify the effects of transfers even in the specifications with household fixed effects. Because some of our specifications rely on cross-household variation, we also estimated the share of the variance accounted for by household factors that might reasonably impact appliance valuations. When we include indicator variables for household size and the age structure of household members instead of household fixed effects, these variables explain less than ten percent of the variation in transfers. Taken together, this decomposition suggests that the randomization, differences in transfers driven by the gender and age-composition of children and the nonlinearities in these transfer schedules account for a substantial share of our variation.

To understand why transfers are not strongly correlated with the number of children in the household, compare the following situations: a household with three girls in grade two of primary school, and a household with three girls in grade eight (junior high school). Both households have three female children but while the first household will receive no school transfers in the current period, the latter household will receive a large monthly transfer. In addition, families with four or more children in junior high school would receive the same transfer amount as the latter household because the cap on total benefits would be binding. Thus, we are able to explicitly control for household size and the number of children in the household in the empirical specification and still have substantial variation in cumulative transfers to identify the coefficient on that variable.

There may be lingering concerns that household demographic structure is correlated with both the cumulative transfer amounts and the propensity to purchase appliances. For instance, households with older girls may have systematically different refrigerator valuations than households with younger girls. We also explicitly test to see whether baseline appliance ownership is correlated with future cumulative transfers and therefore with household demographic structure imbedded in the transfer formula. Specifically, we will present results from placebo tests that suggest that the nonlinear function that translates family structure to cumulative transfers does not predict appliance ownership at baseline (i.e., before the program started). So, as long as any changes in the propensity to buy a refrigerator after the baseline survey were similar across households with different family structures, our specification will yield unbiased estimates of α_1. Finally, we will address other threats to identification in Section 4a, including potential differences in non-transfer income across treatment and control households, differences in expected future transfers and household preferences that change over time.

Because we are controlling for cumulative transfers, α_2 describes differences in refrigerator acquisitions between early and late households who have had the same level of cumulative transfers. To obtain valid estimates of α_2, we want to be sure that the distributions of cumulative transfer levels overlap between the early and late groups. Otherwise, α_2 (and α_3) could simply be picking up nonlinearities in the relationship between cumulative transfers and appliance acquisition.

Table 3 reports cumulative transfer amounts over time for households in the early and late groups that are at different parts of the transfer distribution. We see that households at the 75th percentile of the late group had higher cumulative transfer amounts than households at the 25th percentile of the early group by late 2000 and higher amounts than households at the median of the early group by 2003. This suggests that we will have considerable overlap between the distributions of cumulative transfers by 2003.

Although there will be more overlap in the distributions in later years, we focus on observations through 2003, as in later years, differences between the early and late groups will be smaller relative to their accumulated transfers. For example, Table 3 shows that by 2007 the early group's median actual transfers only exceeded the late group's median actual transfers by less than ten percent, while in 2003, the early group's median was almost 25 percent higher. If we include later years in our estimates of equation (3), the coefficients on the early dummy and the interaction term (α_2 and α_3) are negative but are attenuated to zero, as we would expect with more noise relative to systematic differences between the groups.

Finally, we note that previous related papers have examined the impact of income on appliance acquisitions (Dubin and McFadden, 1984) and ownership (Dargay, Dermot and Sommer, 2007). All of these papers have relied on cross-sectional variation in income and have limited controls for household demographics, meaning that unobserved differences may be correlated with income and taste for appliances. One substantial advantage of our empirical setting is that we can take advantage of the large shocks to income that households received via the transfers, and we use both within-household differences brought on by the nonlinear transfer schedule and cross-household difference driven, among other things, by randomization. We opt not to estimate an income elasticity for several reasons. First, we are primarily interested in the timing of income shocks and not the absolute level of income. Also, our data best measure transfers and not total income, as the Oportunidades households have substantial informal and non-monetary income sources. By examining household responses to transfers, however, we can identify the effects predicted by the model in Section 1.

b. Potential Endogeneity of Transfers

As the actual cumulative transfers that a family receives are determined by choices about whether or not to keep children in school, it is conceivable that the decision to purchase an appliance would be correlated with household-level shocks that altered the parameters of these choices. For instance, if the household experienced a large positive income shock to its non-transfer income, it might be more likely to leave children in school instead of working. The positive income shock could simultaneously make the household more likely to acquire an appliance. This would lead to a positive bias in the coefficient on actual cumulative transfers. In practice, Parker and Skoufias (2000, 2001) find that the program reduces child labor and increases enrollment in junior high (secondary) schools as the opportunity cost of these children being in the labor force is now higher. Schultz (2004) also finds positive effects for primary school and junior high school enrollment for boys and girls. These findings suggest that economic incentives influence schooling decisions, so concerns about potential endogeneity are real.

We address this problem by instrumenting for cumulative transfers with the potential cumulative transfers that a family could achieve if the maximum number of eligible children in the household attended school. At each time t, we compute a family's maximum potential transfer assuming that all eligible children that were enrolled at baseline have advanced one grade per year and met attendance thresholds. Potential transfers are a nonlinear function of the number of children at baseline who could be enrolled in school in period t. This is true because total benefits are capped, the transfer schedule is nonlinear (as in Table 1) and transfers are zero for the first 3 years of school.

Potential cumulative transfers are likely to be valid instruments for three reasons. First, they are a strong predictor of the actual transfers. Second, maximum potential transfers are unlikely to be correlated with asset accumulation via other pathways such as additional income sources. Indeed, they are uncorrelated with changes in children's labor supply due to the program as they are computed assuming that all eligible children enrolled at baseline are still in school and have advanced one school grade per school year. Nonetheless, the transfers could also affect leisure by reducing adult labor supply, which would reduce household income and therefore a household's propensity to purchase assets. Everything else held constant, this would imply a downward biased estimate of α_1. Parker and Skoufias (2000) show that there is no effect of the program on adult labor supply, so we can safely assume that the transfer variables are not correlated with other earned sources of income.

4. Empirical Results on Asset Acquisition

We begin with a preliminary description of the variation in our dependent variable by plotting cross-sectional refrigerator ownership as of 2003 on cumulative transfers through 2003 (Figure 6). We focus on refrigerator acquisitions, by far the most expensive and most energy-intensive household appliance for the Oportunidades population. Following Prediction 1 we expect upward-sloping ownership curves ($\alpha_1 > 0$). Prediction 2 suggests that the line for early households is below the line for late households ($\alpha_2 < 0$), while Prediction 3 implies that the line for early households is less steep than the line for late households ($\alpha_3 < 0$). We see all three of these relationships in the figure. While Figure 6 is consistent with our predictions, estimating the discrete-time hazards described in (3) allows us to include controls and use within-household variation.

Table 4 presents several specifications of equation (3) that focus on prediction 1, the income effect. We estimate (3) using a linear model and report robust standard errors clustered at the village level, i.e. the level of randomization. All specifications include state-by-round fixed effects and either include a number of household controls (detailed in the footnotes to the table) or household fixed effects.

In the first column, the coefficient on cumulative transfers (α_1) is positive as predicted and highly statistically significant. The magnitude of the coefficient suggests that for every ten thousand pesos increase in a household's cumulative transfers, the probability that it acquires a refrigerator goes up by more than two percent. By 2003, the early household at the 75th percentile of cumulative transfers had 20,000 pesos more than the early household at the 25th percentile and only 20 percent of households with median cumulative transfers owned refrigerators, suggesting that differences in cumulative transfers explain important differences across households.

Column (2) instruments for cumulative transfers with a household's potential cumulative transfers in a given period. The instrument is extremely strong, and the first-stage f-statistic, reported at the bottom of column (2), exceeds one thousand. The coefficient estimates are very similar to the OLS estimates in column (1). If anything, the coefficient on cumulative transfers is slightly higher. Column (3) includes household fixed effects, which allow us to control for any remaining differences across households not picked up by the household controls included columns (1) and (2).[17]

Columns (4) to (6) repeat the specifications but separately estimate the transfer effect for households in the top 25% of animal asset ownership at baseline. This is essentially a proxy means test that allows us to identify the Oportunidades households that are relatively better off. Indeed, animal assets were part of the proxy means test used to determine eligibility into the program (Skoufias, et al., 1999). As we explained in Section 1, a positive α_1 is consistent with an S-shaped relationship between income and asset ownership. In addition, if α_1 is increasing in income or wealth, meaning that better off Oportunidades households are more likely to use additional transfers to purchase an asset, the S-shaped relationship will be even more pronounced. Since all the included households are poor, they are all generally below their acquisition threshold. However, those that enter the program slightly better off should be more likely to acquire at a given level of transfers than those that are poorer. We see this effect in columns (4) to (6) as the transfer effect is larger for households that started off richer.

We should note that baseline animal assets are not subject to the randomized treatment and may have various endogeneity concerns. For example, households with more animals may simply value assets more. However, columns (4) and (5) include an indicator identifying households in the top 25% of baseline assets. Column (6) uses household fixed effects, thus controlling for all time invariant household characteristics. Also, specifications using other measures to identify households that are relatively better off, such as total household consumption or consumption per capita, yield similar differences between the relatively better off and other households.

