The Demand for Energy-Using Assets among the World's Rising Middle Classes [*]

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October 24, 2013

We study decisions to acquire energy-using assets in the presence of rising incomes. We develop a theoretical framework to show that credit-constrained, poor households are unlikely to use additional income to buy appliances. The effect of income growth on asset purchases is stronger at higher income levels. We use large and plausibly exogenous shocks to household income generated by the conditional-cash-transfer program in Mexico, Oportunidades, to show that asset acquisition is nonlinear, depends, as predicted, on the pace of income growth, and both effects are economically large among beneficiaries. Our results may help explain important worldwide trends in energy use.

JEL Codes O1 and Q4.

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Energy is a fundamental input to modern life. Without access to commercial energy sources, such as gasoline, natural gas and electricity, people cannot drive vehicles, refrigerate food and medicine, watch television, easily operate farming equipment or participate in many aspects of modern life. Despite this, an estimated 1.5 billion people live without electricity in their homes, and even among those who have access many do not own basic assets such as refrigerators, motorized transport, or washing machines. In fact, Table 1 demonstrates the low penetration of several key energy-using assets for over 4 million people living in the developing world.

However, this situation is changing as incomes rise from economic growth and the expansion of massive poverty alleviation programs. We analyze household decisions to acquire energy-using assets for the first time, focusing on the role of rising incomes in the developing world, where the vast majority of the expected growth in energy use is forecast to happen (EIA, 2011a). Importantly, and unlike the previous literature, we allow for the presence of credit constraints, which, as we show, can have significant implications for the timing of asset acquisitions and, consequently, the demand for energy. This is important as credit is severely constrained throughout much of the developing world, especially for the poor and near poor (Karlan and Morduch, 2010).[1] For example, in rural Mexico, the site of our empirical application, credit opportunities are very limited as only 1 percent of the communities in which our data sample live have a formal credit institution and only 3 percent of households report having active loans, almost all of which are small informal loans from friends, neighbors, and relatives (Gertler et al., 2012).

We are interested in households' acquisition of energy-using assets for two reasons. First, they are important drivers of health and human development (World Bank, 2008). For example, air conditioning lowers heat-related mortality (Barreca, et al., 2012) and refrigeration improves

[1] See also http://datatopics.worldbank.org/financialinclusion/.

child health outcomes (Wolfe and Behrman, 1982). In addition, existing work has established a causal linkage between access to electricity and indicators of development, such as female labor force participation (Dinkelman, 2011), housing values and the UN Human Development Index (Lipscomb, Mobarak and Barham, 2013). While there is some work on the acquisition of energy-using assets in the developed world[2], ours is the first to analyze the acquisition of energy-using assets, which mediate how people actually use energy, in the developing world.[3]

Second, we argue that growth in energy demand driven by rising energy use among first-time purchasers of appliances and other energy-using assets is likely to have important implications for macro-level trends in energy use. In terms of scale, if, for example, half of the households in India who do not currently own refrigerators were to buy one, annual *nationwide* electricity demand, across all sectors – residential, commercial and industrial – would rise by over 10 percent.[4] Rapid first-time asset acquisition is already taking place in some parts of the world. For instance, vehicle ownership in urban China has risen at almost 40 percent *per year* between 2000 and 2010, helping fuel China's rapid growth in oil consumption (China Statistical Yearbook, 2001 and 2011).

Understanding the likely growth in demand for energy is critical for several reasons. First, investments in energy infrastructure require long lead times, and most governments and

[2] See, for example, recent contributions on heating systems by Davis and Killian (2011) and automobiles by Busse, Knittel and Zettelmeyer (2013).

[3] In some countries, there are also large, upfront prices for an electricity connection. In Kenya, for example, the current cost of connecting to the electricity grid is around $400, about half of the average annual income in the country. By contrast, other countries, such as South Africa, have subsidized the cost of the connection entirely. Our model highlights the potential role of income growth and credit markets in increasing connections in places like Kenya.

[4] In 2007, 86.5% of Indian households did not own refrigerators. Extrapolating growth in acquisitions, by 2011, an estimated 84% of households did not own refrigerators (Wolfram, et al. 2012). Population in 2011 was 1.210 billion. Assuming 5 people per household, 205 million households lack refrigerators. Assuming refrigerators use 1000 kWh/year (though new models can be more efficient, this would be a relatively efficient used refrigerator) acquisition by half of the households would be 101,648 GWh/year, which is 10% of generation of electricity of 985,443 GWh in 2011, the last year available (EIA 2011a). Using generation as the denominator understates the potential impact since line losses mean that more electricity needs to be generated than consumed. It is very difficult to get accurate estimates of true line losses in India because "non-technical losses," mostly theft, are very large.

energy companies base their investment decisions on demand projections. Incorrect forecasts can lead to local 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. Second, energy use is a key contributor to climate change as energy-related emissions account for three-quarters of worldwide anthropogenic greenhouse gas emissions.[5] 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.

We first develop a simple theoretical model that suggests a non-linear Engel curve, meaning that as income goes up from initial very low levels, credit-constrained households are not much more likely to purchase an energy-using asset. Above a certain threshold, however, increases in income are much more likely to lead to asset purchases, suggesting a nonlinear relationship between income and asset acquisition. Our theoretical model also predicts that the speed at which credit-constrained households' incomes grow will affect their asset acquisitions. The model further predicts a positive interaction between the rate of income growth and income levels, so that impact of rapid income growth is accentuated at higher income levels.

We next use large and plausibly exogenous shocks to household income generated by the conditional cash transfer program in Mexico, Oportunidades, to show that the nonlinear relationship between income and asset acquisition is important among low-income Mexican households. Considering the rate of income growth, we also find strong empirical support for both of the predictions on the growth rate of income, providing further validation for the importance of credit constraints and the implied nonlinear relationship between income growth

[5] See, for example, http://www.epa.gov/climatechange/science/indicators/ghg/global-ghg-emissions.html.

and asset acquisition.

Our findings on the nonlinear relationship between income and asset acquisition are consistent with the well-known S-shaped relationship between income and asset ownership (Koptis and Cropper, 2005; Dargay, Dermot and Sommer, 2007; Letschert and McNeil, 2007).[6]

Figure 1 uses household data from several of the most populous developing countries to plot the share of households that own refrigerators against household expenditures. The dashed lines in

Figure 1 show the density of households by expenditure level. The top row of graphs depicts 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 inflection point 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 bottom row of graphs, however, shows that there are significant populations poised to buy refrigerators in India, Indonesia and rural China, which together represent more than 2 billion people.

Our penultimate section presents evidence suggesting that the major forecasts have under-estimated growth in energy demand in the developing world, and the underestimates are most pronounced for countries that have experienced pro-poor growth, where the nonlinearities that we identify at the bottom end of the income distribution appear to be the most pronounced. To our knowledge, we are the first in the economics literature to confront this fundamental issue.

