The Daily Grind: Cash Needs and Labor Supply*

Pascaline Dupas† Jonathan Robinson‡ Santiago Saavedra§

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Abstract

We document three facts about the labor supply of Kenyan bicycle-taxi drivers: (1) drivers work more on days with higher cash needs; (2) the quitting hazard increases once the day's need is reached; but (3) randomized cash payouts have no meaningful effect on labor supply. These results are consistent with models in which workers have reference-dependent preferences over earned income targets. A calibration exercise suggests that workers with such preferences earn 19% more than they would with neoclassical preferences. We propose an interpretation of earned income targeting as morphine: it partially numbs the effort cost until the target is reached.

JEL Codes: C93, D12, J22

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†Stanford University, CEPR and NBER, email: pdupas@stanford.edu

‡University of California, Santa Cruz and NBER, email: jmrtwo@ucsc.edu

§Universidad del Rosario, email: santiago.saavedrap@urosario.edu.co

1 Introduction

The majority of people in developing countries are self-employed and can therefore set their own work hours. Self-employment offers the advantage that hours can easily adjust to changing economic conditions, for example as a response to unexpected shocks (Kochar, 1995, 1999; Frankenberg, Smith and Thomas, 2003; Jayachandran, 2006). However, the freedom to choose one's own hours also has the fundamental disadvantage of being susceptible to self-control issues: without a fixed hours schedule, it may be tempting for a worker to quit earlier in the day than he had planned – especially in a physically demanding or monotonous occupation. Recent work with Indian data processors (Kaur, Kremer and Mullainathan, 2015) and Berkeley undergraduates (Augenblick, Niederle and Sprenger, 2015) shows that individuals with time-inconsistent preferences over effort demand external constraints to help them meet work targets.[1] However, such external commitment devices are not typically available outside of formal work arrangements or a laboratory setting. How do self-employed individuals working in low-skill, physically demanding, repetitive occupations motivate themselves to work hard day after day?

This paper studies the labor supply decisions of one specific group of workers: Kenyan bicycle taxi drivers. These workers (all of whom are men) carry passengers or goods on the back of their fixed-gear single-speed bicycles in a tropical climate. This is a very strenuous occupation, so quitting early may be tempting. We study the intertemporal labor supply decisions of these workers, using a novel observational dataset constructed from daily passenger-level logbooks kept by 259 drivers over approximately 2 months. There are two empirical innovations in this data. First, the logbooks included a question on whether respondents had particular cash needs on a given day and, if so, how much money was required to deal with these needs. Second, we generated random variation in cash on hand by giving out experimental cash payouts (in the form of lottery wins) to workers on a few unannounced days.

We document three key stylized facts. First, we find that needs and labor supply are strongly positively correlated. While it may not be surprising that workers work more in response to *unexpected* shocks, we also find a strong correlation even for *expected* cash needs such as a savings club payment coming due. Second, we find that the hazard of quitting increases once workers earn enough to meet what they report as their cash need for the day. Third, we find no effect of the randomized lottery payouts on labor supply – even for workers whose day's need is met with the lottery prize.[2]

[1] In particular, Kaur et al. (2015) show that data entry operators voluntarily enter into employment contracts which penalize them for not meeting daily work targets.

[2] This result is similar to Andersen et al. (2014), who find no effect of windfall payments by mystery

The data cannot be explained by a frictionless neoclassical model, since entirely predictable cash needs should not affect labor supply and there should not be daily income effects. We consider two other possibilities discussed in the literature: (1) the neoclassical model with a binding borrowing constraint; and (2) a reference-dependent model where workers have targets over total income/consumption (Camerer et al. 1997; Köszegi and Rabin 2006). Model (1) can generate a positive response of work hours to the borrowing constraint, but in order for it to explain the responsiveness of daily labor supply to daily needs, the borrowing constraint would need to vary in sync with the need value. That is, the maximum amount a money lender lets a worker borrow would have to change daily with the amount of the day's need. Model (2) would predict an effect of the windfall payment, but we do not find any.

What then explains our results? A possible model is one in which bike taxi drivers have reference-dependent preferences around a daily *earned* income target (rather than a daily target on total consumption). The reference dependence term can be thought of as a "boost" in utility if the target is reached or it can be embedded in the effort cost function – it mitigates the effort cost proportionally until the target is reached. That is, reference-dependence helps to "numb the pain" in a physically demanding job, i.e., reference dependence as morphine.

We calibrate the model to estimate earnings under alternative labor supply models, holding constant effort costs and time preferences. The calibration exercise suggests that if drivers were not target earners they would supply less effort and earn about 19.1% less income. Interestingly, this is true *whether or not the worker is present-biased*. This result illustrates that the problem that earned income targeting helps deal with need not be a "self-control" problem in the sense of procrastination due to present-bias; instead, as we argue it can be a problem of effort being so costly that absent a strategy to numb the pain, the marginal cost of effort exceeds the marginal value of income.[3]

Our paper adds to an active economics literature (starting with Camerer et al. 1997) which tests for reference-dependent labor supply among workers who are free to set their own hours. A number of papers find evidence in support of reference dependence, especially for inexperienced drivers (Chou 2002, Crawford and Meng 2011, Agarwal et al. 2015 and Sheldon 2016 for taxi drivers; Chang and Gross 2014 for fruit packers; Giné et al. 2017 and Hammarlund 2018 for fishermen).[4] [5]

shoppers on the labor supply choices of vendors in India.

[3]Other physically demanding activities where our model could apply include overseas fishing, mining, piece-rate agricultural work (e.g. fruit picking), etc.

[4]In different contexts, See Pope and Schweitzer (2011) for evidence that professional golfers target a goal of par for a hole while Allen et al. (2015) find evidence that marathon runners are loss averse around targets of salient finishing times.

[5]Other studies find evidence in line with a neoclassical model of labor supply, including the extensive margin studies of Oettinger (1999) in the US and Goldberg (2016) in Malawi. See Farber (2005, 2008, 2015)

A key challenge in these studies is that the reference point itself is unobserved and so must be estimated, or reference dependence must be inferred less directly through a negative correlation between labor supply and earnings opportunities. By contrast, our paper uses a survey measure of need which does not require inferring targets from previous quitting decisions. A second challenge is that earning opportunities are endogenous. Two prior studies overcome this by randomly varying wage rates (Fehr and Goette 2008 and Andersen et al. 2014), something we were unable to do. However, we did experimentally vary unearned income. The only other paper we are aware of to do this is Andersen et al. (2014), who also implemented randomized cash windfalls, but in the form of overpayment by naive foreigners (played by confederates). While these windfalls were designed to be perceived as entering "earned income", and therefore the finding of no impact on labor supply is interpreted by the authors as in direct conflict with the prediction of earned income targeting, they could have been perceived by vendors as just "luck income" given that such naive foreigners are rare and far in-between, similar to the lottery windfalls in our study.

The layout of the paper is as follows. Section 2 presents the sample and data. Section 3 presents the empirical findings of interest. Section 4 estimates the economic significance of the labor supply patterns we describe, and proposes and calibrates a target-earning model that rationalizes the findings. Section 5 discusses possible alternative explanations. Section 6 concludes.

2 Sample and Data

2.1 Bike-Taxi Driving

Bike-taxis are ubiquitous in rural and semi-urban areas of Western Kenya and other parts of East Africa, the equivalents of the well-known rickshaws of South Asia, but with a slightly different technology – they carry passengers or goods on the back rack of their bicycles, not in a trolley. By now, they have been partially replaced by motorbike taxis, which are faster and can go longer distances, but are also more dangerous and more expensive. At the time of our study (2009), motorbike taxis were still extremely rare, however.

Bike-taxis are organized in "stages" (at local market centers) and in cooperatives that regulate fares (we have 22 stages in our dataset). A given ride (say from market A to market B) has a pre-set fare (and a preset premium for night rides), and those pre-set fares are

for a set of papers on the labor supply of New York City cabdrivers which show mixed evidence of income targeting. In a recent paper, Thakral and Tô (2017) reanalyze the data in Farber (2015) and find evidence of adaptive expectations, a rejection of the neoclassical model.

well known from customers (exclusively local community members). There is typically no bargaining and no tipping.

2.2 Sampling Frame

The project took place in the Busia district of Western Kenya in Summer and Fall 2009. The sample was drawn in August, and the labor supply logs were collected between September and December.[6] To draw the sample, enumerators conducted a census of all bicycle-taxi drivers (locally known as "bodas") in market places scattered around the district. Individuals were included in the sample only if their primary occupation was as a bicycle taxi driver.

The only sample restriction was that the respondent had to be able to read and fill out the logs. We therefore excluded individuals who could neither read nor write or who had fewer than three years of schooling (24% of those in the census), leaving 303 eligible individuals. We were able to successfully enroll 259 (85%) of these in the study. The remainder could not be enrolled for one of three reasons: they had moved out of the area, had quit boda work, or did not consent to the relatively heavy data collection requirements.

2.3 Data

There are two primary data sources we use for the analysis.

2.3.1 Baseline Survey

Each individual who was enrolled in the study was administered a baseline survey.[7] In addition to basic household demographic information, the survey included a number of measures to inform the subgroup analysis. These include a financial module, a health module, and a module to construct measures of time preferences, risk preferences, and loss aversion.[8]

2.3.2 Logs

Building on the successful use of logs in previous studies in neighboring areas of Kenya (see Robinson and Yeh 2011 and Dupas and Robinson 2013 for data from self-filled daily logs collected among sex workers and market vendors / bicycle-taxi drivers, respectively), we asked each study participant to keep a daily labor supply log for up to four months. The

[6] The logs were introduced on a rolling basis because the fixed cost of training a respondent to keep the log was large so it took some time to train respondents.

[7] This survey, as well as the daily and weekly logs described below, can be found on the authors' websites.

[8] The baseline was conducted in parallel with the beginning of the data collection process. Baseline data is missing for 13 of the workers in our sample.

logs were pre-printed in a two-page questionnaire form with 7 rows per page (corresponding to 7 days, with pre-printed dates) with blanks for study participants to fill in the relevant information. To incentivize participants to fill the logs well, respondents were given in-kind gifts (either soap or cooking oil) worth around 75 Kenyan shillings (Ksh), or 1 US$, for each week in which they filled the log competently.

Respondents were instructed to fill in the log throughout the day, indicating the precise time at which they started working, the timing of each client pickup and dropoff, the fare, and the time they stopped working.[9] The logs also included questions on daily needs. The first question on the log was: "Is there something in particular that you need money for today?" and included codes for a variety of common options such as bicycle repairs, medical expenditures, ROSCA contributions, food, and school fees. There was also a code for "nothing special."[10] If the respondent reported a need, the next question asked the respondent to record the amount necessary to meet this need. The logs also included a few questions on health shocks experienced that day by the individual and other family members.