Table 5 presents several specifications of equation (3) focusing on the effect of transfer timing. The first column, repeated from column (1) of Table 4, reports the basic cumulative transfer effect. When we include the early dummy in column (2), the coefficient on cumulative transfers is virtually unchanged, and the coefficient on early is negative, as predicted, and highly significant. The magnitude suggests that receiving transfers as part of the late group is equivalent to an almost 6,000 pesos increase in cumulative transfers. When we include the interaction between early and cumulative transfers in column (3), the interaction term is

[17] The coefficient on cumulative transfers is larger in column (3), perhaps in part because the household fixed effects capture whether or not the household was in the early or late wave of program treatment, which we show below is an important factor in determining refrigerator purchases.

negative and statistically different from zero, while the coefficient on the early dummy drops in absolute value. As the coefficient on the early dummy in column (3) reflects the early effect at zero cumulative transfers, which is outside the range of our data, we also report the net early effect at median 2003 transfers.

Column (4) instruments for both cumulative transfers and cumulative transfers x early with a household's potential cumulative transfers in a given period and potential cumulative transfers x early. The instruments are extremely strong, and the first-stage f-statistics, reported at the bottom of column (4) exceed one thousand. The coefficient estimates are very similar to the OLS estimates in column (3). If anything, the coefficient on cumulative transfers is slightly higher.

In column (5), we include household fixed effects, which allow us to control for any remaining differences across households not picked up by the household controls included in columns (1) through (4). For example, while the household controls include the number of children, we do not include precise variables measuring their exact gender and age makeup. If across households with the same number of children, the households with older girls, for instance, had higher valuations for refrigerators than the households with younger boys, the coefficient on cumulative transfers might be biased positive. This could in turn lead to a negative bias on the early dummy as, for a given level of cumulative transfers, the early households are more likely to be comprised of young boys.

With household fixed effects, we can control for any time-invariant differences within a household. We have within-household variation in cumulative transfers because of the nonlinear increases in transfers depicted in Table 1 and because children age into or out of the program. We cannot, however, estimate the early dummy as this is a time-invariant household characteristic. The specification in column (5) uses instrumental variables estimation, and is therefore comparable to the results in column (4). The coefficient estimates on cumulative transfers and cumulative transfers x early are remarkably similar across columns (4) and (5) suggesting that our household controls pick up most cross-household differences in tastes.

Table 6 presents results from specifications comparable to those reported in columns (4) and (5) of Table 5 for two additional appliances that require large upfront investments: washing machines and stoves. For comparability, we reproduce the results for refrigerators in the top two rows of the table. The net early effect at the median level of cumulative transfers is negative and statistically significant for both of the additional assets. Early x cumulative transfers is negative across both specifications for all the additional assets in Table 6. It is statistically smaller than zero for stoves. While it is hard to draw strong inferences from only a few assets, the results in Table 6 are generally supportive of our model.

a. Alternative Explanations

The results presented so far are consistent with the model presented in Section 1. They suggest that households are more likely to acquire appliances the higher is their transfer income and the lumpier were their transfer payments. Also, the effects of the lumpy payments are stronger at higher cumulative transfer amounts.

The results may also be consistent with other explanations, however, the most obvious of which we address in this subsection. First, the early dummy is identified by considering households with the same cumulative income, some of whom received transfers steadily at low rates and some of whom received no transfers for eighteen months and then high transfers once they began the program. These households are by construction different from one another, so a natural question is whether the differences are systematically correlated with the household's value for appliances. For example, do households with more female children have higher valuations for refrigerators than households with more male children? The fact that the specifications estimated with household fixed effects are similar to the results that simply include household-level controls gives us some reassurance that the differences across households are not driving our results.

As an additional robustness check, we estimated cross-sectional placebo specifications using data from the baseline survey that was conducted in 1997, before any of the households were receiving transfers. These specifications test whether the particular nonlinear relationship between family structure and transfers embodied in cumulative transfers through 2003 predicts appliance ownership at baseline. The results are presented in the left-hand column of results in Table 7. Each specification is estimated using instrumental variables and including household controls, comparable to the specification reported in column (4) of Table 5. The coefficients on cumulative transfers, early and early x cumulative transfers are insignificantly different from zero, except for cumulative transfers for stoves. This provides additional reassurance that the differential transfer rates experienced by households under Oportunidades are not systematically correlated with the propensity to acquire appliances.

Since the specifications at baseline in Table 7 are cross sectional while the results in Table 5 and Table 6 were estimated as discrete time hazards, we estimated similar specifications for 2003 by way of comparison. These are presented to the right of the baseline specifications for each appliance. These specifications confirm the results in Table 5 and Table 6. In all specifications, the coefficient on cumulative transfers is positive and usually significant, while early and early x cumulative transfers are generally negative.

We also estimated another variant of the placebo test that predicted asset ownership in the period just before a household entered the program (baseline for treated households and round 1 for control households) as a function of the household's first period transfers. This test does not capture the variation induced by the randomization, but it does use transfers in a period closer to the period when households' baseline asset ownership is measured. Though noisier, these similarly showed no statistically significant impact of first period transfers. This test also refutes the hypothesis that household preferences for appliances change over time in a manner correlated with the transfer schedule, which would happen, if for instance, households with nine-year-old boys had similar preferences to households with nine-year-old girls, but preferences diverged when the children were in their teens.

A second concern is that early is an indicator for lower expected future transfers and thus the negative coefficient simply represents lower expected income. Specifically, among early and late households with the same cumulative transfer levels at a given point in time, early households might expect lower transfers in the future since their average transfer rate is lower than the late households.[18] For instance, late households may simply have more girls than early households who are at the same level of cumulative transfers in 2003. Table 8 presents results from several specifications that include future transfers as additional explanatory variables. Column (1) of Table 8 reproduces column (4) of Table 5, and then columns (2) and (3) add information about the household's actual future transfers through 2007. With rational expectations, realized future transfers proxy for expected transfers.

The alternative hypothesis put forward above would suggest that the coefficient on future transfers should be positive. In fact, we find that it is either undetectably different from zero or statistically significant and negative. A negative coefficient is consistent with the intertemporal optimization underlying our framework in Section 1, as it suggests that households expecting higher transfers in the future are less likely to buy an asset now, presumably because they are waiting to buy it when their income is higher.

[18] Because transfer rates vary over time within a household, increasing as younger children enter higher grades and decreasing as older children age out of the program, it is possible that an early household will have the same cumulative transfers as a late household, but will have *higher* expected transfers. For example, the early household could have begun with younger children, accumulating slowly, while the late household began with older children – accumulating quickly at first, but then slowly later when its children age out of the program.

We also considered the possibility that the difference in acquisition is driven by a lack of self-control. Particularly, the logic of the intertemporal optimization in Section 1 suggests that early households have the ability to replicate through saving the time path of transfers of the late households, but instead choose to allocate transfers differently. However, if these households lack self-control or are otherwise myopic it is possible that the temporal effects we observe are the consequence of households spending the transfers as they receive them, rather than optimizing considering both current and future transfers. The negative coefficients on future transfers in Table 8, however, are not consistent with lack of self-control or other myopic behavior.

A final concern is that late households might have earned more non-transfer income than early households during the period before they began receiving transfers, for instance from child labor, which is not reflected in the potential transfers instrument. To allow for this, we estimated the household fixed effect model of Table 5, column (5), excluding the rounds in which the late households did not receive transfers. The estimates are not statistically different from column (5).[19]

5. Empirical Results on Energy Consumption

We next examine the relationship between income and household energy use in order to evaluate the extent to which growth in electricity consumption is driven by households' asset acquisitions. Specifically, we examine whether higher household income, driven by Oportunidades transfers, leads to increased electricity consumption conditional on appliance holdings. We compare the conditional income effect to estimates of the effect of an appliance acquisition on electricity use. While previous research suggests that the response of energy use to income conditional on assets is small, those studies are from the developed world.[20] Our data allow us to obtain estimates from low-income households in Mexico.

Using cross-sectional data from the 2007 ENCEL, we estimate:

[19] The coefficient on Cumulative Transfers is 0.065*** [0.008] and the coefficient on Cumulative Transfers X Early is -0.014* [0.008]. Note that this specification also addresses concerns about whether the control households would behave according to the framework presented in Section 1 if they did not anticipate program transfers for the 18 months before they were enrolled. Without anticipating transfers, the model still predicts increased asset acquisitions via the forced savings effect, but households would not have complementary savings from the period in which they were not enrolled.

[20] See, e.g., Dubin and McFadden, 1984; Hsiao and Mountain, 1985; Reiss and White, 2008.

(5) $$electricity\ use_i = \beta_1 + \beta_2 Current\ transfers_i + \beta_3 a_i + \beta_4 X_i + \delta_v + \epsilon_i$$

where *electricity use*$_i$ is household i's bi-monthly expenditure for electricity and *current transfers*$_i$ is the average Oportunidades bi-monthly cash transfer in 2007 for household i. a_i is a measure of assets – either a variable that takes a value of either 0 or 1 to indicate refrigerator ownership by household i, or an energy-use-weighted sum of electricity appliances owned by household i (described in the appendix).[21] X_i is a vector of household covariates, δ_v captures village-level fixed effects and ε_i is the error term.[22]

Note that we observe only whether or not a household owns a particular type of appliance (e.g. a refrigerator or washing machine) and have no information on its purchase or usage price, nor on any of its other characteristics. We do estimate village-fixed effects, which control for much of the cross-household variation in energy prices, as electricity prices in Mexico are regulated at the regional level. We also observe electricity use only once, in 2007, so our analysis of energy use is purely cross-sectional.

As described in Section 3, transfers vary across households as a nonlinear function of family structure. So long as the variation in the current transfer amounts is not correlated with the propensity to use energy or own an appliance, conditional on household controls, our specification will yield unbiased estimates. On the other hand, unobservable household characteristics may be driving appliance use and acquisition decisions. For example, a negative health shock within a household may increase the utility from a gas stove, and may also make the household more likely to use it.