The next section presents a simple two-period model of asset acquisition in the presence

[6] Note that the existing literature documents the existence of the S-shaped cross-sectional correlations. We provide a model to explain it, and show that the relationship is indeed causal.

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. We discuss several implications of our results in Section 5. Finally, Section 6 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.[7] 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.[8]

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.

[7] 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.

[8] 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 and are surveyed in Karlan and Morduch (2010). There are also studies looking at the novel institutions developed to partially overcome credit constraints including: ROSCAs (Besley, Coate, and Loury 1993) and microfinance (Hossian, 1988). None of these intuitions address household durables, either in intent or scale.

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 the two assets, and no on-going energy costs associated with owning the refrigerator.[9] 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: $Y < P$.[10]

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, the share of households with a given income who own a durable at the end of the second period is S-

[9] 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.

[10] 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.

shaped.[11] 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 change 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.

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:

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

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.[12] 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

[12] 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 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 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.[13] 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.

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.[14] 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.[15] Any multiple period model of asset acquisition with increasing income[16] has three phases: a

[13] 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: $2\left(u_f(T+T')-u_f(T)\right)>u_f(L+\alpha 2T')-u_f(L)+u_f(H+(1-\alpha)2T')-u_f(H)$.

[14] 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.

[15] 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.

[16] Because households can save, this holds even if the increase in income is seasonal or otherwise lumpy.

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.[17] 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, credit constrained, households who are delaying their purchases because of growth in future incomes.

Our model has important implications for thinking about the rate of durable 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 influence asset acquisition.

[17] One can make assumptions on the distribution of preferences for assets or the correlation of preferences with income to generate S-curves. Credit constraints and income growth operate largely orthogonally, and make the S-curve steeper in those settings.

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.[18]

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

[18] These trends do not appear to be 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.

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 the poorest 20 percent of the population.[19]

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

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

for any given household are capped at a pre-determined upper limit.[20]

Table 2 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 provides a yearly stipend to cover the costs of school supplies for children who do not get them at school.

As Table 2 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 2 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

[20] 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.

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 2 to the following formula:

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

where K_{sit} is the number of children of type *s* in household *i actually* attending school in period *t.*[21]

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*).

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). In addition to being marginalized communities, credit is scarce. Only 1.2% of the villages have formal credit institutions, and only 2.8% of eligible households have loans of any kind, mostly from friends, neighbors, and relatives (Gertler, et al., 2012).

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

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

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.

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., 2012).

Our analysis focuses on these 506 communities in 7 States in central Mexico 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 3 and Appendix Table 1 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.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.

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 to that point. 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.[22] 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:

[22] 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.

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

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 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. We also evaluate a stronger form of prediction 1 by interacting $cumulative\ \tau_{it}$ with an indicator for whether the household has high wealthrelative to other households in the sample. Prediction 1 suggests that high wealth households should be more likely to use increases in the amount of transfers to purchase an appliance. 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 key independent variables are $early_i$, $cumulative\ \tau_{it}$, and baseline animal assets, which we use to determine high wealth households. 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 are nonlinear functions of the grade and sex of the 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 in 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:

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

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 Sections 4c-d, 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 4 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 both households at the 25th percentile of the early group by late 2000 and 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 4 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.

Variation in baseline animal assets reflects households' pre-treatment wealth and income, and may have various endogeneity concerns. For example, households with more animals may simply value assets more. However, in all our relevant specifications, we control for a household's baseline animal asset ownership. Our use of baseline animal assets is to show a heterogeneous treatment response of wealthier households. When we do, we also include the direct effect of baseline animal assets or use household fixed effects, thus controlling for all time invariant household characteristics. Further, alternate measures of household wealth, such as total household consumption or consumption per capita, yield similar differences between the relatively better off and other households.

We opt not to estimate income elasticities 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. Finally, transfers are a close, but not perfect, measure of changes in household income because both substitution and investment effects are likely small. We know from previous work that substitution effects are small as they estimate that households' marginal consumption out of transfers is 74%, which is consistent with the marginal consumption out of income in other developing world settings (Gertler et al., 2012). This is consistent with findings suggesting that the only labor supply effects of transfers are on youths with relatively low wages (Parker and Skoufias, 2000 and Skoufias and Parker, 2001). Investment effects in education or household assets would bias measurement of cumulative income in the other direction. However, the 5 years of the program we use are too short for investments in education of primary school aged children to payoff. We also note that investment effects would bias us against finding the predicted difference between early and late households, because early households with the same reported cumulative transfers have received more returns from their investments. Thus, we focus on identifying the effects predicted by the model in Section 1 by examining household responses to transfers.

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 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 2) 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

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.

a. Income Effects

Table 5 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).[23]

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

[23] 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.

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. These results are consistent with the importance of credit constraints steepening the S-curve. However, as discussed in section 3, baseline animal assets are not subject to random treatment. Next, we examine the timing predictions of the model, which uses characteristics of the treatment to show the importance of credit constraints and the timing of asset acquisition.

b. Timing Effects

Table 6 presents several specifications of equation (3) focusing on the effect of transfer timing. The first column, repeated from column (1) of

Table 5, 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 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 2 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.

c. 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 refrigerators the higher is their transfer income, the more delayed were their transfer payments, and the effects of the delayed payments are stronger at higher cumulative transfer amounts. These results may be consistent with a number of alternative explanations. In this section we investigate the most obvious ones.

Future Expectations: Early may be 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.[24] For instance, late households may simply have more girls than early households who are at the same level of cumulative transfers in 2003.

Table 7 presents results from several specifications that include future transfers as additional explanatory variables. Column (1) of Table 7 reproduces column (4) of Table 6, and then columns (2) and (3) add information about the household's actual future transfers through 2007.[25] 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.

Recertification: Recertification could also make households forward looking. While households are promised payments for 6 more years after not being recertified as eligible, households may delay or avoid purchasing refrigerators to maintain future eligibility. This would bias the results of our main specification towards zero as current cumulative transfers are positively correlated with future transfers, and households with more at stake in the future would

[24] 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 also 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.

[25] Specifically, Future Cumulative Transfers are the amount of transfers the household will receive through 2007 less the transfers the household has already received. We interact this with the round and instrument with Future Potential Cumulative transfers.

presumably be more reluctant to purchase a refrigerator to ensure continued participation in the program. The results in Table 7 are consistent with this. Controlling for future transfers, and thus the benefits of recertification, leads to bigger effects of transfers.

Self-Control: 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 7, however, are not consistent with lack of self-control or other myopic behavior.