While the daily logs contain rich information on labor supply, needs, and health shocks, it was not possible to include other questions without making the logs too onerous to complete. Thus, to supplement the daily logs and to regularly check data quality, enumerators visited study participants on a weekly basis. During this visit, the enumerator checked that the logs were filled correctly and collected the completed pages. The enumerator then administered a recall survey to the respondent. For each day in the given week, the enumerator asked about a variety of other outcomes, including labor supply in other jobs (e.g., farming, casual work, selling produce), and, most importantly, shocks (e.g. funeral, illness) and demands on income (e.g. whether a ROSCA payment was coming due) as well as actual outlays for specific items (such as ROSCA payments, bike repairs, medical treatment), making it possible to cross-validate some of information recorded in the daily logs.[11]

As mentioned above, bodas were enrolled into the study on a rolling basis. There is therefore variation in how long bodas were asked to keep logs. Of the bodas in the final sample, logs were kept for between 2 weeks and 4 months. The median boda kept the log for 47 days (the mean is 49 days). Respondents could not always be found to give out new logs, and some respondents did not fill out the logs on all days. We have useable data for 75.4% of the total days in the sample. We have an accompanying 1-week recall survey for 72% of these observations.[12]

[9] Respondents were given watches to record the time.

[10] This code was reported on 7.4% of days. Results look very similar when these days are removed from analysis.

[11] In the interest of time, a general expenditures module was not administered.

[12] The reason why the 1-week recall survey is missing for some days is that enumerators sometimes were not able to find the respondent to collect the daily log (e.g., if the respondent had traveled). In that case,

2.4 Experimental Income Shocks

To introduce random variation in non-labor income across days for a given individual, we invited respondents to participate in a free lottery a few times over the course of the study. On a randomly selected day, field officers were instructed to find the respondents in the given market center and give them a voucher to allow them to play the lottery. The lotteries were not announced in advance. Respondents then brought their voucher to the local market center on the same day and picked a prize from a bag. Lottery participants had a 50% chance to win only 20 Ksh (the small prize), and a 50% chance to win a large prize (namely, a 25% chance to win 200 Ksh, a 12.5% chance to win 250 Ksh, and a 12.5% to win 300 Ksh).[13] The odds and prize sizes were not disclosed to participants. Given that average daily income (conditional on working) is approximately 150 Ksh, the lottery prizes were substantial. The prizes are also large relative to daily cash needs, which (conditional on having a need) average around 200 Ksh (see Table 2).[14]

Each boda was sampled to participate in at least one and up to four lotteries over the course of two months.[15] If a participant could not be located on a given lottery day, he was never told about the lottery he missed.[16]

2.5 Sample Characteristics

Table 1 presents baseline characteristics for our study sample. All study participants are male, since bicycle-taxi driving is an exclusively male occupation. Nearly all are married and the average respondent has been working as a bike taxi drivers for 6.2 years. Respondents are poor but do own assets: the average respondent has 1.4 acres of land and approximately 18,000 Ksh (US $240) in household assets (durables + animals), and 57% own cell phones. 75% of respondents participate in Rotating Savings and Credit Associations (ROSCAs) and 31% have bank accounts. Health status appears relatively poor among bodas. Even though the average age is only 33 years, 39% of bodas in the sample missed at least one day of work in the month prior to the baseline due to sickness.

Reference-dependence requires that individuals be loss averse around a target. Consistent with this, Fehr and Goette (2007) find that lab experimental measures of loss aversion predict

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the enumerator would attempt to find the respondent the following week, but then only administered the 1-week recall survey for that week.

[13]To ensure payments were made correctly, audit and backchecking procedures were implemented.

[14]The exchange rate was approximately 75 Ksh to $1 US during this time period.

[15]Overall, 2% of study participants participated in four lotteries, 47% participated in three lotteries, 38% participated in two lotteries, 6% participated in only one lottery, and 7% did not participate in any lotteries.

[16]As would be expected, almost all respondents who were invited played the lottery that day (typically within minutes of receiving the voucher) – only 4% of respondents who were invited chose not to play the lottery.

behavior in their experiment among bicycle messengers in Switzerland. Following them, we collected measures both of loss aversion and of small-stakes risk aversion. We measure loss aversion by asking respondents whether they would accept a gamble in which there is a 50% chance that they would win some amount and a 50% chance they would lose a smaller amount. Overall, 29% refuse a 50/50 chance of winning 30 Ksh or losing 10 Ksh, while 57% refuse a 50/50 chance of winning 120 Ksh or losing 50 Ksh. To measure small-stakes risk aversion, respondents were asked to divide 100 Ksh between a safe asset in which they kept the amount invested for certain and a risky asset in which the amount invested would be multiplied by 4 with 50% probability and would be lost with 50% probability. Note that because the stakes are so low, an expected utility maximizer should be close to risk neutral over this sort of gamble and so should invest close to the full amount (Rabin 2000). Loss averse respondents, by contrast, may invest less. Indeed, the average respondent in our sample invested just over half (56.3 Ksh) in the asset, further suggesting that a significant fraction of respondents in our sample may be loss averse.

2.6 Summary Statistics from Logs

Table 2 presents summary statistics from the logs. We exclude Sundays from the data when showing these summary statistics because Sunday is typically the rest day – only 39% of Sundays are worked compared to 80% for other days of the week, and individuals are also much less likely to report a cash need on Sundays. (It is quite prevalent for families to attend church service for several hours every Sunday). However, our results are qualitatively unchanged (and if anything stronger quantitatively) when including Sundays (see Table A3).

Consistent with Table 1, bike taxiing is the primary source of income – respondents received other income on 31% of days. Conditional on working, average income is 145 Kenyan shillings (Ksh), or around $2 per day, and total work time averages 8.8 hours per day. However, only around 27% of this time is spent riding with passengers, which means their wait time is somewhat longer than that observed for cab drivers in cities (e.g. Agarwal et al. 2013 show that Singaporean taxi drivers spend about 50% of their shift time with a customer). There is substantial heterogeneity in hours worked, however, both across and within drivers. The across-worker standard deviation in hours worked (conditional on working) is 1.72, and the within-worker standard deviation is 2.27. Another way to think about the regularity in labor hours across days is to look at the share of workers who supply the same number of hours every day. Defining as having a fixed hours rule any worker who, for at least 2/3 of his work days, works a total number of hours within 30 minutes of his median work hours over the sample period, we find that only 2.3% of workers have such a rule. If we relax the rule to be within one hour of the median, this share becomes just around 18%. Looking at distance from the modal number of total hours or doing this exercise separately by day of the week suggests that very few workers in our sample have a fixed hours or day-of-the-week-specific fixed hours rule.

Panel B of Table 2 shows that cash needs are very common: respondents report a specific cash amount needed on 90% of days. Conditional on having a need, the average amount required is quite substantial: at around 200 Ksh, it exceeds average income. There is also substantial variation in needs: needs range from a minimum of 5 Ksh to over 15,750 Ksh, and the standard deviation is 334 Ksh. Much of this variation is within individual across days: the within-individual standard deviation (288 Ksh) is larger than the inter-individual standard deviation (169 Ksh). There is a lot of heterogeneity in reported needs: the most common needs are food (mentioned 60% of the time a need is reported), bicycle repairs (26%), ROSCA payments due (18%), medical expenses (11%), "nothing special" (7%), funerals (6%), and school expenses (3%). An important question is whether these needs are binding – the preliminary evidence in this table suggest that they are likely not, since people earn enough for the needs only 41% of the time. We return to this in much greater detail when we discuss the lottery results.

2.7 Determinants of reported daily needs

How are daily needs set? In other words, what does it mean for workers to report daily needs? While our logs were not set up to examine this issue in detail, in Table A1 we run regressions of reported needs (whether a need was reported and its amount, as per the daily log) on demands on income ("shocks") as reported for the same day in the weekly recall survey. Specifically, we exploit the within-driver variation in shocks and payment dues across days to estimate:

$$N_{it} = S^u_{it}\gamma^u + S^e_{it}\gamma^e + \eta_{s(i)t} + \mu_i + \epsilon_{it} \tag{1}$$

where the dependent variable is a measure of the cash need reported by individual i at date t (obtained from the daily logbook), while S^u_{it} represent unexpected shocks (such as sickness or funeral expenses) and S^e_{it} represent expected events which require cash (such as ROSCA payments or school fees coming due) on that same date t, as recorded in the weekly recall survey. We consider both dummies for shocks (odd columns) and the cash value of the shocks (even columns) when applicable. We include individual fixed effects (η_i), as well as stage-date fixed effects ($\eta_{s(i)t}$) to capture any potential stage-date level common shocks or day of the week effects. Standard errors are clustered at the individual and date level.

We find that several of the idiosyncratic shock measures (whether expected, such as ROSCA contributions) or unexpected (such as bike problems and funerals) predict reported daily cash needs, suggesting that workers report cash needs on the day payments are due.

In Table A2, we cross-check the needs reported on the daily logs with the actual expenditures for that day as reported in the weekly recall survey. Specifically, we regress whether a specific type of need was recorded on the daily log (e.g. for ROSCAs, school fees, funeral expenses, bike repairs) on whether the respondent reported expenditures of that same type on that same day, as per the weekly survey. First, reported needs and actual expenditures are strongly correlated for all types of spending. Another important result comes from the even-numbered columns, which include controls for whether the respondent will have that expenditure in the next few days. For example, Column 2 shows whether the respondent reports needing money for a ROSCA in the two days before the ROSCA payment is actually due. Interestingly, the coefficients are negative and significant, again suggesting that people delay reporting pending expenses as things they need to raise cash for until they are actually due. Since ROSCA payments and school fees are due on specific days outside an individual's control, this helps to rule out endogenous reporting of needs.[17]

3 Results

3.1 Daily life events and labor supply

We start by providing reduced form evidence that the daily labor supply is affected by contemporaneous life events. For this, we again exploit within-driver variation across days. In particular, we estimate the following:

$$L_{it} = S_{it}^u \gamma^u + S_{it}^e \gamma^e + \rho BP_{it} + \eta_{s(i)t} + \mu_i + \epsilon_{it} \tag{2}$$

where the dependent variable is a measure of daily labor supply for individual i at date t (obtained from the daily logbook). As above, S_{it}^u represent unexpected shocks and S_{it}^e represent expected events which require cash on that same date t (obtained from the weekly recall survey). BP_{it} is a dummy for whether the respondent won a big lottery prize that day (this information comes from our administrative research records). To control for local supply and demand conditions on that day, we include stage-date fixed effects. The regressions also include individual fixed effects. Standard errors are clustered at the individual level.