To address the endogeneity concerns, we instrument for appliance ownership using specifications analogous to those described in Section 3 and presented in Section 4. We instrument for asset ownership with potential cumulative transfers, potential cumulative transfers interacted with early status, and asset ownership in 1997.[23] This means that our first stage is essentially a cross-sectional version of the asset acquisition specifications discussed in Section 4. As such, our specification is identified by variation in potential cumulative transfer

[21] With some assets, such as air conditioning, fans, and lighting, the consumer has considerable latitude to adjust usage, suggesting that income might affect that decision. For other assets, like water heaters and refrigerators, the consumer has less control over how much energy it uses.

[22] Although this equation is similar to specifications used to estimate an income elasticity, we did not use a log-log specification since transfers represent a varying share of total income (transfer plus earned) across our households. Results are qualitatively similar when we use a log-log specification.

[23] We do not use the early indicator by itself as an instrument because it is collinear with the village fixed effects. We obtain similar results if we estimate state instead of village fixed effects and include early as an instrument.

amounts and randomized early status. So long as that is not correlated with energy utilization conditional on asset ownership, our specification yields unbiased estimates.

It is conceivable, however, that there is additional endogeniety if the age structure and gender of children influences the value of using and/or owning assets. Because our data is only cross-sectional, we cannot employ the fixed-effects approach in the acquisition estimation. However, the similarity between the estimates of the asset acquisition models using household controls and those using fixed effects suggest that the included household controls capture the relevant variation in the value of owning an asset. So, we include the same set of household controls as we did in Tables 4-7. In addition, because of the same endogeniety concern described with respect to asset acquisition regarding actual transfers, we instrument for current transfers using potential current transfers.

Table 9 presents several specifications of equation (5) using a linear model. As above, we report robust standard errors clustered at the village level. Columns (1) and (2) do not control for asset ownership, and estimates suggest a marginal propensity to consume electricity out of transfers of about 1%. Columns (3) adds a control for asset ownership, and the coefficient suggests that for every additional aggregated 100-kWh per month of energy-using assets a household owns, bi-monthly energy expenditure increases by 43 pesos.[24] Once we control for assets, the marginal propensity to consume electricity is not significantly different than zero. When we instrument to allow for potential endogeniety, the estimated effects of asset ownership are larger and the marginal propensity to consume is even smaller. Columns (5) and (6) report the same specifications but replace the asset aggregate with a dummy for refrigerator ownership with similar results. Using the coefficients in Column (5) adding a refrigerator to a household has the equivalent energy expenditure effect of increasing their transfers by 7,900 pesos. These results are consistent with the hypothesis that the main pathway by which increases in income lead to energy use is through appliance acquisition, not through increased usage of existing appliances.

6. Aggregate Energy Use

We next consider the implications of our model for aggregate, country-level energy consumption. Figures 4 and 5 suggest that the trends identified in the Oportunidades sample are representative of the overall Mexican population: at a threshold income level, reached by

[24] The implied retail cost of electricity suggested by this coefficient is lower than the rates faced by even low consuming Mexicans, though the coefficient could be biased downwards by measurement error.

households in lower and lower deciles over time, refrigerator ownership and household electricity consumption increase rapidly.

Yet, on its face, it may seem implausible that the household-level patterns we have described will influence macro-level energy use since residential energy use (not including transportation) accounts for only about 15 percent of total energy use in the developing world (EIA, 2011). By comparison, the residential sector accounts for over 20 percent of all energy used in the United States (EIA, 2011). While this difference is certainly consistent with the hypothesis that economic growth will lead to large gains in residential sector energy use as a country develops, the residential share in the U.S. is still a relatively small component of overall energy use. On the other hand, beyond residential energy use, many commercial and industrial activities are at least indirectly supplying local consumer demand. So, as more consumers buy refrigerators and air conditioners as well as cell phones and other electronics, local industry will use more energy to produce at least part of the value-chain and the commercial sector will grow to supply them (Wolfram, Shelef and Gertler, 2012). For these reasons, we believe it's worthwhile to examine how income growth at different points on the income distribution impact growth in aggregate energy demand.

To evaluate whether our model of household behavior has implications for aggregate, country-level energy consumption, we follow several papers that have analyzed the relationship between aggregate energy consumption and GDP, showing that the "income elasticity" is higher when countries are at low income levels (Galli, 1998) and that the income elasticities at a particular income level have if anything increased over time, contrary to energy "leapfrogging" and possibly reflecting changes in consumption bundles (Van Benthem, 2010). We disagree with the interpretation of the estimates as income elasticities for reasons explained below, and consistent with concerns expressed in some of the previous literature, such as Van Benthem (2010).

Forecasts from basic estimates of the relationship between income and energy use, however, have been influential in policy debates about how economic growth is likely to affect both the demand for energy and climate change. So, while we do not favor the causal interpretation of the models, we believe that it is useful to ask how these forecasts might vary when accounting for possible differences across countries with more or less pro-poor growth. This serves as an additional check on our model and provides preliminary evidence on the size and importance of the effects we have identified.

Following the existing literature, we begin with a simple specification:

$$\ln(Energy_{it}) = \alpha \ln(Income_{it}) + \beta \ln(Price_{\text{it}}) + \delta_i + \theta_t + \varepsilon_{it} \quad (6)$$

for country i in year t, where energy is total final energy consumption per capita, income is measured as GDP per capita and price is either oil price adjusted for exchange rates and the local CPI or a constructed price index, incorporating, for instance, local taxes.[25] δ_i captures country-level fixed effects, reflecting factors such as climate and natural resource endowment and θ_t captures worldwide trends, for instance, in technology.

α is usually described as the income elasticity, although since there are no controls for supply-side factors and price is measured with considerable imprecision, it is best thought of as a descriptive parameter which captures the correlation between income and energy use.[26] We drop the price term, as, consistent with previous estimates from the developing world, we find the coefficient on price to be either zero or positive, suggesting that the variable is picking up something other than a price response. Because we allow for a time trend and estimate country fixed effects, this coefficient could capture responses to country-specific price shocks, which are likely endogenous to local demand and regulation.

The first prediction of the model in Section 1 is that households at higher income levels will be more likely to acquire energy-using assets. At a macro level, this suggests that asset ownership, and hence energy use, will be positively related to GDP per capita. This is a very straightforward prediction, and, at the most basic level, is confirmed by *all* the existing papers in the literature as they estimate positive coefficient on logged income.

However, our model also suggests that the coefficient on logged income should be higher in countries that have experienced pro-poor growth than in countries that have lifted few households out of poverty. Our model suggests that countries where GDP growth mainly benefits the wealthy, who already own most energy-using assets, will not experience the same growth in energy use. Pro-rich growth that does not lead to substantial asset accumulation moves energy demand along the intensive margin, which is small. Indeed, using the Mexican data, our results in Section 5 indicate that the response of energy use to transfers, conditional on asset ownership, is very low. However, as pro-poor growth lifts households out of poverty to

[25] Data were generously provided by Arthur Van Benthem and are described in Van Benthem (2010). “Final” energy consumption covers energy supplied to the final consumer for all energy uses. It does not include, for instance, coal burned to create electricity, but it does include electricity.

[26] Several recent papers explore the impact of electrification on various measures of economic development, suggesting causality could run from energy use to income (Dinkelman, 2011 and Lipscomb et al., 2011).

an income level where they begin to acquire energy-using assets like refrigerators, the demand for energy moves along the more explosive extensive margin.

To test whether prediction 1 is more relevant in countries with pro-poor growth, we estimate:

$$\text{(7)} \quad \ln(Energy_{it}) = \alpha \ln(Income_{it}) + \gamma_1 \ln(Income_{it}) \times ProPoorGrowth_i + \delta_i + \theta_t + \varepsilon_{it}$$

To estimate (7) we use data for 37 developing countries over 27 years, from 1980 to 2006. Our main results define the variable *ProPoorGrowth* at the country level as the decrease in the average Gini coefficient from the beginning of the sample (1980-1993) to the end of our sample (1994-2006). On average, inequality is increasing in the countries in our sample, as the mean of *ProPoorGrowth* is -1.25, but there is a wide range from -13 to 13.[27] Our prediction is that γ_1 will be positive.

Prediction 2 of our model is that faster growth will lead to more asset acquisition. To evaluate this prediction, we include a variable measuring the percent change in per capita GDP as well as its interaction with *ProPoorGrowth*:

$$\text{(8)} \quad \begin{aligned} \ln(Energy_{it}) = \alpha \ln(Income_{it}) + \mu\, IncomeGrowth_{it} + \gamma_2\, IncomeGrowth_{it} \\ \times ProPoorGrowth_i + \delta_i + \theta_t + \varepsilon_{it} \end{aligned}$$

Our model predicts that μ will be positive. Previous literature has included lagged GDP per capita on the hypothesis that energy use might adjust slowly to income. This would suggest a negative estimate of the parameter μ. In the end, the estimates will reflect the net of (at least) these two effects. Because our model relies on credit constraints and high assets prices relative to current income, it is most relevant for households at the lower end of the income distribution meaning the effect will be stronger in countries with *ProPoorGrowth*, suggesting that γ_2 will be positive.