Family Structure: Another concern is that 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. Because of the randomization, the population of households in the early and late groups are comparable. However by construction, households in the different groups with the same cumulative transfers have different family structures. 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.

d. Placebo Tests

As an additional robustness check, we estimated cross-sectional placebo specifications using asset ownership before the households received transfers. These specifications test whether the particular nonlinear relationship between family structure and transfers embodied in cumulative transfers predicts appliance ownership prior to the impact of the transfers themselves. The results are presented in in Table 9. Each specification is estimated using instrumental variables and including household controls, comparable to the specification reported in column (4) of Table 6. Column (1) uses ownership from the baseline survey that was conducted in 1997 and cumulative transfers through 2003. The coefficients on Cumulative Transfers, Early and Cumulative Transfers X Early are insignificantly different from zero.[26] 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 9 are cross sectional while the results in Table 6 and Table 8 were estimated as discrete time hazards, we estimated similar specifications for 2003 by way of comparison. These are presented in column (4). These specifications confirm the results in Table 6 and Table 8. The coefficient on cumulative transfers is positive and significant, while the net effect of Early and Early x Cumulative Transfers is negative.

Columns (2) and (3) report another variant of the placebo test that predicts asset ownership in the period just before a household entered the program (baseline for treated households and 1999 for control households) as a function of the household's first period transfers. These tests do not capture the variation induced by the randomization, but do use transfers in a period closer to the period when households' baseline asset ownership is measured. If there were meaningful correlations between family structure (and thus transfer rates), such as the ages of children and girls versus boys and valuations of refrigerators we should expect a

[26] Results are similar for placebo tests on other assets.

relationship between first period transfer rates and asset ownership driven by preferences and not transfers. This test takes advantage of the fact that households with high first period transfers are those with older and more female children, not necessarily those who will eventually have high cumulative transfers. Though noisier, these similarly show no statistically significant impact of first period transfers. These tests also refute the hypothesis that household preferences for appliances change over time in a manner correlated with the transfer schedule, for example, if 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 final concern is that late households might have earned more non-transfer income than early households 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 6, column (5), excluding the rounds in which the late households did not receive transfers. The estimates are not statistically different from column (5).[27]

e. Additional Assets

Table 8 presents results from specifications comparable to those reported in columns (3) of Table 7 and (5) of Table 6 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. Cumulative Transfers X Early is negative across both specifications for all the additional assets in Table 8. It is statistically smaller than zero for stoves. While it is hard to draw strong inferences from only a

[27] 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.

few assets, the results in Table 8 are generally supportive of our model.

5. Macro Implications

Our results suggest that credit-constrained households in the developing world are likely to acquire energy-using assets such as refrigerators at rapid rates as their incomes rise above a certain threshold. While these assets help improve health and human development, as we noted in the introduction, the energy they use can be significant. Energy forecasters concur that the bulk of the growth in energy demand and associated greenhouse gas emissions is likely to come from the developing world (EIA, 2011a; IEA, 2012). Their analyses suggest growth of over 90 percent through 2035 in the developing world while only about 15 percent in the developed countries. Several pieces of evidence suggest, however, that existing forecasts have not allowed for the possible nonlinear relationship between income growth, especially pro-poor growth, and energy demand suggested by our model.

The data in Figure 7 indicate that this omission could be important. Figure 7 plots per-capita energy consumption against per capita GDP, both demeaned at the country level. We include observations for 37 developing countries using data from 1980-2006. We separate countries into two equally sized bins according to the change in the reported GINI coefficient.[28] Figure 7 suggests that increases in energy use for a given increase in per capita GDP have been *twice* as high in countries with pro poor growth (red).[29]

The pattern suggested by Figure 7 is consistent with our model. If growth lifts households

[28] Demeaning the data controls for the level of inequality, level of energy use and other fixed country-specific attributes.

[29] Since the GINI coefficient measures relative wealth over the entire income distribution, decreases may be driven by slowed growth at the upper end of the income distribution as well as rising prosperity at the bottom, and it is only the latter effect that we are interested in capturing. In practice, changes in the GINI coefficient are very highly correlated with other measures of pro-poor growth, which show similar patterns. GINI coefficients are also the most reported measure, so it allows us to include the most countries. Data on GINI coefficients and other measures of pro-poor growth are from the World Bank Development Indicators. We include countries for which both energy use and multiple GINI measures are available.

out of poverty and into the middle class, their consumption of commercial energy sources is likely to increase dramatically. Although a series of nonlinear increases can be approximated by a linear or near-linear relationship, the linear approximation breaks down when households start from zero – essentially consuming no commercial energy sources. Refrigerators, which account for about a third of total household electricity consumption in Mexico and China[30], will play a large role in this discrete increase for electricity. Our model also applies to vehicle purchases, which will drive a discrete increase in oil consumption. This nonlinear increase could be more dramatic if large numbers of families emerge from poverty at the same time as happened with the expansion of the conditional cash transfer programs in Mexico and Brazil.

It is important to note that Figure 7 presents correlations. While the correlations are consistent with our model, they could suggest that countries with pro-poor growth are also investing more in energy infrastructure, for example through electrification programs, or that a growing manufacturing sector leads to both increased energy consumption and reduced inequality. And, though household asset decisions are important, they are unlikely to explain the full magnitude of the difference between pro-poor and all other countries.[31]

On the other hand, while we have focused on households' asset acquisition and the implied direct energy consumption, the impact of asset acquisition on energy consumption may be greater. For example, it is also important to consider indirect energy consumption, such as the energy used to manufacture the refrigerator, including the energy embodied in the steel. Existing work in engineering estimates these "lifecycle energy estimates." For a refrigerator, existing

[30] Household refrigerators in China consumed approximately 145 terawatt-hours (TWh) of electricity in 2009 (Zhou et al. 2011; personal communication) while total residential electricity was 490 TWh (National Bureau of Statistics 2010). The Mexico figures are from Johnson et al. (2009).

[31] In the appendix, we show that Oportunidades households' electricity consumption respond very little to transfers conditional on assets. As such, it seems these correlations are not driven by short-run income elasticities that are decreasing in income.

estimates suggest that the embodied energy is about 10 percent of the lifetime energy (Gonzalez et al. 2012). Given that the lifetime is more than 10 years, though, the embodied energy will more than double the energy consumption in the year it is purchased. Given the international trade in these assets, these energy expenditures are generally not accounted for in the country that drives the demand, but they will drive up global energy use. In any case, the differences in the magnitudes represented in Figure 7 are stunning – two times as much growth in energy for a given growth in GDP – and certainly merit further inquiry.