One question for this and the subsequent analysis is what the appropriate measure of labor supply (L_{it}) should be. For taxi drivers, money is earned only when carrying passengers, and

[17] See Appendix C for a discussion of the potential issues associated with need reporting on the daily logs.

the effort costs of riding with a passenger are likely higher than for waiting for passengers between rides.Here we present results for both the total time spent on the job (total hours) and the effort expended on the job (total hours carrying passengers). Measures of effort on the job are the more appropriate measure if effort costs dominate time costs such as the opportunity cost of time or boredom; time costs are more appropriate if effort costs of riding are low.

Results of estimating equation (2) are reported in Table 3. We have relatively few measures of unexpected shocks that do not directly affect labor supply: many shocks, like funerals or own illness, mechanically reduce labor supply directly. However, we still find evidence for unexpected shocks mattering: respondents are more likely to work when their bike needs repair (note that this is not reverse causality since needs were supposed to be reported before work started). More surprisingly, we find evidence that some *expected* needs affect labor supply: people work significantly more hours when a ROSCA payment comes due. (The results on school fees go in the same direction but are much noisier due to the low frequency of school payments coming due). In contrast, we see no impacts of winning the lottery prize on labor supply.

3.2 Reported Cash Need and Daily Labor Supply

In this section, we provide evidence that the reduced form relationship observed above between daily life events requiring cash payments and daily labor supply is mediated by earned income targeting, where the earned income target is a function of the total cash need of the day.

3.2.1 Cross-Sectional Evidence

We start by showing simple correlations between the cash need and labor supply intensity (at the day level). We pool all individuals together for this exercise, so that comparisons are both across days and across individuals. Results are shown in Figure 1A for average hours (top panel) and average income earned (bottom panel). We limit the sample to cash need amounts with at least 50 observations (that is, 50 individual-days), and observations are weighted by the frequency of that need amount (represented by the size of the circle). The figure shows a very clear positive relationship between the cash need for the day and the labor supply that day.

In Figure 1B we plot in 3D the relationship between quitting behavior, running hours and the day's need. The key take-away from the figure is that for a given number of hours worked, the probability of quitting decreases with the need.

3.2.2 Within-Driver Variation Across Days

In Table 4, we examine how labor supply responds to needs at the day level, within individual. The table presents specifications with two measures of the need: the odd numbered columns include a dummy for having a need, while the even numbered columns include the log of the cash need for those that have one. We look at the extensive margin in Panel A, and the intensive margin in Panel B. The observation is a worker-day, and the regressions include individual fixed effects and stage-date fixed effects as in Tables A1 and 3. As expected, the results are consistent with the reduced form results: on days in which they have needs, individuals are more likely to work (and therefore earn more money). The effect sizes are substantial: individuals are 15 percentage points more likely to work when they have a need and, conditional on having a need, a 100% increase in the need amount translates into approximately a 12% increase in earned income. Note that the need amount, conditional on having a need, does not increase the likelihood of working (column 2), possibly because some high need days are sickness days that preclude working. Thus the effect of need size on total income, conditional on having a need, is not driven by the extensive margin.

We focus on the intensive margin effects in Panel B of Table 4. Conditional on working, and conditional on having a need, individuals with a higher need earn more income, have more passengers, work longer hours, spending the extra work time both in more time waiting for customers and more time carrying passengers. All these results are robust, and in fact even stronger, when Sundays are included in the analysis (these results are shown in Table A3).

Our decision to consider the "day" as the relevant period is based on the existing literature. Yet in theory targets could be set over a different horizon, e.g. the week. This may be necessary for large needs that cannot possibly be reached within one day's work at the prevailing implicit wage rate. Table A4 replicates the analysis of Table 4 at the week-level. Of course, in the presence of daily targeting, we should mechanically see a correlation between earnings (hours) and needs at the week level. Interestingly, we find that this correlation is stronger at the week level than at the day level: a doubling in the need yields a 29% increase in total income at the week level compared to 11% at the day level. We take this as suggestive that earned income targeting may be set over a horizon longer than the day in some cases or for some individuals.

Despite the norm of not competing in prices set by the cooperative (see section 2.1), there could potentially be adjustment on the fare as well (i.e. the driver gives a discount) – see Keniston 2011 for evidence of significant bargaining between rickshaw drivers and passengers in India. This is unlikely for short rides (since the norm is of a minimum fare of 20 or 30 Kenyan shilling for within-market and within-community fares, respectively), but could be relevant for longer, uncommon rides. While it is difficult for us to check this (since we do not know how uncommon or how long a particular ride is, in distance), we can provide some evidence by looking at the average fare per minute of a given ride. If anything, we find that the average fare increases when the need is higher (see column 12 of Table 4, Panel B). This could be because the hazard rate of stumbling upon a customer who needs a ride out of town is constant and so the daily odds of it happening increases mechanically with hours worked.

The within-driver relationship between daily needs and daily labor supply is not consistent with the standard lifetime neoclassical labor supply model. In contrast, the observed impacts of the experimental lottery are largely consistent with such a model: winning a large payout in our experimental lottery has no impact on most measures of labor supply, including whether a driver worked or the total hours a driver worked. Conditonal on working, winning the lottery has no effect on income but does have a small, marginally significant effect on the number of passengers: winning the lottery is associated with a reduction in the number of passengers by 0.17-0.20, equivalent to about a 4-4.5% reduction, and has a small, marginally insignificant effect on total hours. These are small effects – we can rule out an effect on passengers as small as 9% – and they disappear immediately (there are no lagged effects). We take these results as indicative of a minimal effect of unearned income on labor supply.

3.2.3 Within-Driver, Within-Day Hazard Analysis

In this section, we test for targeting more precisely by estimating the hazard of quitting around the daily need amount. Note that under earned income targeting, since the cash need is potentially only one component of the (unmeasured) target, the estimated effect of reaching the reported cash need will underestimate the effect of reaching the (unobserved) target.

We estimate the hazard with the following non-parametric regression

$$q_{ipt} = \sum_{b=-10}^{10} \gamma_b D_{ib(p)t} + \delta_1 HR_{ipt} + \delta_2 HR_{ipt}^2 + \psi_1 HW_{ipt} + \psi_2 HW_{ipt}^2 + \eta N_{it} + \mu_i + \eta_t + \epsilon_{ipt} \quad (3)$$

where q_{ipt} is a dummy for quitting after passenger p on date t, HR_{ipt} is hours riding up to that passenger, HW_{ipt} is hours waiting, and N_{it} is the need amount for that date. The key parameters of interest are the γ_b coefficients, which are dummies for being in income bin b, relative to the need amount (these bins are of width 20 Ksh).[18] If the daily needs enter

[18]The overall pattern looks similar with other bin sizes (results available on request).

the daily earned income target, we would expect the coefficients γ_b to be larger after the threshold has been reached ($b \geq 0$), compared to those before the threshold ($b < 0$).

We plot these coefficients, and associated 95% confidence intervals, in Figure 2. As can be seen, there is a clear increase in the probability of quitting at the need amount.[19] The probability of quitting continues to rise after that point, as well (note that this graph is the conditional probability of quitting, so that the cumulative probability is larger).[20]

Lastly, we run parametric regressions to formally test whether reaching the need affects quitting behavior. We first replicate the specification in Farber (2005), regressing quitting hazard on cumulative income and hours, in column 1 of Table 5. Unlike Farber we find a positive and significant effect of cumulative income on quitting behavior. In column 2 we add an indicator on whether the earned income has exceeded the daily need, and find a significant coefficient, but the coefficient of cumulative income decreases and is no longer significant. This means that what matters is whether income is above our measure of the cash need. The magnitude is more than a third the mean probability of quitting.[21]

We then perform a version of the Farber (2005) specification allowing for quadratic costs of effort, and allow for the cost of riding to be different than the cost of waiting for customers. We draw two important conclusions from the coefficient estimates in this specification, shown in column 3 of Table 5: (1) cumulative income matters for quitting behavior even while controlling more flexibly for running hours; (2) waiting time is positively correlated with quitting – in other words, the opportunity cost of time for workers in our sample is far from zero (see Figure A1a which plots the estimated functions by type of effort). In column 4, we add the indicator for whether the driver has earned enough to meet the need of the day. The coefficient is significant and the magnitude of the coefficient of earned income decreases. As a placebo test, we reassign a boda's needs across their days randomly and run the same specification as Column 4 multiple times. The coefficient of the true regression shown in column 4 is 40% larger than the maximum coefficient obtained across 100 simulations with

[19]Note that while the graph appears to show a flat hazard below the threshold, the hazard is *conditional on total hours worke*d (and the square of total hours). Without a control for hours worked, there is a small increase in the hazard below the threshold.

[20]A potential complication in estimating the hazard is that need amounts vary across day so there is a (mechanical) potential sample composition issue in comparing coefficients (for example, observations in bins far over the threshold mostly involve days in which the need amount is very low). Note, however, that this issue is much less severe right around the threshold than at points further away (since on average sample composition should not change discontinuously at that point).

[21]In Appendix B, we estimate the elasticity of labor supply with respect to the wage, using the same approach as papers like Camerer et al. (1997), which famously finds a negative elasticity, and Farber (2015), who finds a positive elasticity in the 0.2-0.6 range. Like Camerer et al. (1997), the estimated elasticity of hours with respect to the wage is negative in our data; however, the elasticity of passengers is positive though modest. This suggests that on high-wage days, work is more intense (more passengers per hour). This points out how hours may not be a perfect proxy for effort in this setting.

random reassignment.

We then estimate the following equation:

$$q_{ipt} = \alpha + \gamma_1 O_{ipt} + \beta_1 D_{ipt} + \theta_1 D_{ipt} * O_{ipt} + \delta_1 HR_{ipt} + \delta_2 HR_{ipt}^2 + \psi_1 HW_{ipt} + \psi_2 HW_{ipt}^2 + \eta N_{it} + \kappa BP_{ipt} + \mu_i + \eta_t + \epsilon_{ipt} \quad (4)$$

where D_{ipt} is the difference between the daily need and income earned until passenger p and O_{ipt} is a dummy equal to 1 if earned income has exceeded the daily need, and as above BP_{ipt} is a dummy equal to 1 if the driver earned a big cash prize in our experimental lottery before passenger p. From the figures, we anticipate that both γ_1 and θ_1 should be positive. This analysis is presented in column5 of Table 5. We estimate an increase in the hazard of 3 percentage points (significant at the 1% level), which is sizable compared to the average hazard of 9 percentage points (see last row).