Finally, prediction 3 of our model is that the effects of faster growth will be more pronounced at higher income levels. We evaluate this hypothesis by estimating:

$$\text{(9)} \quad \begin{aligned} \ln(Energy_{it}) = \alpha \ln(Income_{it}) + \mu\, IncomeGrowth_{it} + \rho IncomeGrowth_{it} \\ \times \ln(Income_{it}) + \gamma_1 \ln(Income_{it}) \times ProPoorGrowth_{it} \\ + \gamma_2\, IncomeGrowth_{it} \times ProPoorGrowth_{it} + \gamma_3 \ln(Income) \\ \times IncomeGrowth_{it} \times ProPoorGrowth_{it} + \delta_i + \theta_t + \varepsilon_{it} \end{aligned}$$

[27] Data on Gini coefficients and other measures of ProPoorGrowth are from the World Bank Development Indicators. We include countries for which both energy use and multiple GINI measures are available.

Our model predicts that γ_3 will be positive.

The results reported in Table 10 are consistent with our model. In the first column, we find that $\gamma_1 > 0$. In the second column, we find that $\gamma_2 > 0$ and in the third column, we find $\gamma_3 > 0$. The sizes of the coefficients suggest that the effect we have identified is quite large. Consider, for instance, the results in column (1). The income response for a country such as Brazil, which is at the 75th percentile of *ProPoor Growth* is over 1, while a country such as Argentina, which is at the 25th percentile of *Pro Poor Growth* has an income response almost half the size.

We have performed several robustness tests, including re-estimating the specifications in Table 10 on a balanced sample, measuring income growth over a longer time period, varying the cut-off date used to determine changes in inequality and replacing *ProPoorGrowth* with a dummy variable indicating that the country had above the median changes in inequality. The results are all very similar to those reported in Table 10.

Though consistent with the hypothesis that countries with pro-poor growth have *much* larger energy income elasticities, the results in this section should be viewed as suggestive. We have discussed how the coefficient on income should not be interpreted causally. Equally, the interactions with pro-poor growth could reflect an omitted variable. It is possible, for example, that countries that pursue pro-poor growth policies also promote energy use, for instance, through electrification projects.

A final concern is that our results may simply reflect the fact, already established in the literature, that income elasticities vary with income. Considering the results in column (3), this is more likely to be the case in countries with pro-poor growth, which provides support for our model over other explanations offered for income elasticities that vary with income.

We were motivated to explore the relationship between income and energy use because it appears to be an important component of energy growth projections. Our results suggest that energy growth will be considerably faster in countries with more pro-poor growth. If China and India, the two largest developing countries, continue successfully bringing families out of poverty, this finding suggests that current energy forecasts could be underestimates (Wolfram, Shelef and Gertler, 2012). Clearly, more work remains to be done to establish this important relationship.

7. Conclusion

Accurate forecasts of energy demand are critical as investments in energy infrastructure require long lead times. If the global demand for energy increases faster than anticipated, there could be significant shortages and increases in energy prices. In addition, country-specific energy forecasts are critical inputs into international climate agreements. And, international climate negotiations can break down if the parties have different expectations about emissions paths.

Much of the future increase in the demand for energy will come from low- and middle-income countries (EIA 2010). We show that there will likely be a surge in the demand for energy as more and more households currently living in poverty gain from overall economic development or explicit anti-poverty programs and enter the middle class. The primary reason is that raising the income of the poor moves their demand for energy along the extensive margin as they buy energy-using assets for the first time. Acquiring an energy-using asset for the first time leads to a considerable increase in a household's energy use. While income growth also affects energy consumption on the intensive margin, the effect is trivial compared to the effect of accumulating more energy-using assets. As the poor come out of poverty their demand moves mostly along the extensive margin leading to a large discrete jump in demand for energy.

We also show that the speed at which the poor come out of poverty affects the size of this increase in energy demand, which has important implications for different countries. For example, we show that two countries that are at the same current level of income per capita may have different refrigerator ownership rates, with the country where recent growth was fast having a much higher ownership rate than the country that grew more slowly. Our model also has implications for how poverty alleviation policies such as cash transfer programs affect asset accumulation. Specifically, we show that the rate of the payments should matter for asset acquisition rates. For instance, a program that distributes transfers on a quarterly basis may lead to more refrigerator acquisition than a program that distributes transfers bi-weekly.

We provide empirical support for these conclusions from an investigation of the causal impact of an increase in the stream of income on asset accumulation and energy use in the context of Mexico's conditional cash transfer program, Oportunidades. We find that the increase in income through the transfers had a large effect on asset accumulation, and that effect on asset accumulation is substantially great when the cash is transferred over a shorter time period.

Finally, we applied the lessons learned from the household to the aggregate energy forecast models using country-level panel data. We show that if a country's growth has been pro-poor, the income elasticity of energy is nearly double that of a country with GDP growth that has been less favorable to the poor. These results suggest that not accounting for pro-poor growth would grossly underestimate future energy use.

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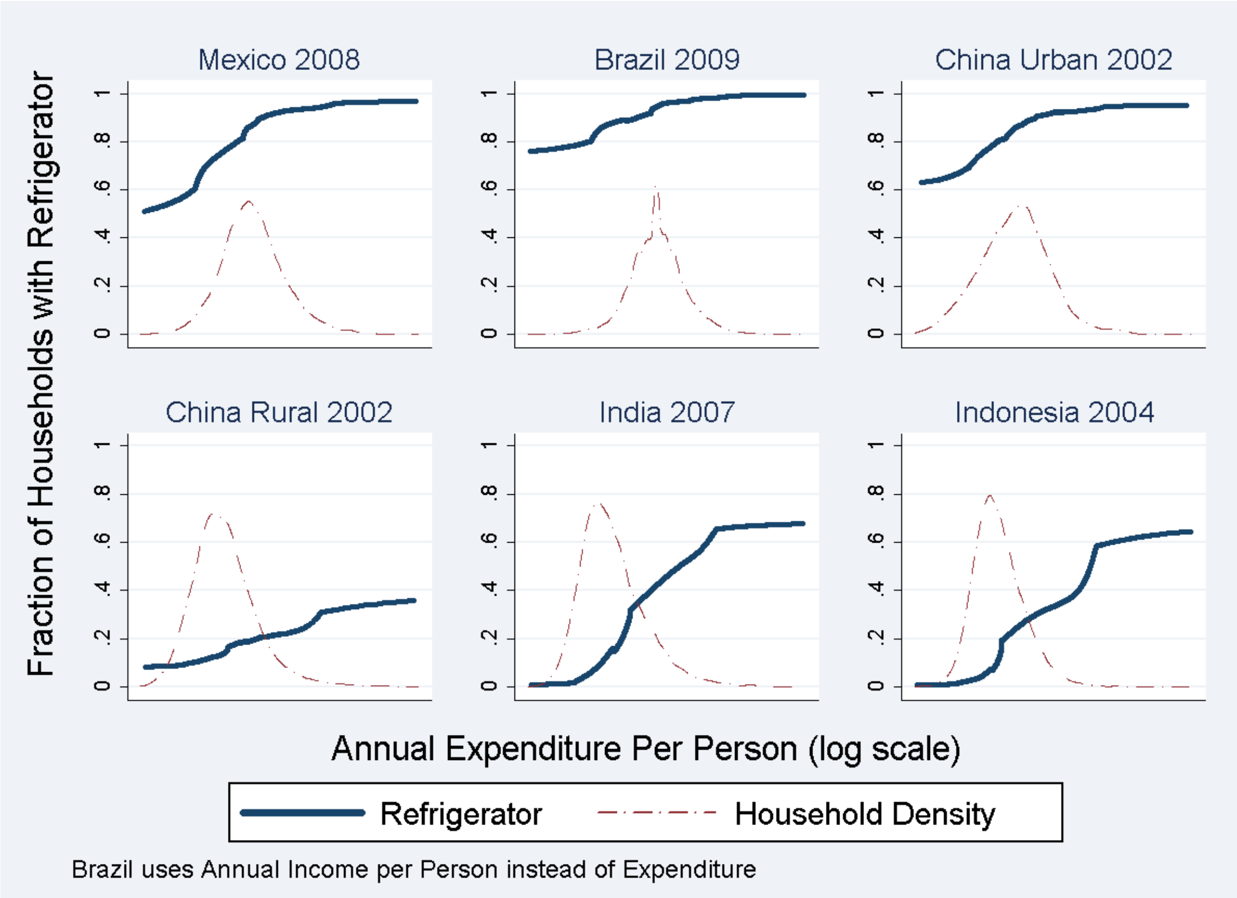
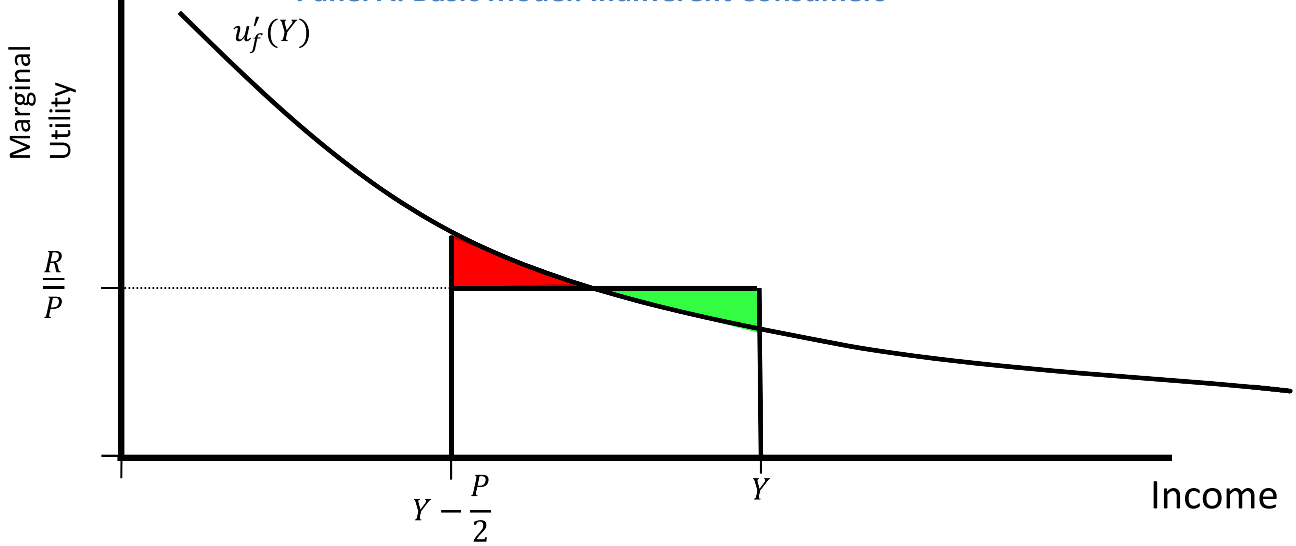
Figure 1: Refrigerator Ownership and Household Expenditure Level