How do we know that the existing estimates do not capture differences between pro-poor countries and others? First, we can look historically at near-term forecasts and compare them to realized energy demand. For example, in its *World Energy Outlook 2000*, the Energy Information Administration forecast that China's energy demand in 2005 would be 55 quadrillion BTUs. Actual energy demand that year was a stunning 25 percent higher. In part, this reflects the fact that the EIA under-estimated China's GDP growth, but even adjusting for the higher GDP growth, the estimate is still 15 percent too high. Similarly, the EIA under-estimated energy demand in Brazil, a country with aggressive anti-poverty programs, for 2005 by more than 25%. By contrast, in India, a country that has had less success than Brazil and China lifting the income of the very poor, the EIA estimate for 2005 was much closer, only low by 3 percent.

Existing forecasts, which are all highly consonant with the EIA forecasts, rely on assumptions on the form of the relationship between GDP growth and energy use, but they do not appear to distinguish between pro-poor growth and more regressive growth. For example, EIA (2011b) provides extensive documentation on the models underlying its energy forecasts. The models are involved, so it is impossible to point to a single assumption that may lead to the underestimate. Assumptions reported for the residential component of the model indicate that the EIA is using exactly the same income elasticity of demand for electricity in India and China, though the countries' success lifting households out of poverty has diverged significantly.

In sum, existing energy forecasts do not appear to distinguish between countries where many households are coming out of poverty and countries where growth favors households at higher income levels. The forecasts also seem to have under-estimated energy demand for countries, such as China, with pro-poor growth. The pattern in Figure 7 suggests that the relationship between energy demand and growth is much different in countries that have had pro-poor growth. Clearly, more work needs to be done to understand different growth rates in energy demand around the world, but our model provides a first attempt to address this important issue. Importantly, the existing estimates are not simply under-estimating growth in energy demand for some developing countries and over-estimating for others, but they have systematically under-estimated growth in the developing world. Given the share of the world population living in China, under-estimating Chinese demand is a significant flaw.

6. Conclusions

Over the next several decades, wide-scale poverty alleviation programs as well as continued economic growth will lift the incomes of many of the world's poor. At the same time, governments, major lending organizations and private companies are spending hundreds of billions of dollars a year rolling out the energy infrastructure in the developing world. As incomes rise and as energy access increases, families formerly living in poverty will for the first time purchase refrigerators, water pumps, air conditioners, washing machines, vehicles, and other energy-using assets.

We develop a model and provide empirical analysis that highlights how households faced with credit constraints become much more likely to purchase energy-using assets with additional income once their income passes a threshold level. Our results speak to the rate at which households will be able to reap the benefits associated with energy access, including cooling from fans or air conditioners, labor saving from washing machines, and improved nutrition and health with access to refrigeration. They also inform the likely pace of energy demand growth.

Our results have implications for both micro- and macro-level policies. On the micro-scale, as we have noted, our two-period model is general enough to have implications for credit constraints and both the timing of cash transfers and the speed of economic growth on asset acquisition. Our results speak to the potential impacts of credit availability, and especially credit programs for appliances. There is anecdotal evidence that retailers are beginning to sell appliances on credit in some parts of the developing world. For example, Wal-Mart's Banco de Wal-Mart offers credit cards for purchases at Wal-Mart, but at annual interest rates of 60%. This should lower the income levels at which households acquire appliances, but also could reduce the aggregate nonlinear relationship between income and energy use at a macro level. Also, our results show that the rate of the payments in government transfer programs matter for asset acquisition rates. More generally, in the presence of credit constraints, the timing and rate of transfer payments and the path of economic growth are important, not just the amounts.

As more and more households in the developing world become first-time owners of energy-using assets like refrigerators and vehicles, policies that promote more energy-efficient appliances, such as subsidies for high efficiency models, labeling or other information programs, or minimum efficiency standards, become increasingly important. While a considerable body of research considers US households' willingness to tradeoff a high upfront cost for an energy efficient model versus lower usage costs, more work needs to be done to understand household energy efficiency decisions in the developing world, where the range of products offered, information about efficiency, energy prices and industrial organization of appliance sales all may differ. Our results help pinpoint the locations where appliance acquisitions are likely to happen most rapidly, and, therefore, where energy-efficiency programs are most likely to target a large number of first-time purchasers. Because our Oportunidades data do not contain information on the specific make and model of appliances, though, we are unable to address these issues in the current analysis. Understanding the factors that influence choices around the energy efficiency of different assets remains an important area for future research.[32]

While the macro-scale implications of our analysis are more speculative, the suggestions are profound. 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 the structure of international climate agreements. Furthermore, negotiations over these agreements 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 2011a). 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.

[32] Davis, Fuchs, and Gertler (2013) analyze the "Cash for Coolers" program, through which the Mexican government offered subsidies to households that exchanged older, presumably inefficient, refrigerators and air conditioners for new models. They show that the program led to significantly lower energy savings than ex-ante analyses had forecast.

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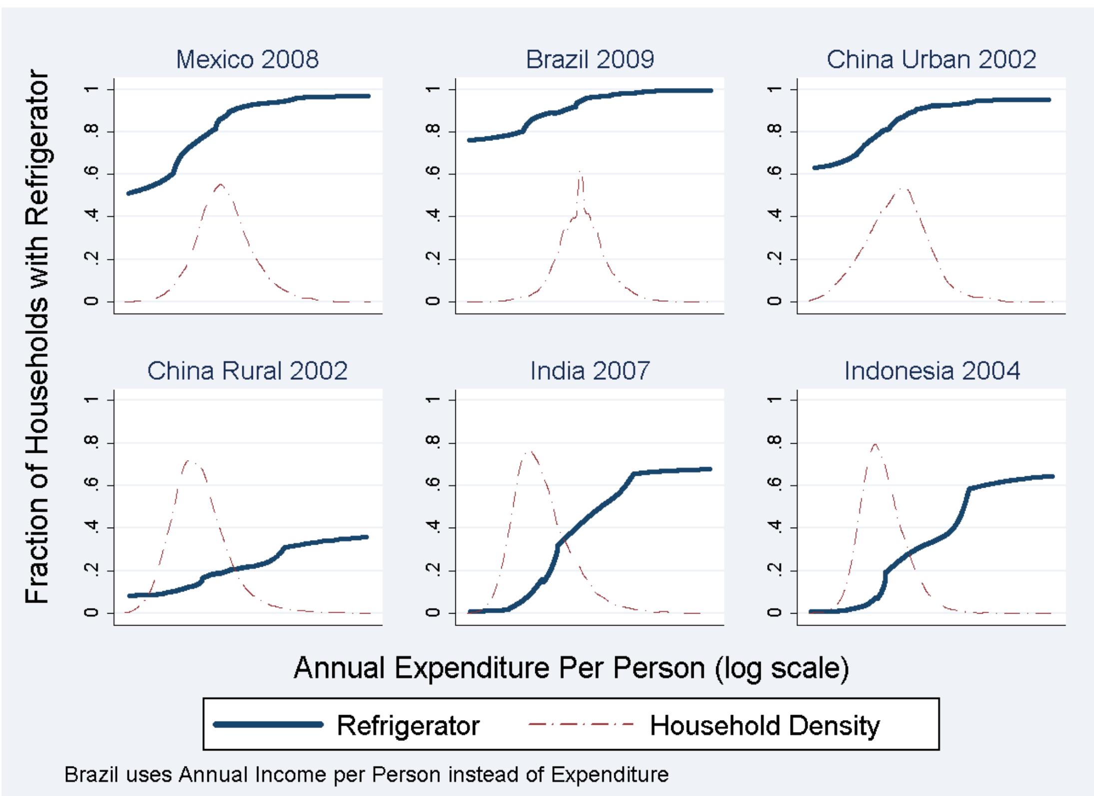
Table 1: Energy Using Asset Ownership in the Developing World