In column 6, we add an interaction term between the earned income crossing the need and having won the lottery earlier in the day. If the effect of crossing the need was not present after a lottery win, we would expect to see a coefficient of -0.03 on this interaction term, but we find a positive, insignificant coefficient suggesting that the lottery win does not attenuate the earned income targeting behavior. In column 7, we estimate a model where we instead add a dummy for whether, conditional on playing the lottery, cumulative total income (earned income + lottery win earlier that day) has crossed the need threshold – in other words, the lottery pushed total income above the need. Not only do we see no effect of crossing the need thanks to the lottery on the hazard of quitting, we also find that controlling for total income does not affect γ_1, the coefficient on the dummy for *earned* income crossing the need, confirming that it is indeed the relationship between *earned* income and the need that governs labor supply decisions rather than total income. Finally, in column 8 we restrict the sample to rides on lottery days only. This considerably shrinks the sample size and hence increases the standard errors, but nevertheless the patterns are unchanged – even on lottery days, there is a jump in the probability of quitting as *earned income* crosses the daily need amount.[22] We repeat the specifications of Table 5 in Table A5 including hour of the day fixed effects. The indicator for whether the driver has earned enough to meet the need of the day is still significant for all specifications.

[22]Our results are of course closely related to the previous literature on daily income targeting and the wage elasticity of labor supply. See Appendix B for a discussion of how our results relate, and of why the wage elasticity is not our direct object of interest here.

Other Determinants of the Daily Earned Income Target

In the formulation of Köszegi and Rabin (2006), workers form expected earnings and hours targets based on rational expectations. To test whether such expectations go into targets among workers in our sample, we follow the approach of Crawford and Meng (2011), who use average daily income or hours (by driver and day of the week) in previous weeks as a proxy for income and hours targets. We replicate that analysis in Table 6. The odd numbered columns replicate Crawford and Meng, while the even numbered columns include a dummy for being over the need amount. We replicate the finding that reaching either the income or hours target increases the likelihood of quitting in all specifications. When we add in our need measure, we find that all three coefficients are significant, suggesting that both point expectations (in hours and income) and the daily need matter and affect the target.[23,24]

4 Economic Significance and Rationale

4.1 Time costs of targeting

In our setting (unlike for example with Uber surge pricing), there is little or no observed variation in the fare – the cost of a ride of a given length is always the same. Thus, there is no way to reduce overall effort while preserving income by reallocating labor over time. A worker could, however, reduce his total *time* at work (by minimizing his waiting time) if he worked less on high need but low-earnings day (which are days with higher waiting times) and more on low need high-earnings day. The valuation of this then depends entirely on the opportunity cost of time. Our evidence suggests significant valuation of time – Table 5 and Figure A1a show that quitting increases in waiting time, implying some benefit from taking on more rides in a given period of time.

To get a rough sense of how many hours could be saved, we perform a back of the envelope calculation in which we construct a counterfactual in which riders work an equal number of hours every day of the week (allowing for weekly totals to vary across weeks due to idiosyncratic shocks). We reallocate hours *across days of a week* only, to be conservative (i.e. we do not allow workers to be able to save money from one week to the next). We present a CDF of the percentage decrease in hours that adopting such a rule would yield in

[23] Figure A2 replicates the hazard figures with estimated targets based on Crawford and Meng (2011) – as can be seen, an increase in quitting behavior appears evident, but is much less crisp than with these estimated targets rather than elicited needs.

[24] Note that the need amount appears uncorrelated with earning expectations based on previous earning history in the data (results not shown).

Figure 3. We find that the mean and median hours reduction would be 2.1% and 1.3%.[25]

4.2 A Model of Earned Income Targeting

In this section we propose a model that can qualitatively replicate the three main empirical facts observed in our data: (i) Drivers work more when they have a higher cash need; (ii) The probability of quitting increases at the need; and (iii) There is no response of hours worked to an exogenous income shock (the lottery payout). Results (i) and (ii) are not consistent with the neoclassical model and suggest an income targeting model may be more appropriate. On the other hand, result (iii) is not aligned with a basic total income targeting model. Our results can thus be explained jointly if there is some constraint on the fungibility between earned income and the experimental income shocks. We propose one possibl model, calibrate it, and use it to estimate what the counterfactual labor supply would be under alternative models, keeping constant the time preference parameters.

We consider a daily dynamic optimization program of labor supply with anticipated and unanticipated needs. Following Köszegi and Rabin (2006), we assume the driver's utility has two components: (1) neoclassical utility, itself additively separable in utility from consumption $u(c)$ and disutility from labor $v(h)$; and (2) gain-loss utility $g(c, h, T)$. Where c is consumption, h the number of rides and T the target. Thus, in each period the utility function is of the form:

$$U(c, h) = u(c) - v(h) + \lambda g(c, h, T)$$

In our simulations, we present two potential functional forms for the gain-loss utility term, which we compare with each other and with the neoclassical model. We also consider the possibility of hyperbolic discounting with parameter β. Note that the neoclassical model is nested in our set-up: it can be recovered by setting $T = 0$ and $\beta = 1$. The functional form we favor for the gain-loss utility term is what we call the morphine or painkiller model:

$$g^{PK}(c, h, T) = v(\min\{h, T/f\})$$

where f is the average fare, such that fh is total earned income from riding. In this model (labeled "Painkiller EI" in the figures), the effort cost is smaller up to the earned income target T.[26] This can be seen if we rewrite total utility at each period in its mathematical

[25] We calculate that the mean and median income increase from supplying a fixed hours rule for the same total number of hours would be 3.4% and 0.7%. These figures are only relevant if effort costs of riding (above and beyond effort costs of being at work) are zero such that only total time at work matters.

[26]

equivalent of:

$$U(c,h) = u(c) - (1 - \lambda\mathbb{I}(fh < T))v(h) + \lambda\mathbb{I}(fh \geq T))v(T/f)$$

Note that the "PK" functional form we set is mathematically equivalent to the more familiar $g^B(c,h,T) = \mathbb{I}(fh < T)(u(fh) - u(T))$ (reaching the target creates a boost in utility) if we set $\lambda^B = \lambda^{PK}/(1-\lambda^{PK})$. We focus on the "PK" one because it formalizing it this way is on par with the psychology literature on goal setting. The numbing effect applies even on the first unit of effort, but it becomes pivotal when the worker is tired (the effort cost is higher). This is also consistent with marathon runners in the last mile (Allen et al. 2015).

An alternative functional form for the gain-loss utility term, in line with that of Köszegi and Rabin (2006) but not consistent with our data, is one where riders have a consumption target:

$$g^{KR}(c,h,T) = \mathbb{I}(c < T)(u(c) - u(T))$$

We call this the "consumption targeting" model (labeled "Gain-Loss C" in the figures).

4.3 Calibration

All parameters used to calibrate the model, and their sources, are shown in Table A8. We impute several parameters from earlier work (β, σ) or fill them in based on details from the local economy (r). We use average ride lengths (t_r) observed in our data. We draw the cash need and waiting times from the empirical distribution. With these parameters, we still need to input values for the effort cost parameters (θ_r and θ_w) and the reference-dependence factor λ . We calibrate the effort costs parameters by matching the average daily hours worked by those not exhibiting target-earning behavior in our sample (details on who is identified as a target earner and who is not are provided in section 4.5 below). Since we are matching two effort parameters with just one moment, there is obviously some implicit choice we make, but we note that the main patterns in the results qualitatively hold irrespective of how we weight the different types of efforts. In particular, they hold if we set the effort cost of waiting for customers to zero ($\theta_w = 0$), i.e. making the neo-classical agent exhibit negative wage elasticity.

Once we have calibrated the effort parameters using the labor supply of non-target earners, we calibrate the reference-dependence parameter by matching the average daily hours of those identified as target earners (see section 4.5).[27]

4.4 Simulation Results

With these calibrations, we simulate the labor supply of drivers over a month, starting them with zero savings on the first day. We do the simulation under three possible models: the case with $\lambda = 0$, which we call as a shorthand the "neoclassical model" even if $\beta < 1$; the consumption targeting model (as in Köszegi-Rabin 2006, where the target is over total income and there is no savings so it is identical to consumption); and our proposed model with a target on earned income. We present the simulation results in Figure 4.

In the top panels of Figure 4, we consider the quasi-hyperbolic case ($\beta = 0.7$) and in the bottom panels we consider the exponential case ($\beta = 1$). The figures plot labor supply in a given day, as a function of the cash need that day, once in "steady state" savings. On the left (Panels A1 and A2) we show two possible scenarios for each model – a high wage or a low wage that day. On the right (Panels B1 and B2) we plot the effect of the lottery on labor supply for the low wage day (so the solid lines are the same as the left panels).

By construction the neoclassical labor supply does not change with the level of the cash need, for a fixed borrowing constraint. Despite the high effort cost, there is some positive wage elasticity, meaning that with our calibration neoclassical workers are not on the backward bending portion of the labor supply.

In Figure A6 we illustrate what happens when we vary the borrowing constraint. For a given level of savings, a driver that is more credit constrained works more hours. This is because he anticipates he cannot borrow as much if needed in the future. However note that for a given level of borrowing constraint, the number of hours worked is independent of the need. So the only way that our results could be explained by credit constraints is if the need and borrowing constraint are positively correlated.[28]

In contrast, the reference-dependence models, be it with a consumption or an earned income target, generate a positive relationship between cash need for the day and labor supply. Where the reference-dependence models differ from each other however is in the impact of a cash windfall: The consumption targeter model predicts a reduction in hours worked when receiving a cash windfall, while the labor supply of agents targeting on earned income does not respond to a cash windfall (Figures 4, panels B1 and B2), as observed in our experimental data.

[27] If we instead choose the parameter to match the average daily hours for the whole sample, we would estimate a value for λ of 0.06 instead of 0.12.

[28] For example, if a driver needs to pay his ROSCA contribution today, and his only lending source is the ROSCA group.

A direct consequence of having an earned income target is that it increases labor supply for needs which are not small but not too high, compared to the neoclassical model.[29] This immediately follows from the gain-loss term in the utility function, and it is true whether or not the worker is present-biased. This is worth pointing it out, as it illustrates that the problem that earned income targeting helps deal with need not be a "self-control" problem in the sense of procrastination due to present-bias; instead, as we argue it can be a problem of effort being so costly that absent a strategy to numb the pain, the marginal cost of effort exceeds the marginal value of income. We also show how the probability of quitting increases more drastically at the need for the Earned Income targeting model (Figure A4). Importantly, note that even under Earned Income targeting, the model predicts no discontinuity in the probability of quitting at the need for low needs (see Figure A5). In the data, if we replicate Figure 2 for low need levels, we also find no discontinuity: this is shown in Figure 5 Panel A.