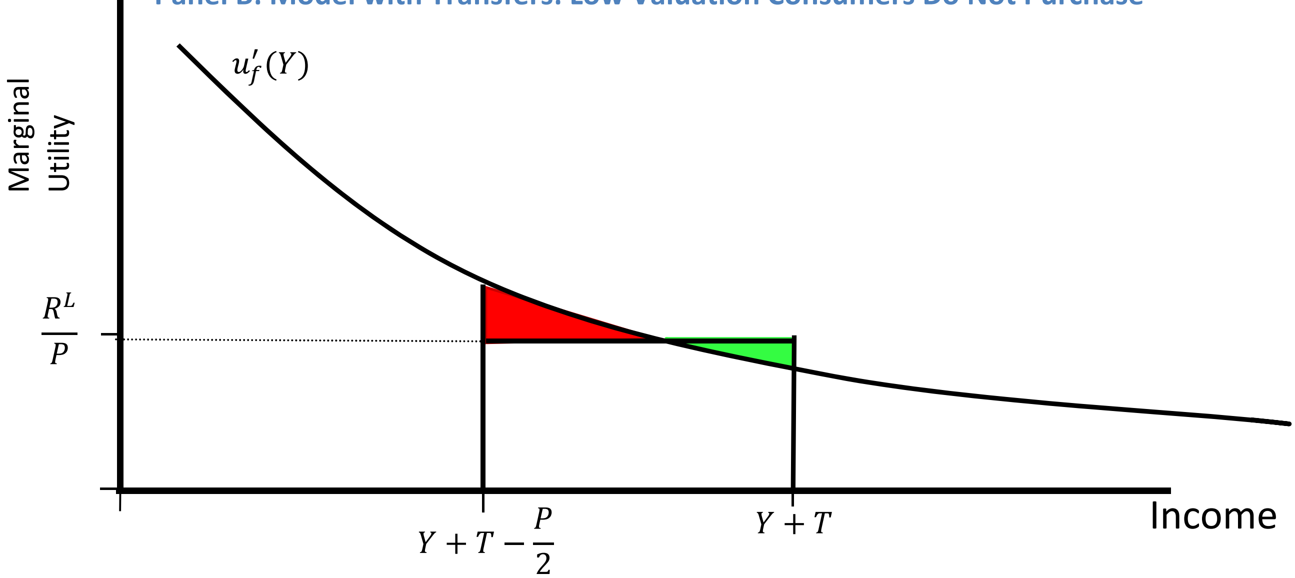
Sources: Mexico, 2008, *Encuesta Nacional de Ingreso y Gasto de los Hogares.* Brazil, 2009, *National Household Sample Survey – PNAD.* China, 2002, *Chinese Household Income Project.* India, 2008, *National Sample Survey.* Indonesia, 2004, *National Socio-Economic Survey – Susenas.* Annual Expenditure and Income Per Person calculations divides household expenditure and income by the number of adult equivalents in the household, where each household member less than 12 years of age is treated as half an adult. Frequency weights are used for all surveys other than China, which do not report weights.