	Electricity Access (% of population)	Refrigerators (Share of Households)	Cars (per 1000 people)	Population (millions)
Brazil	98.7	93%	209	197
China	99.7	69%	58	1,344
India	75.0	13%	18	1,221
Indonesia	73.0	17%	60	245
Mexico	97.9	83%	275	119
Sub-Saharan Africa	32.5	11%	28	886
Total	70.8	38%	53	4,012

Notes: Population numbers are from the World Bank for 2011. Data on electricity access and cars are from World Bank for the most recent year available (2008-2010). Mexico electricity access from Comisión Federal de Electricidad (2012). China (for 2010) refrigerators come from the Chinese Statistical Yearbook. Refrigerator shares come from a variety of country-specific nationally-representative surveys for the following years: Brazil (2009), India (2007/2008), Indonesia (2004), Mexico (2008), Sub-Saharan Africa (2006). For sources and additional details see Wolfram, Shelef, and Gertler (2012).

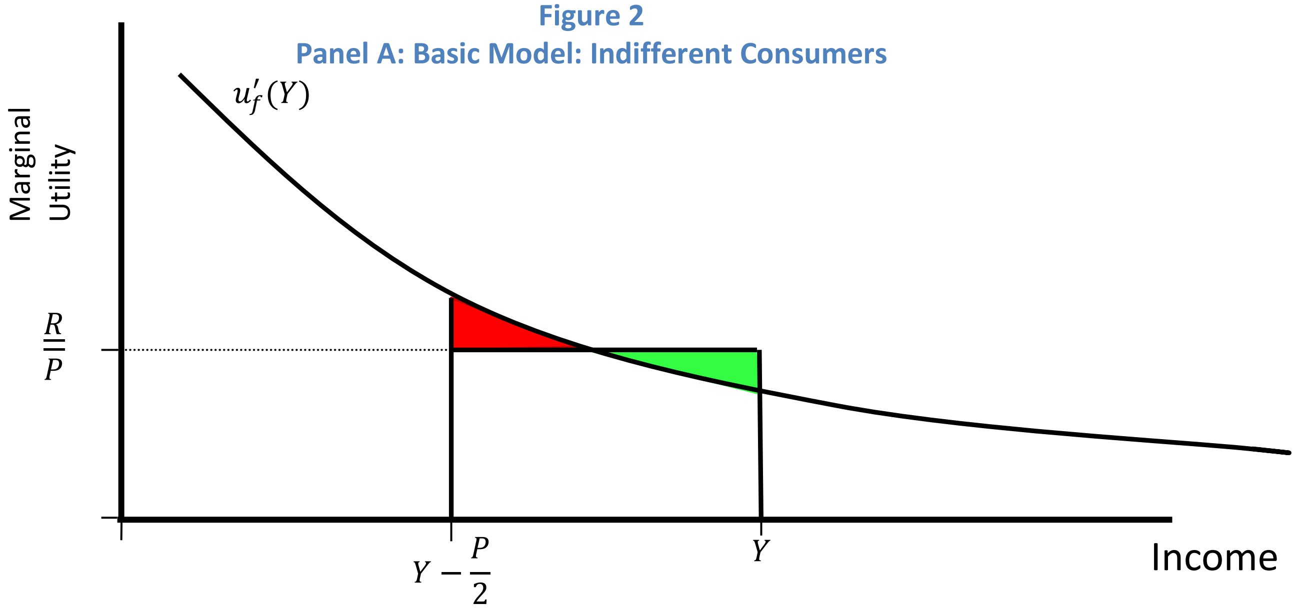
Figure 1: Refrigerator Ownership and Household Expenditure Level



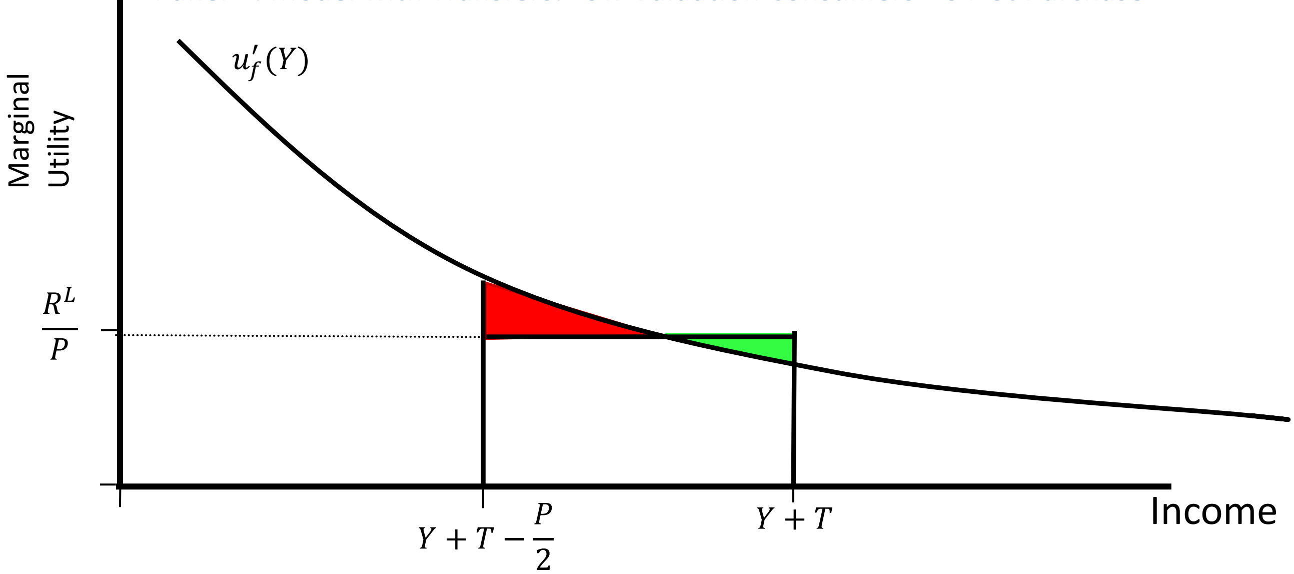
Sources: Mexico, 2008, *Encuesta Nacional de Ingreso y Gasto de los Hogares.* Brazil, 2009, *National Household Sample Survey – PNAD.* China, 2002, *Chinese Household Income Project.* India, 2008, *National Sample Survey.* Indonesia, 2004, *National Socio-Economic Survey – Susenas.* Annual Expenditure 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