Another important feature of the simulation results is that, with the calibration that fit the data best, optimal savings levels are very low in both the neoclassical model and target earner models – the workers live close to hand to mouth. This is not primarily due to the low interest rate used for the calibration, as simulations with a higher rate suggest also very low savings levels. Instead, this is driven by the fact that the effort costs are high, and that drivers are guaranteed work every day in the model. By contrast, those targeting on consumption save somewhat more. This is because they have the additional utility boost of meeting the target using their savings. Drivers targeting on consumption thus save in days when the need is low and dissave when the need is high, and more so if they discount exponentially. Earned income targeters only get the utility benefit of meeting the daily need with that same day effort, so do not save more than neoclassical workers.

To quantify what earned income targeting enables in terms of increasing labor supply, we simulate 200 drivers, with different realizations of needs and wages over a month, under each model. We present the resulting estimates in Table 7. For the Painkiller model, we estimate that even exponential discounters would earn 19.10% less income (the standard deviation across the 200 workers in the simulation is 19.76%) if they were in the counterfactual neoclassical world rather than target earners (for present-bias drivers, this figure is almost identical (20.32%), because the optimal savings are close to zero in both cases).

Of course, it may be that neoclassical workers and reference-dependent workers differ along other parameters as well (for example, effort costs). In our model, the total income of the two types of workers is equalized if we set the effort cost parameters 6.5% lower for

[29] If needs are extremely high, targeting has little effect since the effort costs dominate; for low needs, effort costs are irrelevant.

neoclassical workers. This means that the numbing effect of goal setting is akin to a 6.5% reduction in effort costs.

We also estimate that, while targeting earned income or consumption yield the same income under present-bias, exponential discounters earn around 0.32% less if they target consumption rather than income. Figure A3 shows how sensitive these simulation results are to the calibration of the effort cost parameters and to the calibration of the inter-day variation in the wage rate. Both variants of the earned income targeting model yield the highest income for a large share for the parameters space.

A moment of the data we did not target in the calibration was the percentage of target earner driver-days in which the target is met. In the data, the need is met 41% of the cases, while in our painkiller model simulation the percentage is 52%, suggesting a good fit. We can also use the model to test whether we can reproduce the three main anomalies in the data (positive elasticity of labor supply to need, discontinuous increase in the probability of quitting at the need, and zero effect of lottery win) without reference-dependence. For that, we do simulations that set λ=0 and then try many possible combinations of the other parameters, including negative interest rates, but can never reproduce the labor supply patterns in the data.

4.5 Who is a target earner?

An open question is whether bicycle-taxi drivers voluntarily manipulate their utility function in order to achieve this higher income path, or whether having reference-dependent preferences is a "trait" that has evolved over time (i.e. if having earned income targeting preferences is an evolutionarily successful strategy in the terminology of the "indirect evolutionary approach", see Guth and Yaari 1992). While we do not take a stand on this, in this section we estimate the share of workers in our sample that seem to exhibit this type of preferences/behavior and attempt to identify observable predictors of such behavior.

Since our analyses above are done within individual, we can run them individual by individual in order to estimate individual-specific parameters. We run the day-level analysis of Table 4 separately for each individual and classify as "target-earner" anyone with a coefficient on "log need" in a regression akin to Table 4 column 6 that is statistically significantly positive at the 10% level in a one-sided test. Just around 33% of drivers appear to be target-earners according to this definition. Panel B of Figure 5 then runs the hazard analysis for high need days separately for those classified as "target earners" based on this, and those not. Consistent with this classification, we see a very large jump in the hazard at the need for those who exhibit responsiveness to the need in the day-level analysis, but no such jump for those who do not.

In Table A9, we estimate the correlates of exhibiting target earning behavior. The main correlates we consider are loss aversion (our approach to measuring this follows exactly the approach described in Fehr and Goette 2007), experience (as in Camerer et al. 1997), health status, family structure, and education. We find no clear correlates. In particular, unlike Fehr and Goette (2007), we find no correlation between loss aversion and reference dependence (if anything the effect goes in the opposite direction, as the coefficient estimate on loss aversion is negative). We also find no evidence that more experienced drivers are less likely to exhibit the behavior. While this may come from the fact that our individual-specific estimates of target earning are noisily estimated, and we also have few drivers in the dataset, so the analysis is underpowered, we do nevertheless find two significant predictors: not owning the bike used for work, and being future-biased.

5 Alternate hypotheses

In this section, we briefly discuss several possible alternative explanations for the results. See Appendix C for a discussion of robustness checks regarding daily needs reporting.

5.1 Logbook-generated goal setting

We argue that our data suggest workers set a daily goal based in part on their cash needs that day. One question is whether this behavior is apparent in the data because our data collection system made workers behave this way. Specifically, the act of having to record a "need amount" every day at the top of the log could have led workers in our sample to *start* setting goals for themselves, even if they were not doing this before we showed up. If that were the case, then our proposed model would still be relevant, the only difference would be in the question of how the target T is set. It may be set at 0 (making the preferences look as those of a neoclassical individual) until an outside intervention or nudge creates a new reference point for T. In this case, the intervention would be the logbook making the daily need salient and leading the target to be based on the need. In other contexts, it could be an expected average daily income or hourly earnings advertised by an employer (e.g., Uber advertising city-specific hourly earnings on Craigslist).[30]

[30]There are other potential problems with people self-reporting needs, which we discuss in Appendix C.

5.2 Risk Sharing

Bicycle taxi drivers in our sample work in a specified area (or "stage"). Since riders know each other, it is possible that workers have developed a risk-sharing institution in which customers are funneled towards those workers who most need the money. Though we view this as unlikely given that it is likely hard to observe each others' needs and income, we check for this by examining how earnings opportunities vary with the cash needs of other workers at the stage (results on request). We find that the coefficients for others' needs are insignificant in nearly all specifications.

5.3 Intra-Household Issues

Nearly all of the workers in our sample are married, so their labor supply decisions are likely related to the behavior of their spouses – is it possible that the wife's labor supply adjusts in such a way to make the household's labor supply patterns look more neoclassical? For example, perhaps the wife works less when the lottery is received, or increases her labor supply when need amounts are met. We view this as very unlikely, since it requires detailed, timely information on each other's behavior and previous work suggests that spouses do not typically have such detailed information on each other (i.e. Robinson 2012). Further, intra-household explanations would tend to predict different labor supply responses to individual needs like ROSCA contributions compared to household needs such as school fees or food. However, we find little difference in behavior for the two types of needs (Tables A8 and A9).

Moving beyond intra-household labor supply, it is entirely possible that the spouses help workers achieve their targets, just like coaches for athletes, as goal setting may work better if there is a "witness" to the goal – e.g. bike drivers may be able to exploit the painkiller benefits of goal setting if they tell their wife, upon leaving their house in the morning: "I will not come home until I have 180 Ksh for food and my ROSCA contribution".

6 Conclusion

We find that bicycle-taxi drivers in rural Kenya work more on days when they need money, quit more after earning enough to pay for that need, but do not respond to unexpected cash payouts. These results are consistent with a labor supply model in which people have reference-dependent preferences and form income targets but – unlike the previous literature – these targets are over *earned* rather than total income. Why do they behave this way? Camerer et al. (1997) discuss how income targets could be an internal commitment device to provide effort, i.e. a way to avoid succumbing to the temptation of quitting early.[31] Along those lines, we conjecture that people treat *earning enough for their immediate needs* as a personal goal, day after day. We argue that such goal setting enables workers to push themselves to work through the pain, working beyond the point where the marginal cost of effort would exceed the marginal value of income, absent the painkilling effect of striving towards the goal. This interpretation of our results is consistent with the psychological literature on goal setting, which has shown goals can induce persistence: individuals who set goals are more likely to carry through hardship compared to those who have not (for example among athletes – Kyllo and Landers 1995). Goals appear to be set over short horizons within which needs are mostly exogenous, determined by (soft) commitments made earlier based on consumption path aspirations, thus offering a both reachable and non-renegotiable goal to work towards.

Simulations calibrated on our data show that workers with reference dependence over an earned income target earn about 20% more than those without such preferences. Welfare implications depend on whether reference dependent preferences reflect true hedonic experiences or are merely mistake. In our proposed model of earned income targeting as morphine, striving towards a goal is a way to work through the pain without feeling it as intensely. If so, then income targeters can be considered better off from the fact that they can achieve higher income despite the higher effort.

From simple introspection, the painkiller model we propose does not sound that far-fetched – staying up longer than usual in order to finish a paper draft or a referee report is a common occurrence among academics. Running exactly 26.2 miles before collapsing from exhaustion right at the finish line is another example. In fact, many marathoners do so within a pre-set timeframe, maintaining a relatively higher effort level in the last mile in order to meet their time target (Allen et al. 2015). In the case of bicycle taxi drivers, our data suggests that daily goal-setting is a way to commit to working harder than the pain would otherwise allow.

Our results have several implications. First, workers with such preferences may be able to better smooth their labor supply if they have access to outlay commitments, for example loans with high-frequency repayment schedules or ROSCAs that meet at high frequency. Second and perhaps more directly, people may benefit from employment contracts (as discussed in Kaur, Kremer and Mullainathan 2010). The finding that a movement to wage work could be beneficial relates to recent work suggesting that many self-employed individuals in poor countries are much more similar (in terms of preferences, attitudes, cognitive ability,

[31] See Hsiaw (2013) for a formal treatment, in the related context of a present-biased decisionmaker solving an optimal stopping problem.

motivation, etc.) to wage workers than to large firm owners (e.g de Mel et al. 2010).

We leave several issues to future work. One such issue is how needs themselves are set – our data collection was geared towards understanding how labor supply responded to given needs, and not as to how individuals decide what outlay commitments to take on, or more generally, what consumption path to aspire to. A growing literature explores the role of aspirations in development, as well as the determinants of aspiration levels. Our findings suggest that workers aspiring to a higher consumption path (e.g. committing to regular savings club payments or registering their children in school) are able to harness the power of goal setting to earn more and move closer to their aspired path, consistent with the proposition of Dalton et al. (2016) that higher aspirations are motivators of greater effort; but our data does not enable us to study how aspirations themselves are formed.