Figure 2

Panel A: Basic Model: Indifferent Consumers



Panel B: Model with Transfers: Low Valuation Consumers Do Not Purchase



Panel C: Model with Different Per-Period Transfer Levels: Consumers Save

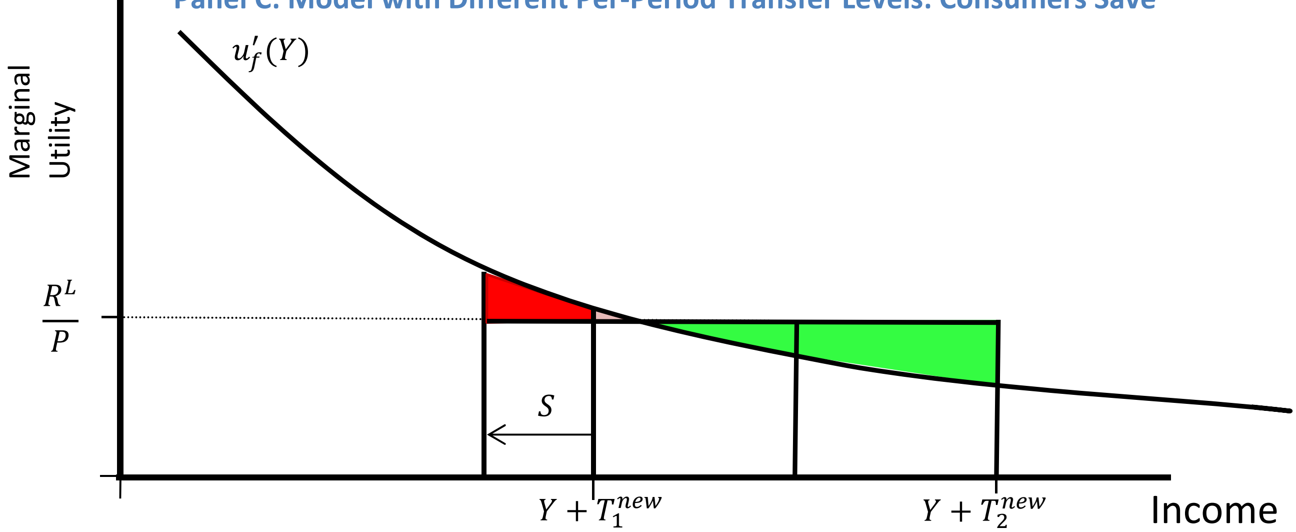


Figure 3: Hypothetical GDP Paths

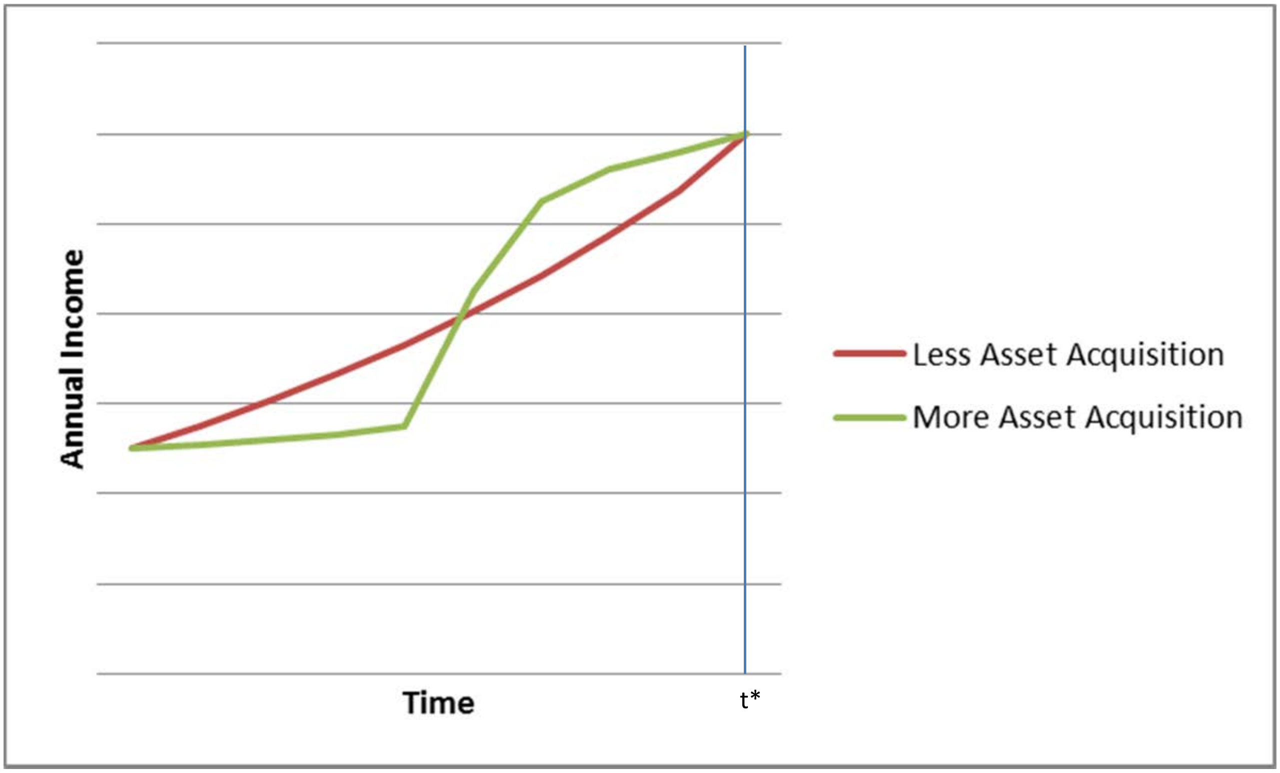
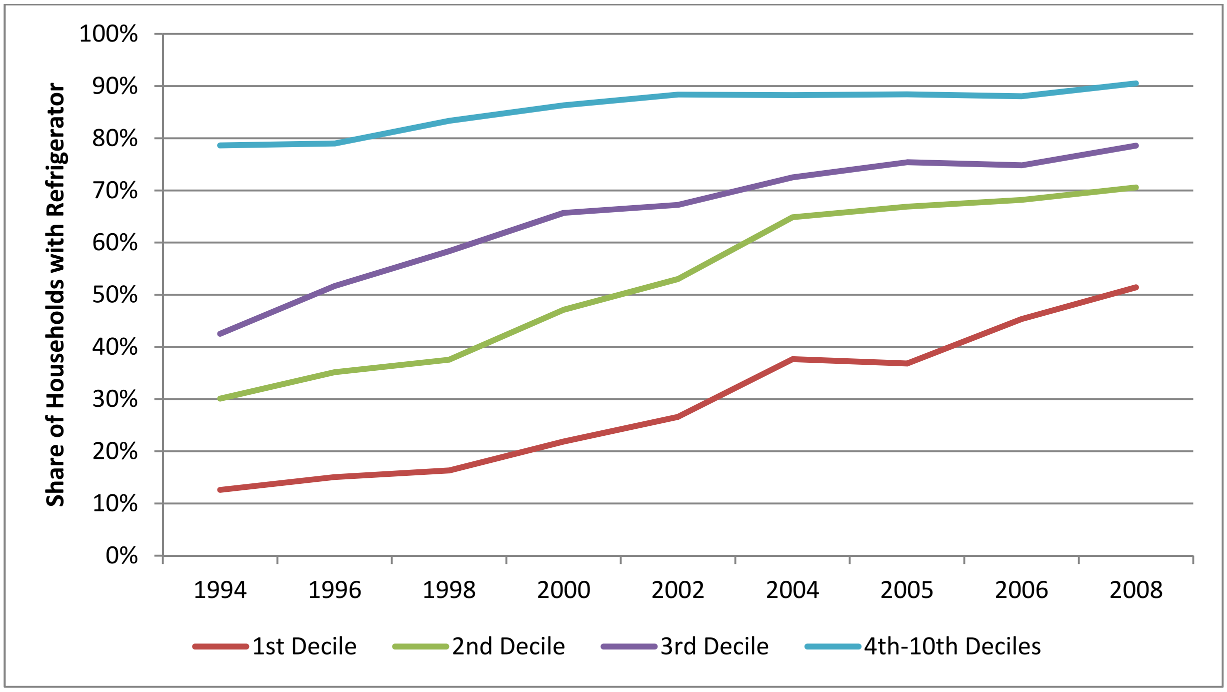
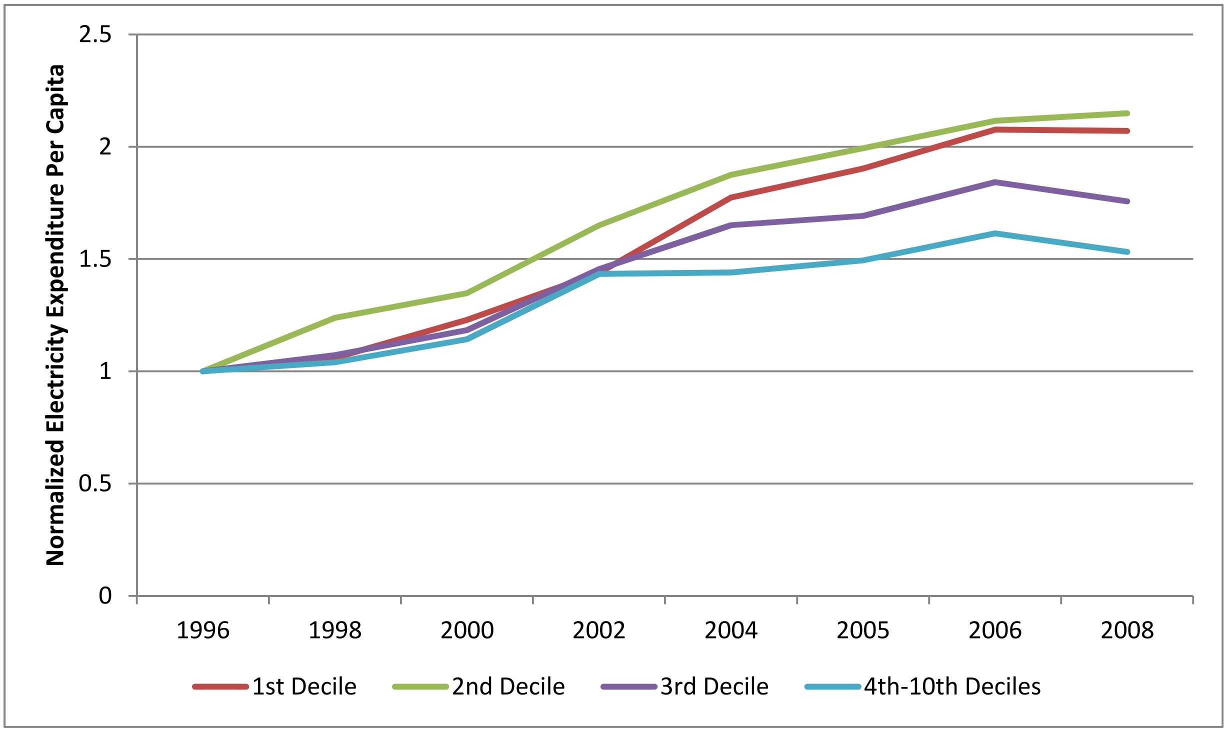


Figure 4: Growth in Refrigerator Ownership by Consumption Quartile for Mexico



Source: Mexico *Encuesta Nacional de Ingreso y Gasto de los Hogares* (1996, 1998, 2000, 2002, 2004, 2006, 2008).

Figure 5: Growth in Electricity Expenditures by Consumption Quartile for Mexico



Source: Mexico *Encuesta Nacional de Ingreso y Gasto de los Hogares* (1996, 1998, 2000, 2002, 2004, 2006, 2008).

Table 1: Oportunidades Bi-Monthly Support Levels in 2003 (pesos)

Basic Support:	155	
Educational Scholarship:		
Grade	Boys	Girls
Third	105	105
Fourth	120	120
Fifth	155	155
Sixth	205	205
Seventh	300	315
Eighth	315	350
Ninth	335	385
Tenth	505	580
Eleventh	545	620
Twelfth	575	655

A household can receive a maximum of 1,025 pesos with children through 6^{th} grade or 1,715 pesos with children in 7^{th} grade or higher.

An additional 200 pesos for children in 3^{rd}-6^{th} grades and 250 pesos for children in 7^{th} grade or higher are provided once a year for school supplies.

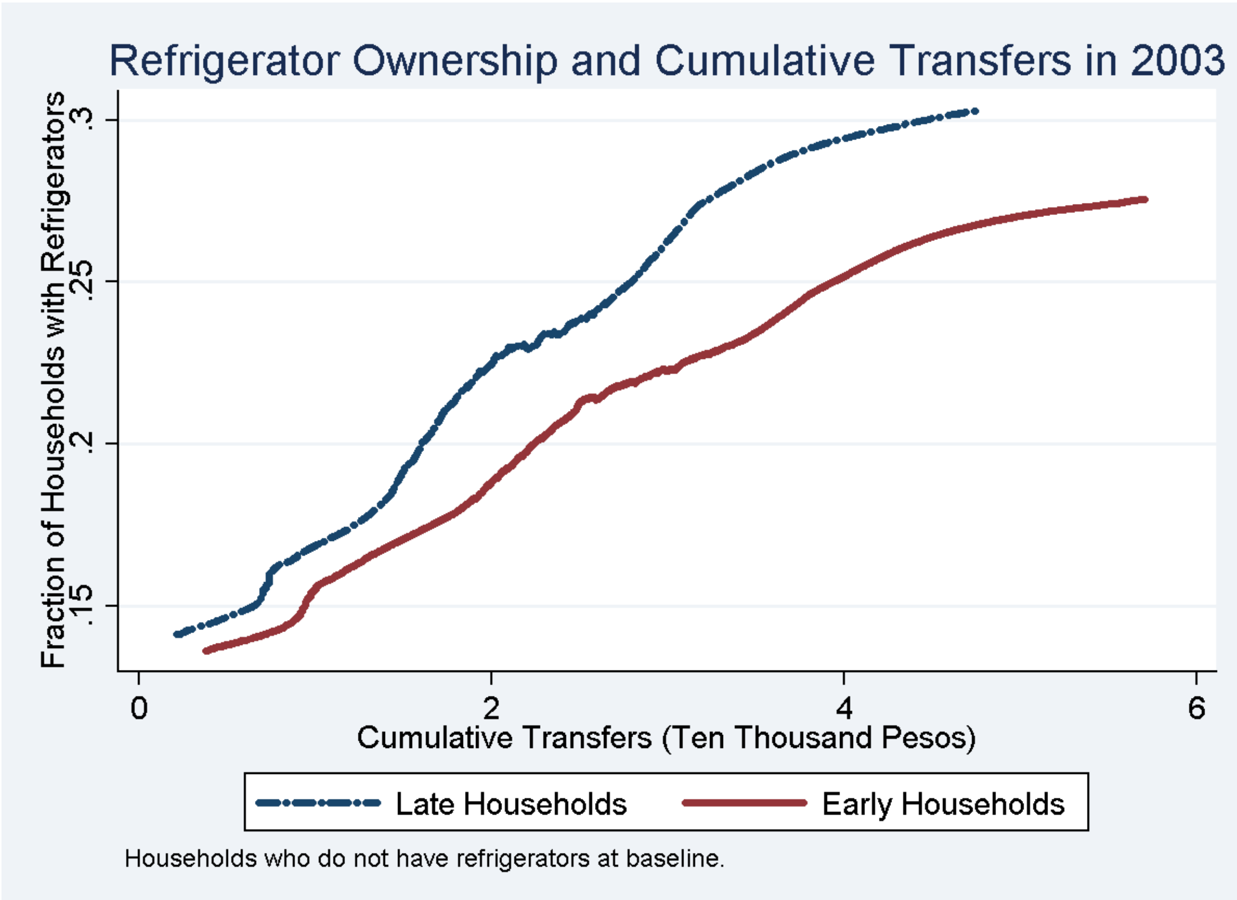
Table 2: Summary Statistics: Dependent Variables