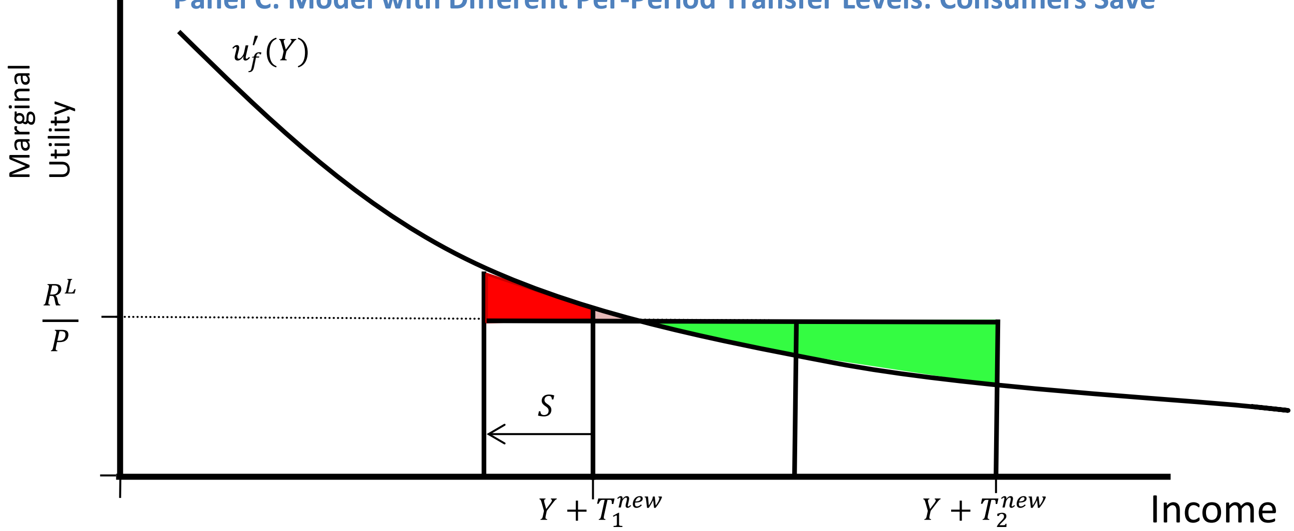


Figure 3: Hypothetical GDP Paths

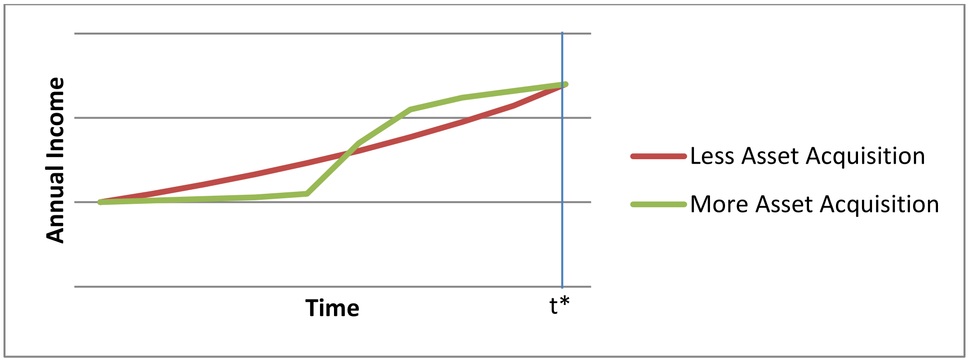
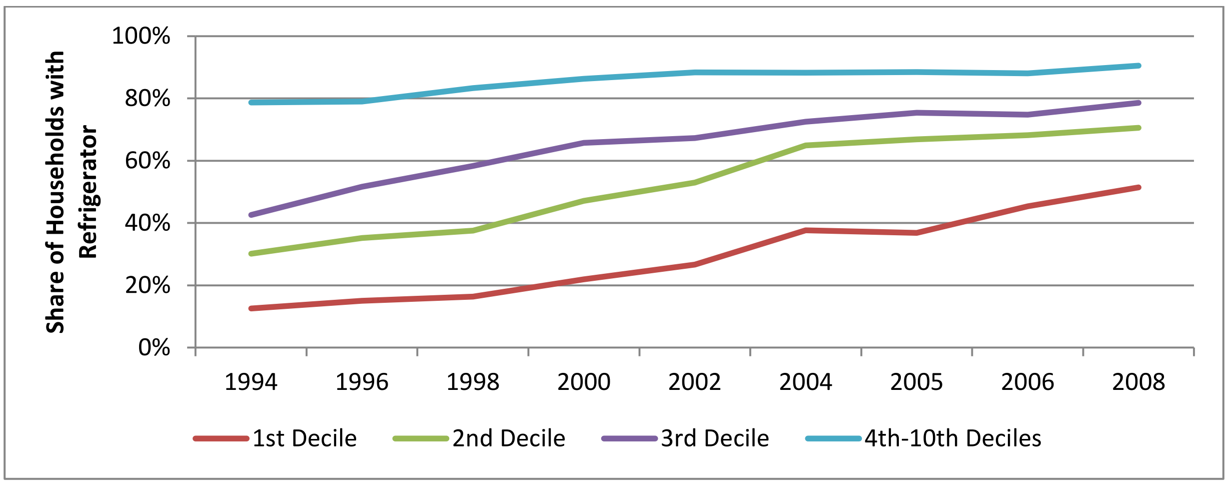
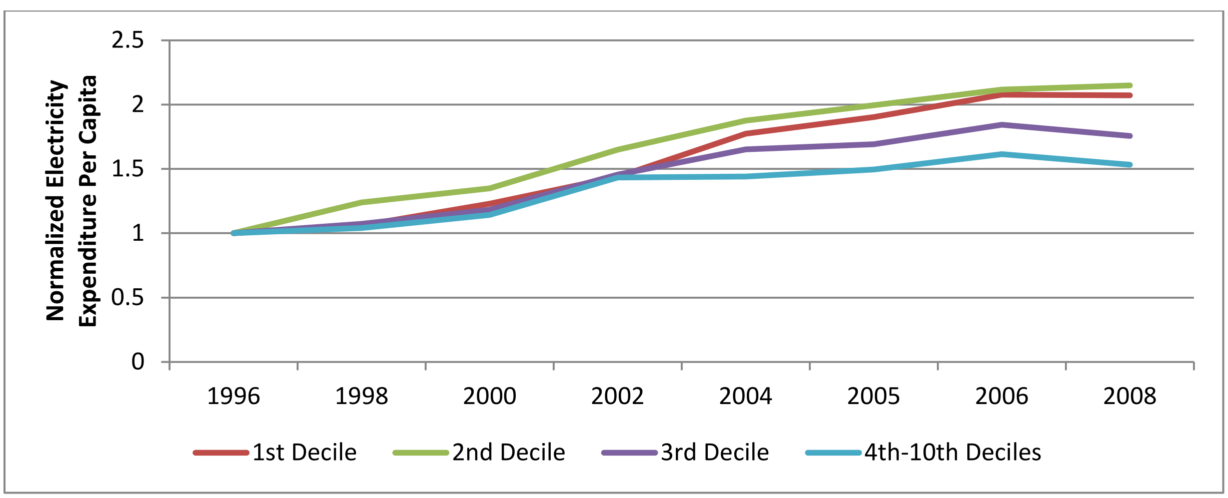