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Figure 1A. Cross-sectional Correlation beetween Cash Need for the Day and Labor Supply

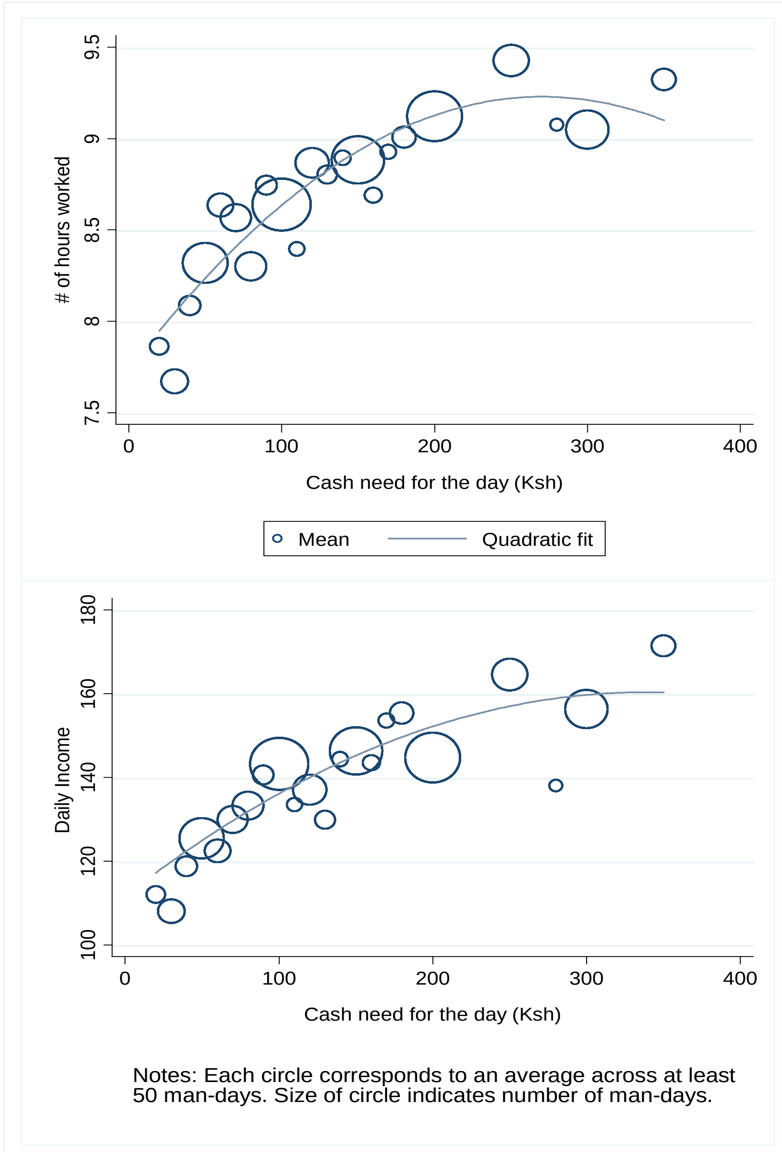


Figure 1B. Quitting behavior: Daily Cash Need vs. Running hours

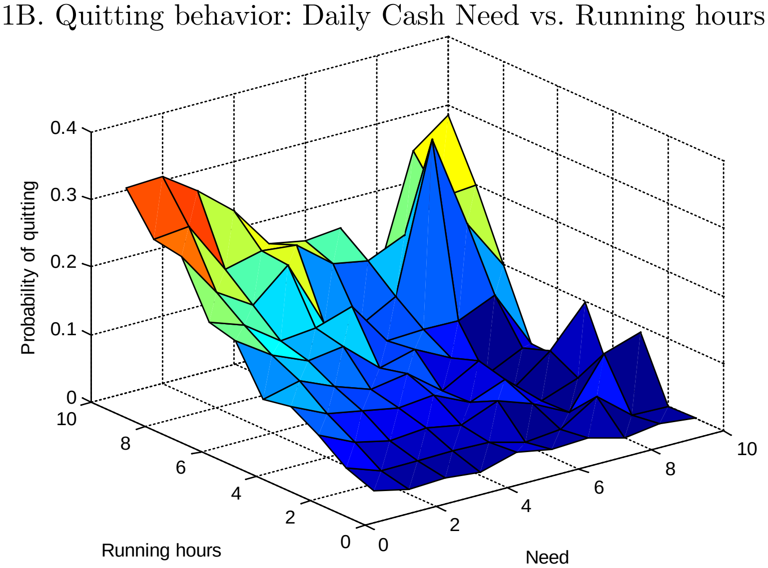
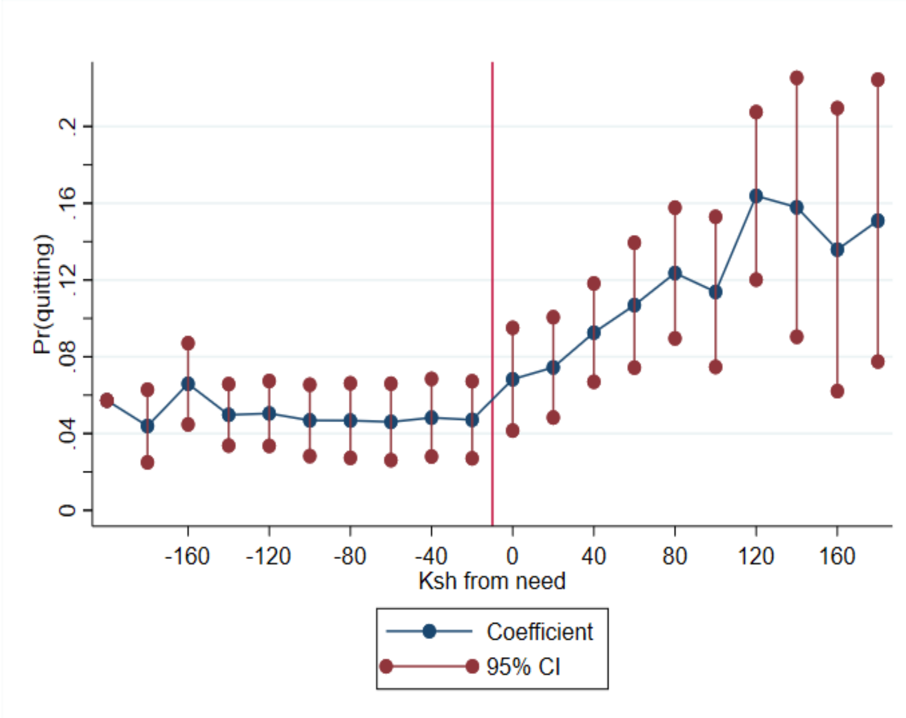
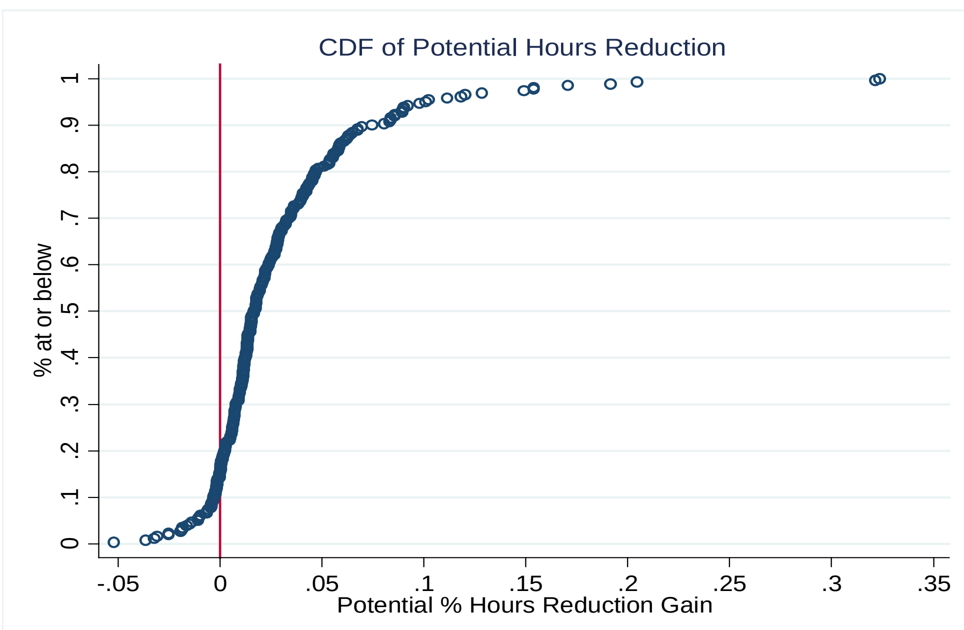


Figure 2. Coefficients from Hazard Regressions



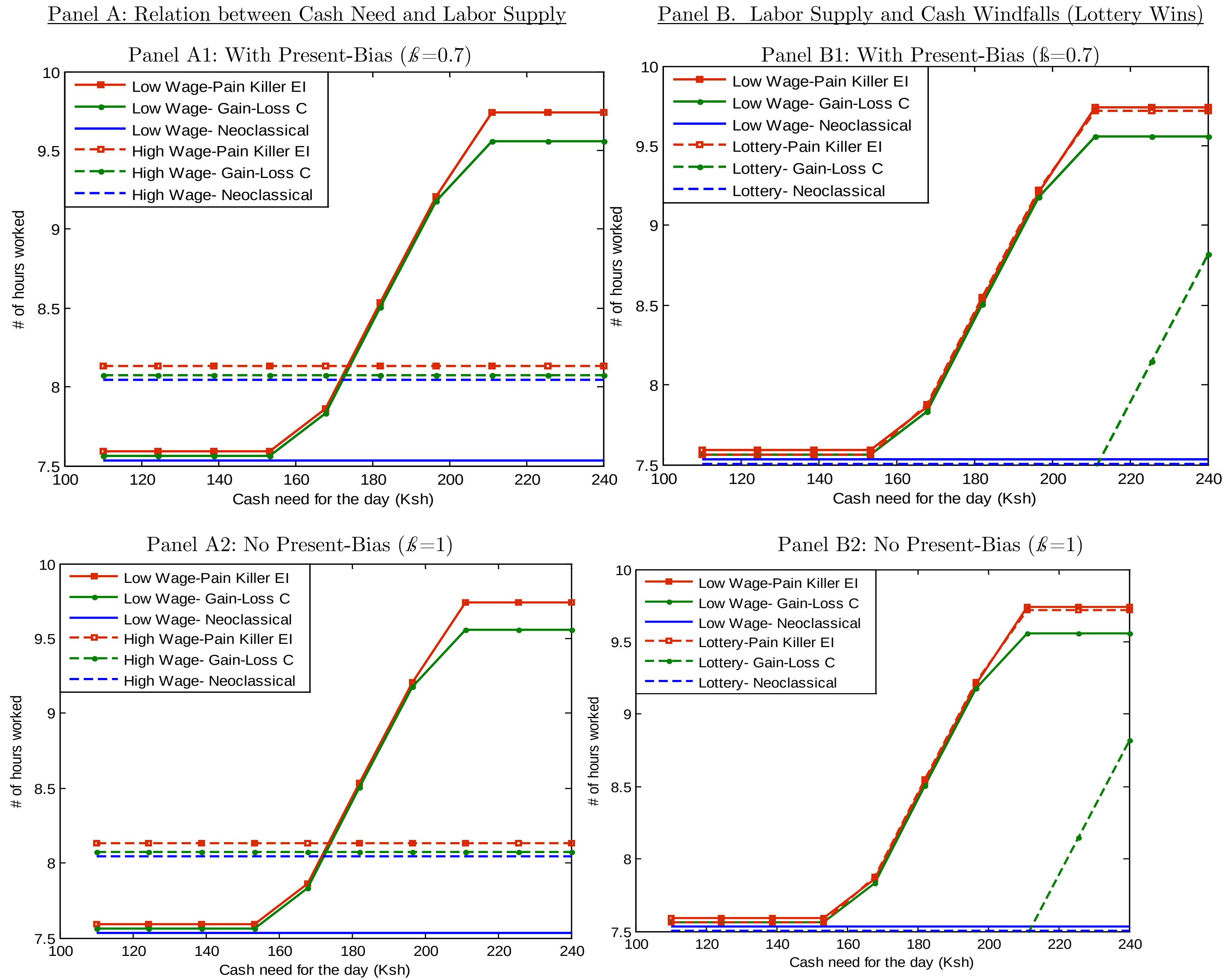
Notes: This plots coefficients, and associated 95% confidence intervals, of being at a given distance from the daily cash need on the hazard of quitting work for the day (See text section 3.2.3 for details).