	Late Households			Early Households			Difference	
	Mean	SD	N	Mean	SD	N	Mean	P-Value
Assets - Dependent Variables At Baseline								
Refrigerator	0.038	0.191	3341	0.044	0.205	5185	-0.006	0.540
Washing Machine	0.012	0.109	3342	0.014	0.119	5184	-0.002	0.600
Stove	0.165	0.371	3342	0.158	0.364	5186	0.007	0.777

Table 3: Summary Statistics: Cumulative Transfers (Ten Thousands of Pesos (2003))

	Late Households			Early Households		
	25%	Median	75%	25%	Median	75%
1998				0.09	0.13	0.21
1999				0.24	0.38	0.61
2000m	0.06	0.09	0.16	0.32	0.51	0.82
2000n	0.18	0.33	0.53	0.45	0.79	1.23
2003	0.93	1.69	2.63	1.24	2.19	3.36
2007	2.36	3.89	5.67	2.63	4.33	6.35

Figure 6: Refrigerator Ownership and Cumulative Transfers in 2003



Lowess regressions. Excludes the bottom and top 2% of cumulative transfers in each group.

Table 4: Basic Results - Refrigerator - Income Effects

	(1) OLS	(2) IV	(3) IV	(4) OLS	(5) IV	(6) IV
	Discrete Time Hazard		Household FE	Discrete Time Hazard		Household FE
Cumulative Transfers	0.023***	0.029***	0.048***			
	[0.004]	[0.005]	[0.005]			
Cumulative Transfers X Bottom 75% of Baseline Assets				0.020***	0.024***	0.043***
				[0.004]	[0.005]	[0.005]
Cumulative Transfers X Top 25% of Baseline Assets				0.032***	0.040***	0.058***
				[0.006]	[0.007]	[0.007]
N	30,414	30,414	30,258	30,414	30,414	30,258
R-squared	0.100			0.100		
F Stat on Excluded Variables - Cumulative Transfers		3,156	2,262			
F Stat on Excluded Variables - Cumulative Transfers X Bottom 75%					3,161	3,767
F Stat on Excluded Variables - Cumulative Transfers X Top 25%					1,635	1,596
Number of Households			6,655			6,655

Note: All specifications include state by round- fixed effects. All rounds through 2003 included. Specifications in columns (1), (2), (4), and (5) include household controls including number of children seven and younger, number of children 8 to 17, number of males 18 to 54, number of females 18 to 54, number of adults 55 and over, number of individuals with unreported ages, head of household's gender, head of household's and spouse's age, and education, and whether the household owns the house they live in, farm assets at baseline, number of other social programs the household is the beneficiary of, and village characteristics including migration intensity, marginalization and distance to nearest city. Columns (4) and (5) also include an indicator if the household is in the Top 25% of baseline animal assets. In column (2) and (3), instruments include Potential Cumulative Transfers. In column (5) and (6), instruments include Potential Cumulative Transfers X Bottom 75% of Baseline Animal Assets and Potential Cumulative Transfers X Top 25% of Baseline Animal Assets. Column (6) including household fixed effects drops 156 singletons.

Robust standard errors clustered by village in brackets.

*** p<0.01, ** p<0.05, * p<0.10.

Table 5: Basic Results - Refrigerator – Timing Effect

	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	IV	IV
		Discrete Time Hazard			Household FE
Cumulative Transfers	0.023***	0.028***	0.039***	0.056***	0.061***
	[0.004]	[0.004]	[0.007]	[0.007]	[0.007]
Early		-0.016***	-0.007	-0.009*	
		[0.005]	[0.005]	[0.005]	
Cumulative Transfers X Early			-0.015**	-0.021***	-0.018**
			[0.006]	[0.007]	[0.007]
Net Early Effect at 2003 Median Cumulative Transfers			-0.025***	-0.033***	
			[0.008]	[0.008]	
N	30,414	30,414	30,414	30,414	30,258
R-squared	0.100	0.100	0.101		
F Stat on Excluded Variables - Cumulative Transfers				1,554	1,226
F Stat on Excluded Variables - Cumulative Transfers X Status				1,974	1,889
Number of Households					6,655

Note: All specifications include state by round- fixed effects. All rounds through 2003 included. Specifications in columns (1) – (4) include household controls including number of children seven and younger, number of children 8 to 17, number of males 18 to 54, number of females 18 to 54, number of adults 55 and over, number of individuals with unreported ages, head of household's gender, head of household's and spouse's age, and education, and whether the household owns the house they live in, farm assets at baseline, number of other social programs the household is the beneficiary of, and village characteristics including migration intensity, marginalization and distance to nearest city. In columns (4) and (5), instruments include Potential Cumulative Transfers and Potential Cumulative Transfers X Early. Column (5) including household fixed effects drops 156 singletons.

Robust standard errors clustered by village in brackets.

*** p<0.01, ** p<0.05, * p<0.10.

Table 6: Basic Results - Other Assets

	Cumulative Transfers		Early X Cumulative Transfers		Early		Net Early Effect		N
Refrigerator									
DTH	0.056***	[0.007]	-0.021***	[0.007]	-0.009*	[0.005]	-0.033***	[0.008]	30,414
HH FE	0.061***	[0.007]	-0.018**	[0.007]					30,258
Washing Machine (ex 99)									
DTH	0.018***	[0.005]	-0.005	[0.004]	-0.004	[0.004]	-0.011**	[0.005]	26,166
HH FE	0.021***	[0.005]	-0.007	[0.005]					26,035
Stove (LP Gas)									
DTH	0.029***	[0.008]	-0.017***	[0.006]	-0.008	[0.006]	-0.027***	[0.008]	26,007
HH FE	0.031***	[0.008]	-0.016**	[0.007]					25,798

Note: All specifications include state by round- fixed effects and household controls, as described in the notes to Table 4. Instruments include: Potential Cumulative Transfers and Potential Cumulative Transfers X Early. All rounds through 2003 included except where noted. Washing machine not reported in 1999. Refrigerator entry repeats results from Table 4. Net early effect is estimated at 2003 median cumulative transfers. DTH indicated Discrete Time Hazard. HHFE indicated Household Fixed Effects. Cross Section indicates that the regression is a cross section of all households with asset at baseline as a control.
Robust standard errors clustered by village in brackets.
*** p<0.01, ** p<0.05, * p<0.10
F-stat on excluded variables not reported. All exceed 200.

Table 7: Placebo Test: Do Cumulative Transfer Predict Asset Ownership at Baseline?

	Baseline Asset Ownership		2003 Asset Ownership	
Refrigerator				
Cumulative Transfers in 2003	0.006	[0.006]	0.055***	[0.011]
Early	0.005	[0.012]	0.028	[0.026]
Cumulative Transfers X Early	-0.001	[0.005]	-0.030***	[0.011]
Net Early Effect	0.004	[0.008]	-0.007	[0.018]
Washing Machine				
Cumulative Transfers in 2003	0.003	[0.004]	0.009	[0.007]
Early	0.007	[0.007]	-0.025	[0.016]
Cumulative Transfers X Early	-0.001	[0.004]	0.004	[0.014]
Net Early Effect	0.005	[0.003]	-0.022**	[0.011]
Stove				
Cumulative Transfers in 2003	0.045***	[0.012]	0.041***	[0.012]
Early	-0.005	[0.026]	0.013	[0.032]
Cumulative Transfers X Early	-0.015	[0.011]	-0.029**	[0.012]
Net Early Effect	-0.022	[0.018]	-0.021	[0.023]

Note: For each asset, we report results from two different specifications, one estimated using asset ownership data at baseline and the other using data from 2003. All specifications include state fixed effects and household controls, as described in the notes to Table 4. All specifications estimated using IV with Potential Cumulative Transfers and Potential Cumulative Transfers X Early as instruments. Net early effect is estimated at 2003 median cumulative transfers.
Robust standard errors clustered by village in brackets.
*** p<0.01, ** p<0.05, * p<0.10
F-stat on excluded variables not reported. All exceed 400.