Figure 4: Growth in Refrigerator Ownership by Consumption Quartile for Mexico



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 2: 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 6th grade or 1,715 pesos with children in 7th grade or higher.An additional 200 pesos for children in 3rd-6th grades and 250 pesos for children in 7th grade or higher are provided once a year for school supplies.

Table 3: 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

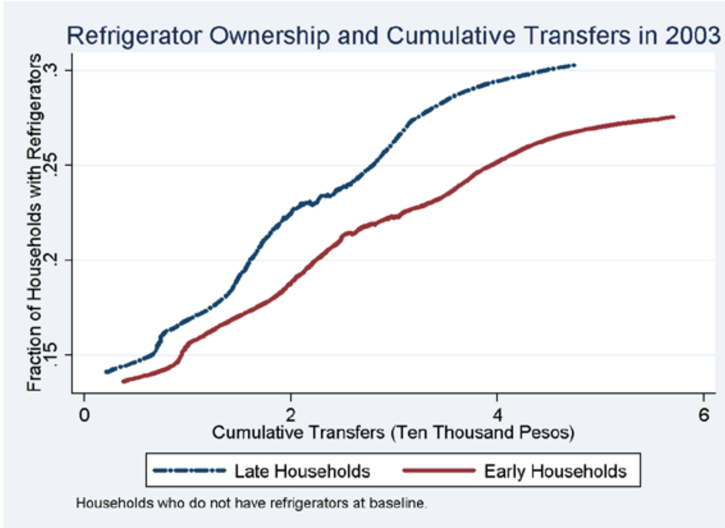
Source: *Encuesta de Características Socioeconómicas de los Hogares* (1997)

Table 4: 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

Source: Oportunidades Evaluation Survey (ENCEL) surveys (1998, 1999, March 2000, November 2000, 2003, and 2007)

Figure 6: Refrigerator Ownership and Cumulative Transfers in 2003



Lowess regressions. Excludes the bottom and top 2% of cumulative transfers in each group. Source: ENCASEH (1997) and ENCEL (1998, 1999, March 2000, November 2000, 2003, & 2007) surveys.

Table 5: Basic Results - Refrigerator - Income Effects

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	IV	OLS	IV	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. Source: ENCASEH (1997) and ENCEL (1998, 1999, March 2000, November 2000, 2003, & 2007) surveys. Robust standard errors clustered by village in brackets. *** p<0.01, ** p<0.05, * p<0.10.

Table 6: Basic Results - Refrigerator – Timing Effect

	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) 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 and household controls described in the notes to Table 5. 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 7: 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 5. 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 6.
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 8: Basic Results - Other Assets

	Cumulative Transfers		Early X Cumulative Transfers		Early		Net Early Effect		N
Refrigerator									
DTH	0.084***	[0.011]	-0.026***	[0.007]	-0.015***	[0.005]	-0.045***	[0.009]	30,414
HH FE	0.061***	[0.007]	-0.018**	[0.007]					30,258
Washing Machine (ex 99)									
DTH	0.026***	[0.005]	-0.006	[0.004]	-0.007	[0.004]	-0.014***	[0.005]	26,166
HH FE	0.021***	[0.005]	-0.007	[0.005]					26,035
Stove (LP Gas)									
DTH	0.049***	[0.011]	-0.020***	[0.006]	-0.013*	[0.007]	-0.036***	[0.009]	26,007
HH FE	0.031***	[0.008]	-0.016**	[0.007]					25,798

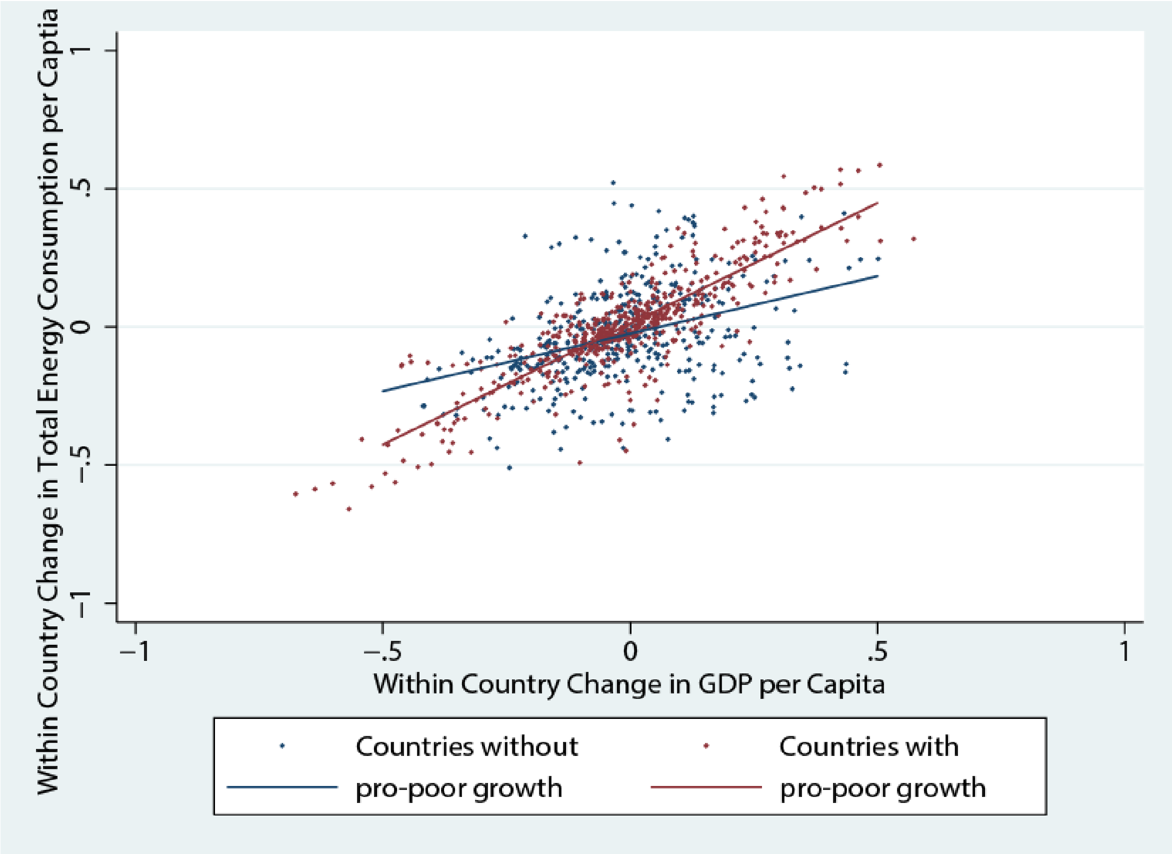
Note: All specifications include state by round- fixed effects and household controls, as described in the notes to Table 5. Instruments include: Potential Cumulative Transfers and Potential Cumulative Transfers X Early. DTH specifications include Future transfers instrumented for as described in notes to Table 7. All rounds through 2003 included except where noted. Washing machine not reported in 1999. Refrigerator entry repeats results from Tables 6 & 7. Net early effect is estimated at 2003 median cumulative transfers. DTH indicated Discrete Time Hazard. HHFE indicated Household Fixed Effects. 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: Placebo Test: Do Cumulative Transfer Predict Refrigerator Ownership at Baseline?