Figure 3. Potential Hours Reduction from a Fixed Hours Schedule



Notes: This graph shows the cumulative distribution function of the counter-factual hours reduction (as a percentage) workers could achieve by working a fixed hours schedule. For each individual, we calculated the number of hours they would have to work to earn the same income working a set number of hours per day. The calculation assumes that the local wage rate on the day in question would have prevailed if hours were reallocated to and from that day.

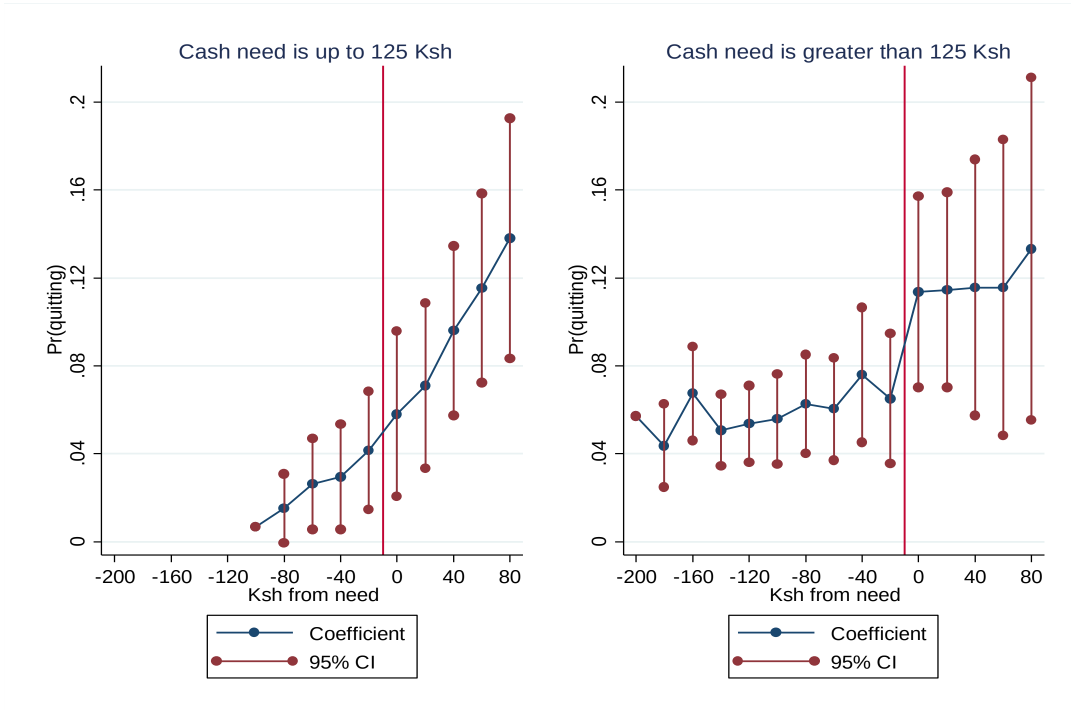
Figure 4. Calibration: Comparison of proposed model with two others (neo-classical and consumption targeting)



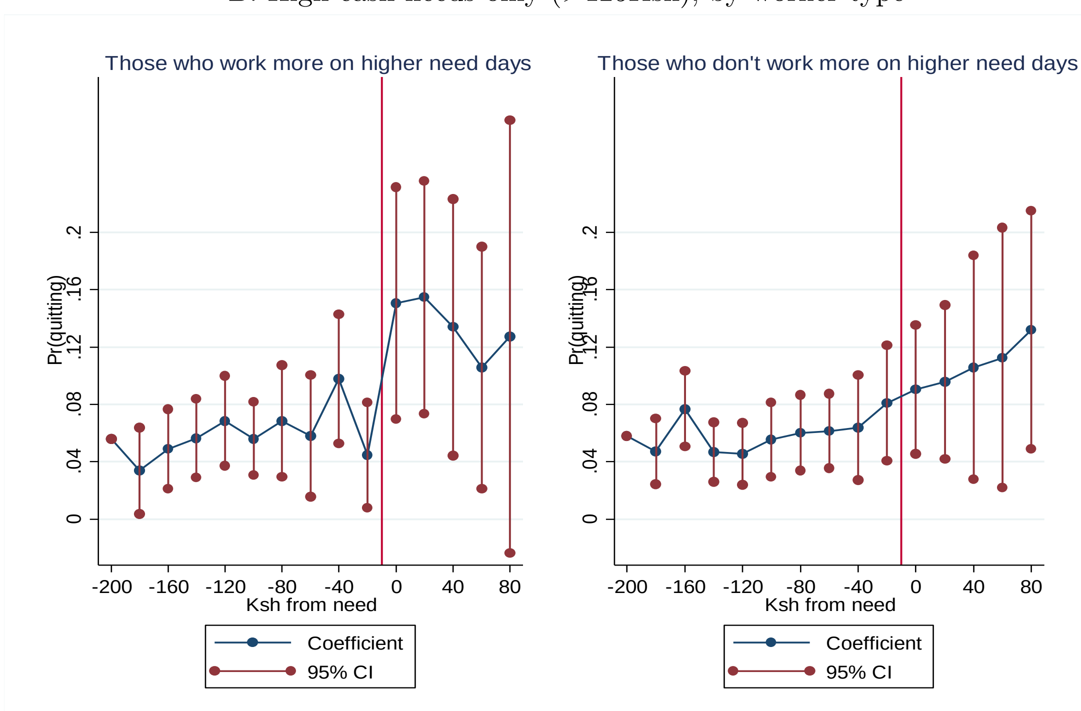
Notes: We compare three models -- the standard neo-classical model (blue lines), a model of reference dependence with a target over consumption (C, green lines) and the model that we argue fits our results best, namely a model of earned income targeting with pain killer effects (red lines). The actual values have been slightly modified to be able to present all lines. The three models coincide for small needs.

Figure 5. Quitting Hazard by need size and work types

A. All



B. High cash needs only (>125Ksh), by worker type



Notes: These plot coefficients, and associated 95% confidence intervals, of being at a given distance from the daily cash need on the hazard of quitting work for the day (See text section 3.2.3 for details). Panel B split workers based on the responsiveness of their daily labor supply to daily need (in regressions akin to those in Table 4 column 6 but estimated separately for each worker).

Table 1. Sample Characteristics: Summary Statistics from Baseline Survey

	(1) Mean	(2) Std. Dev.
Panel A. Demographic Information		
Age	33.06	8.11
Years working as bike taxi	6.22	4.71
Married	0.96	0.19
Number of Children	3.41	2.27
Education	6.75	2.23
Owns Cell Phone	0.57	0.50
Value of Durable Goods Owned (in Ksh)	11039	8372
Value of Animals Owned (in Ksh)	6882	9835
Acres of land owned	1.41	1.44
Total Bike-Taxi Income in Week Prior to Survey (in Ksh)	573	339
Has another regular source of income	0.15	0.35
If yes, income in average week from other income	576	525
Has seasonal income	0.20	0.40
If yes, income in normal season	6632	10702
Panel B. Financial Access		
Participates in ROSCA	0.75	0.43
If yes, number of ROSCAs	1.06	0.84
If yes, ROSCA contributions in last year (in Ksh)	5972	7881
Owns Bank Account	0.31	0.47
Received gift/loan in past 3 months	0.25	0.43
If yes, amount	2174	2319
Gave gift/loan in past 3 months	0.29	0.46
If yes, amount	1244	1942
Panel C. Health		
Overall, how would you rate your health (scale 1-5)?[1]	2.59	0.74
Missed work due to illness in past month	0.39	0.49
If yes, number of days missed	2.19	1.79
Panel D. Time Preferences, Small-Stakes Risk Aversion and Loss Aversion		
Time Consistent	0.12	0.32
Present Bias	0.15	0.36
Future Bias	0.13	0.33
Extremely impatient today and in the future	0.60	0.49
Amount invested (out of 100 Ksh) in Risky Asset[2]	56.34	26.07
More loss averse: Refuses the 50-50 gamble (win 30 or lose 10)	0.29	0.45
More loss averse: Refuses the 50-50 gamble (win 120 or lose 50)	0.57	0.50

Notes: All variables are from the baseline. There are 246 observations in the baseline.

Exchange rate was roughly 75 Ksh to US $1 during the study period.

[1]Codes: 1-excellent, 2-good, 3-OK, 4-poor, 5-very poor.

[2]The risky asset paid off 4 times the amount invested with probability 0.5, and 0 with probability 0.5.