Table 8: Future Transfers and Refrigerator Acquisition

	(1) OLS	(2) OLS	(3) IV
Cumulative Transfers	0.039***	0.040***	0.084***
	[0.007]	[0.007]	[0.011]
Early	-0.007	-0.008	-0.015***
	[0.005]	[0.005]	[0.005]
Cumulative Transfers X Early	-0.015**	-0.015**	-0.026***
	[0.006]	[0.006]	[0.007]
Net Early Effect at 2003 Median Cumulative Transfers	-0.025***	-0.025***	-0.045***
	[0.008]	[0.008]	[0.009]
Future Cumulative Transfers X 03		<0.001	-0.047***
		[0.004]	[0.011]
Future Cumulative Transfers X 00n		-0.004***	-0.013***
		[0.001]	[0.003]
Future Cumulative Transfers X 00m		<0.001	-0.006**
		[0.001]	[0.002]
Future Cumulative Transfers X 99		>-0.001	-0.003
		[0.001]	[0.002]
Future Cumulative Transfers X 98		<0.001	-0.001
		[0.001]	[0.002]
N	30,414	30,414	30,414
R-squared	0.101	0.101	

Note: All specifications include state by round- fixed effects and household controls described in the notes to Table 4. All rounds through 2003 included. Instruments include Potential Cumulative Transfers, Potential Cumulative Transfers X Early, and Potential Future Cumulative Transfers by round. Column (1) repeats results from Table 5.
Robust standard errors clustered by village in brackets.
*** p<0.01, ** p<0.05, * p<0.10
F-stat on excluded variables not reported. All exceed 200.

Table 9: Effect of Transfers on Energy Demand Oportunidades Households (2007)

	Dependent Variable: Bi-Monthly Electricity Expenditures					
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Appliance Aggregate			432.1***	687.6***		
			[41.4]	[254.0]		
Refrigerator					54.2***	103.0**
					[5.4]	[44.4]
Current Transfers	94.6**	200.6	62.2	-37.0	68.8	-30.3
(Bi-Monthly, 10,000 2007 pesos)	[45.5]	[197.0]	[43.9]	[213.5]	[43.9]	[218.7]
N	3,960	3,960	3,960	3,960	3,960	3,960
R^2	0.256		0.507		0.261	
First-stage F-stat (Asset Index/Refrigerator)				36.97		22.55
First-stage F-stat (Current Transfers)		24.93		24.85		24.61

Note: All specifications include village fixed effects and household controls described in the notes to Table 4. IV instruments include: Potential Current Transfers, Potential Cumulative Transfers, Potential Cumulative Transfers X Early, Asset Aggregate in 1997 (4 only), Refrigerator Ownership in 1997 (6 only). Includes only households with reported positive electricity expenditures. Asset Aggregate scaled to estimated MWhr/month.
Robust standard errors clustered by village in brackets.
*** p<0.01, ** p<0.05, * p<0.10.

Table 10: Aggregate Country-Level Energy Consumption

	(1)	(2)	(3)
Income (log)	0.925***	0.856***	0.909***
	[0.087]	[0.104]	[0.088]
Income Growth		-0.324	0.307
		[0.201]	[0.726]
Income (log) X Income Growth			0.097
			[0.116]
Income (log) X ProPoorGrowth	0.073***		0.057***
	[0.017]		[0.016]
Income Growth X ProPoorGrowth		0.122**	0.893***
		[0.053]	[0.233]
Income (log) X Income Growth X ProPoorGrowth			0.146***
			[0.037]
Country Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Observations	907	892	892
R-squared	0.981	0.981	0.983

Robust standard errors clustered by country in brackets.
*** p<0.01, ** p<0.05, * p<0.10.

APPENDIX

Appendix Table 1 describes the weights used to create the asset aggregate reflected in Table 9: Effect of Transfers on Energy Demand Oportunidades Households (2007) above. The aggregate was constructed using data from two sources. The first is a document from the Mexican Ministry of Social Development based on data from the Federal Electricity Commission (CFE). The document estimates average monthly electricity consumption of a typical Mexican household through the use of appliances and the time spent in their use. They consider the average power needed for each appliance, as well as the average time a typical Mexican household (not necessarily a poor household) uses each appliance per month. We use the average monthly electricity usage to assign each appliance a KW-hour value in the aggregate and then use data from the ENCEL to select the appliances that the population of interest possesses. Thus, if a household owns all of the appliances in the table and lives in a 3 room house, the corresponding asset aggregate for that household would be equal to 199. However, if the household lives in a one room house and only owns a TV and a refrigerator, the corresponding aggregate would be equal to 158.

Appendix Table 1: Asset Aggregate Construction: Household Appliance Use and Average Monthly Kilowatt Consumption in Mexico

	Average Power in Watts	Time use per day	Time use per month	Kilowatts hours per month
Refrigerator	500 watts	8 hours/day	240 hours	120
Light bulbs (1 + 1 per room)	60 watts	5 hours/day	150 hours	9
Washing Machine[1/]	400 watts	1.3 hours/day	32 hours	13
TV	50 watts	6.3 hours/day	180 hours	10
Radio/ Stereo/CD Player	50 watts	5 hours/day	150 hours	8
Blender	400 watts	10 minutes/day	5 hours	2

1/ The use of the washing machine is 4 hours twice per week.

Source: "Tabla de consumo" (2010), http://www.cfe.gob.mx/sustentabilidad/ahorroenergia/Paginas/Tabladeconsumo.aspx, Federal Electricity Commission (Comisión Federal de Electricidad, CFE).

Note that these numbers were obtained assuming average electricity consumption for typical Mexican households, not necessarily for households living in poverty.

Appendix Table 2: Summary Statistics

	Late Households			Early Households			Difference		
	Mean	SD	N	Mean	SD	N	Mean	P-Value	
Panel A: Household Socio-Economic Characteristics at Baseline									
Age of Head of Household	42.287	13.906	3336	41.575	13.337	5168	0.711	0.119	
Male Head of Household	0.929	0.257	3342	0.929	0.256	5187	<0.001	0.947	
Home Owner	0.929	0.256	3342	0.944	0.229	5187	-0.015	0.094	*
Age of Spouse	36.422	11.753	3017	36.244	11.793	4664	0.178	0.661	
Spouse Education - Incomplete Primary	0.609	0.488	3020	0.633	0.482	4676	-0.024	0.374	
Head of Household Education - Incomplete Primary	0.666	0.472	3342	0.668	0.471	5187	-0.002	0.902	
Spouse Education - Primary	0.028	0.165	3020	0.025	0.157	4676	0.003	0.573	
Head of Household Education - Primary	0.029	0.167	3342	0.035	0.183	5187	-0.006	0.259	
Spouse Education - More Than Primary	0.002	0.045	3020	0.003	0.058	4676	-0.001	0.272	
Head of Household Education - More Than Primary	0.006	0.075	3342	0.008	0.087	5187	-0.002	0.304	
Indigenous Spouse	0.315	0.465	3008	0.334	0.472	4651	-0.019	0.686	
Indigenous Head of Household	0.400	0.490	3330	0.384	0.486	5161	0.016	0.762	
Number of Other Social Programs	0.600	0.689	3253	0.468	0.591	5096	0.132	<0.001	***
Number of children 7 and under	1.744	1.276	3235	1.721	1.285	5055	0.024	0.571	
Number of children 8 to 17	1.905	1.561	3235	1.865	1.559	5055	0.040	0.396	
Number of Males 18-54	1.039	0.594	3235	1.042	0.606	5055	-0.003	0.852	
Number of Females 18-54	1.128	0.555	3235	1.123	0.570	5055	0.005	0.783	
Number of adults 55 plus	0.355	0.660	3235	0.337	0.637	5055	0.018	0.358	
Number of Age unknown	<0.001	<0.001	3235	<0.001	0.001	5055	>-0.001	0.317	
Electricity	0.652	0.476	3236	0.618	0.486	5062	0.034	0.453	
Horses	0.281	0.701	3232	0.283	0.692	5051	-0.002	0.947	
Mules	0.322	0.701	3229	0.332	0.712	5054	-0.010	0.808	
Oxen	0.053	0.412	3230	0.083	0.458	5055	-0.031	0.034	**
Goats	0.856	3.374	3233	1.085	3.962	5054	-0.229	0.214	
Cows	0.574	1.945	3230	0.607	1.857	5058	-0.032	0.708	
Chickens	6.476	6.337	3224	5.891	6.083	5051	0.584	0.073	*
Pigs	1.126	1.934	3226	0.971	1.777	5052	0.155	0.279	
Rabbits	0.175	1.690	3231	0.121	1.474	5061	0.055	0.317	
Hectares Irrigated	0.035	0.349	3236	0.037	0.340	5061	-0.002	0.902	
Hectares	1.778	2.715	3227	1.669	2.603	5047	0.109	0.427	
Hectares Grazing	0.121	1.149	3236	0.164	1.329	5062	-0.043	0.378	
Baseline Animal Assets	2372	4555	3236	2462	4473	5062	-89.780	0.690	

Appendix Table 2: Summary Statistics (Continued)

	Late Households			Early Households			Difference	
	Mean	SD	N	Mean	SD	N	Mean	P-Value
Panel B: Village Characteristics								
Migration Intensity	0.056	1.024	168	0.039	0.991	272	0.017	0.864
Degree of Marginalization Low or Moderate	0.077	0.267	168	0.091	0.288	274	-0.014	0.608
Degree of Marginalization High	0.756	0.430	168	0.719	0.450	274	0.037	0.389
Degree of Marginalization Very High	0.167	0.373	168	0.190	0.393	274	-0.023	0.536
KM to Nearest City	101.033	43.548	171	102.285	41.002	275	-1.252	0.763