	(1) Baseline Ownership	(2) Baseline Ownership	(3) 1999 Ownership	(4) 2003 Ownership
	All Households	Early Households	Late Households	All Households
Cumulative Transfers in 2003	0.006			0.055***
	[0.006]			[0.011]
Early	0.005			0.028
	[0.012]			[0.026]
Cumulative Transfers X Early	-0.001			-0.030***
	[0.005]			[0.011]
Cumulative Transfers in 1998		0.065		
		[0.151]		
Cumulative Transfers in 2000			0.120	
			[0.225]	
Net Early Effect at 2003 Median Cumulative Transfers	0.004			-0.007
	[0.008]			[0.018]

Note: We report results from three different placebo cross-sectional specifications, estimating refrigerator ownership before transfers, and, for comparison one estimated using refrigerator ownership at 2003. All specifications include state fixed effects and household controls, as described in the notes to Table 5. Columns (1) and (4), estimated using IV with Potential Cumulative Transfers and Potential Cumulative Transfers X Early as instruments, show no relationship between cumulative transfers at through 2003 and baseline ownership. Net early effect is estimated at 2003 median cumulative transfers. Columns (2) and (3), estimated using IV with Potential Cumulative Transfers, show no statistical relationship between cumulative transfers in the first period available and ownership at the cross-section immediately prior to the beginning of 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.

Figure 7: Relationship between GDP and Energy Demand:Pro-poor Countries versus All Other



Note: Total Energy Consumption per Capita and GDP per Capita demeaned at the country level. Countries are categorized as having pro-poor growth if the decrease in the reported GINI coefficient exceeds the median. Includes 37 developing countries using data from 1980-2006. Data on GINI coefficients and other measures of pro-poor growth are from the World Bank Development Indicators. We include countries for which both energy use and multiple GINI measures are available. Lines are OLS regressions.

APPENDIX (Not for Publication)

Appendix Table 1: 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 1: 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

Empirical Results on Energy Consumption

Previous research suggests that the response of energy use to income conditional on assets is small.[33] However those studies are from the developed world and non-poor. We examine the relationship between income and household energy use in order to evaluate the extent to which growth in electricity consumption is driven by higher income directly or as a consequence of 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. Our data allow us to obtain estimates from low-income households in Mexico.

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

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

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).[34] X_i is a vector of household covariates, δ_v captures village-level fixed effects and ε_i is the error term.[35]

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, along with our instruments discussed below, 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.

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

[34] For each electricity using asset the household owns, we assign a weight, according to estimates by the Comisión Federal de Electricidad (2010) of average electricity consumption for the asset for typical Mexican households. Those weights, in kWhr/month are: Refrigerator, 120; Light bulbs (1+1 per room), 9; Washing Machine, 13; TV, 10; Radio/Stereo/CD Player, 8; Blender, 2.

[35] 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.

As described in the text, 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 a cross-sectional specification analogous to those described in the text. We instrument for asset ownership with potential cumulative transfers, potential cumulative transfers interacted with early status, and asset ownership in 1997.[36] Our specification is identified by variation in potential cumulative transfer amounts and randomized early status.

It is conceivable, however, that there is additional endogeneity 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 5-9. In addition, because of the same endogeneity concern described with respect to asset acquisition regarding actual transfers, we instrument for current transfers using potential current transfers.

Appendix Table 2 presents several estimates 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.[37] Once we control for assets, the marginal propensity to consume electricity is not significantly different than zero though the

[36] 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.

[37] The implied retail cost of electricity suggested by this coefficient is about a third to half of the rates faced by low consuming Mexicans. The coefficient could be biased downwards by measurement error or systematic correlations between transfers and energy efficiency, miscalled due to more efficient appliances than indexed or reporting of monthly instead of bimonthly electricity bills, and this may reflect electricity theft or payment at the even lower agricultural rates.

size of the coefficient is consistent with short run-income elasticities from the developed world (Hsiao and Mountain, 1985). This is consistent with electricity use being dictated by the extensive margin of asset acquisition, not an intensive margin of income. When we instrument to allow for potential endogeneity, the estimated effects of asset ownership are larger and the marginal propensity to consume is even smaller.[38] 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 current bi-monthly 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. Because of this, understanding energy using asset acquisition, not simply income growth, is important to understanding the likely growth in demand for energy.

APPENDIX REFERENCES

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[38] Because these households do not own energy using assets whose electricity usage is easy to meaningfully change, such as air conditioners, it is plausible that these households would have electricity usage which is less responsive to income than those in the developed world.

Appendix Table 2: Effect of Transfers on Electricity Demand Conditional on Assets

	Dependent Variable: Bi-Monthly Electricity Expenditures (Mean= 145)					
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Appliance Aggregate			432.1***	687.6***		
(Mean =0.114)			[41.4]	[254.0]		
Refrigerator					54.2***	103.0**
(Mean =0.493)					[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 5. 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.