Table 3. Demands on Income and Labor Supply

	(1)	(2)	(3)	(4)
	Worked Today	Total income	Total Hours	Total time carrying passengers
ROSCA contribution due today	0.06***	12.15***	0.52***	0.20***
	(0.02)	(4.09)	(0.18)	(0.06)
School fees due today	0.06*	2.47	0.53	0.05
	(0.03)	(8.11)	(0.36)	(0.11)
Bike repairs needed today	0.06***	10.23***	0.63***	0.22***
	(0.01)	(2.72)	(0.12)	(0.04)
Funeral to attend and contribute to	-0.11***	-15.63**	-0.89***	-0.20**
	(0.03)	(6.23)	(0.31)	(0.10)
Somebody in household is sick today	-0.01	3.03	-0.07	-0.02
	(0.01)	(3.30)	(0.13)	(0.05)
Respondent sick today	-0.36***	-56.89***	-3.35***	-0.90***
	(0.03)	(5.13)	(0.27)	(0.08)
Won big lottery prize today	0.03	3.69	0.07	0.09
	(0.03)	(6.13)	(0.25)	(0.08)
Observations (individual-days)	10,863	10,692	10,752	10,662
Number of IDs	259	259	259	259
R-squared	0.19	0.14	0.19	0.16
Mean of Dep. Var.	0.800	116.3	7.080	1.890
Std. Dev. of Dep. Var	0.400	102.6	4.350	1.520

Notes: Standard errors are in parentheses, clustered at both the individual and date level. All monetary values in Ksh. Regressions include individual fixed effects, and stage-date fixed effects. ***, **, * indicates significance at 1, 5 and 10%.

Table 4. Effect of Day's Need and Lottery Payment on Day's Labor Supply

	(1)	(2)	(3)	(4)
	Worked Today		Total Income	
Panel A. Extensive Margin				
Has a need	0.15***		16.12***	
	(0.02)		(4.87)	
Log (cash need)		-0.01*		12.15***
		(0.01)		(2.21)
Won big lottery prize today	0.04	0.03	3.91	2.26
	(0.03)	(0.03)	(6.21)	(6.99)
Won big lottery prize yesterday	0.02	0.01	0.37	-3.36
	(0.03)	(0.03)	(4.87)	(5.60)
Observations (individual-days)	10,863	9,406	10,692	9,272
Number of IDs	259	258	259	258
R-squared	0.19	0.21	0.14	0.16
Mean of Dep. Var.	0.80	0.82	116.30	118.60
Std. Dev. of Dep. Var	0.40	0.38	102.60	100.60

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Log (Total Income)		Number of passengers		Total hours		Passengers per hour		Total time spent carrying passengers		Average fare per hour carrying	
Panel B. Intensive Margin (conditional on working)												
Has a need	-0.03		-0.03		-0.15		0.00		-0.07		-1.46	
	(0.02)		(0.10)		(0.12)		(0.01)		(0.05)		(0.99)	
Log (cash need)		0.11***		0.21***		0.27***		0.01		0.19***		1.20**
		(0.01)		(0.04)		(0.06)		(0.01)		(0.03)		(0.59)
Won big lottery prize today	-0.01	-0.02	-0.17*	-0.20**	-0.19	-0.31*	0.00	0.00	0.10**	0.05	-2.35	-1.92
	(0.04)	(0.05)	(0.09)	(0.10)	(0.17)	(0.16)	(0.01)	(0.02)	(0.04)	(0.06)	(1.69)	(1.69)
Won big lottery prize yesterday	-0.01	-0.02	0.04	-0.02	0.36**	0.23	-0.01	0.00	0.07	0.01	0.23	0.39
	(0.03)	(0.04)	(0.14)	(0.15)	(0.18)	(0.18)	(0.02)	(0.02)	(0.05)	(0.05)	(2.48)	(2.82)
Observations (individual-days)	8,543	7,596	8,720	7,735	8,627	7,672	8,627	7,672	8,537	7,591	8,540	7,594
Number of IDs	259	258	259	258	259	258	259	258	259	258	259	258
R-squared	0.15	0.18	0.16	0.18	0.16	0.17	0.11	0.12	0.13	0.14	0.11	0.12
Mean of Dep. Var.	4.81	4.81	4.38	4.40	8.83	8.83	0.55	0.55	2.36	2.35	68.82	68.57
Std. Dev. of Dep. Var	0.59	0.58	2.21	2.20	2.85	2.83	0.36	0.35	1.33	1.32	25.70	25.34

Notes: Regressions are at the worker-date level. Log(need) is measured in Log(Ksh). All regressions include individual fixed effects and stage-date fixed effects. Even columns exclude days without a need. Regressions also control for whether the respondent reports being sick that day. We have fewer observations for the hour variables since the stopping time was left blank in some cases. Standard errors are in parentheses, clustered at both the individual and date level. ***, **, * indicates significance at 1, 5 and 10%.

Table 6. Daily Needs, Income Targets, and Hours Targets

	(1)	(2)	(3)	(4)
Dependent variable = 1 if quit work after dropping off passenger				
Cumulative Hours Worked (Units = Hours / 10)	-0.05	-0.08**	-0.12***	-0.14***
	(0.04)	(0.04)	(0.04)	(0.04)
Cumulative Hours Worked Squared			0.33***	0.36***
			(0.04)	(0.04)
Cumulative Income Earned (Units = Ksh / 1000)	0.13	0.02	0.57***	0.41***
	(0.10)	(0.09)	(0.10)	(0.10)
Cumulative Income Earned Squared			-0.73***	-0.60***
			(0.18)	(0.17)
Cumulative Hours > Estimated Target	0.07***	0.07***	0.08***	0.07***
	(0.01)	(0.01)	(0.01)	(0.01)
Cumulative Income > Estimated Target	0.03***	0.03***	0.02***	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)
Over need		0.04***		0.03***
		(0.01)		(0.01)
Observations	38,132	33,826	38,132	33,826
Number of bodas	259	259	259	259
R-squared	0.15	0.16	0.15	0.16
Mean of dependent variable	0.09	0.09	0.09	0.09

Notes: These estimates follow Table 3 Crawford and Meng (2011). Targets are estimated as average daily income or hours on days up to but not including the day in question. Targets are estimated by day of the week. All regressions include individual fixed effects and controls for week and day of the week fixed effects. Standard errors are in parenthesis, clustered at both the individual and date level. *, **, and *** indicate significance at 10%, 5%, and 1% respectively.

Table 7: Main simulations results

Model	Gain-loss EI
Exp. Discounting: Average income change if no targeting (λ=0)	-19.10%
Std. Dev. of income change across 200 drivers	*-19.76%*
Hyp. Discounting: Average income change if no targeting (λ=0)	-20.32%
Exp. Discounting: Average income change if target consumption	0.32%
Percentage of driver days the target is met	52%
Percentage of driver days the target is met if target consumption	50%

Appendix A: Appendix Figures and Tables

Figure A1a. Estimated Effort Costs

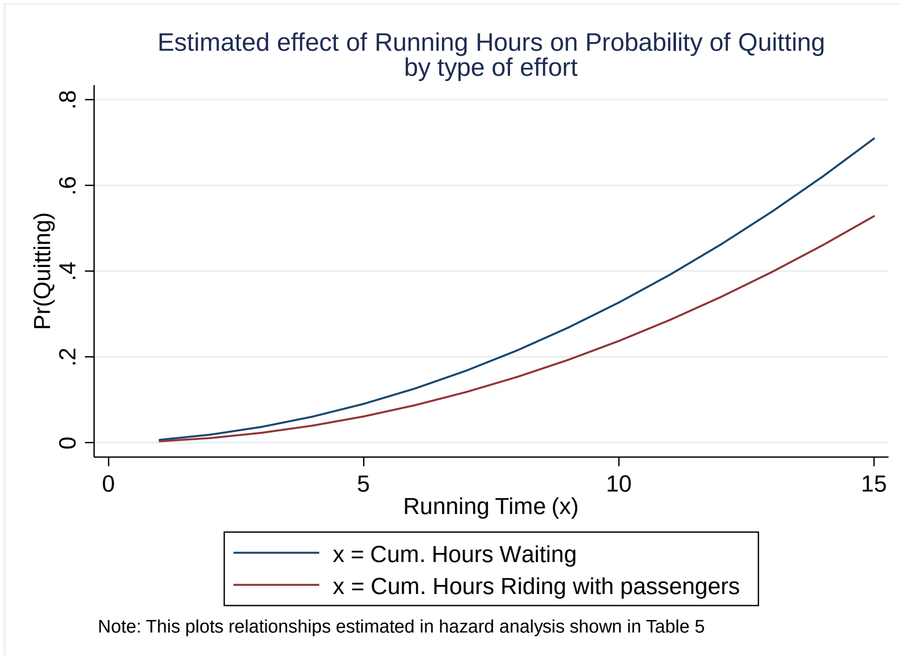
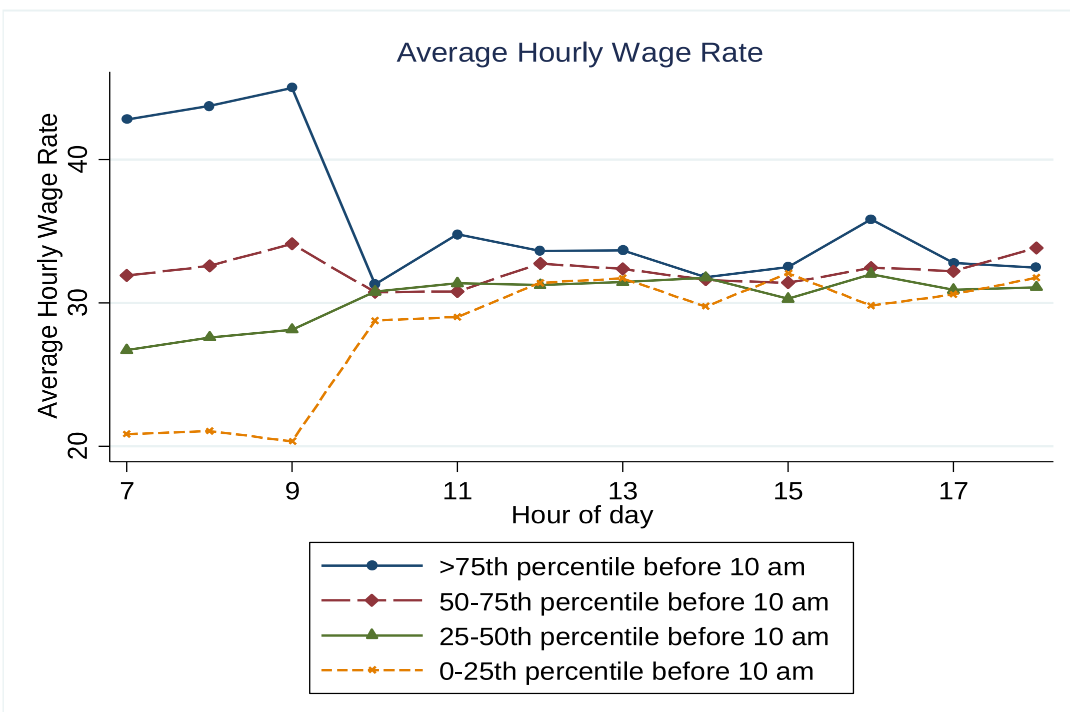


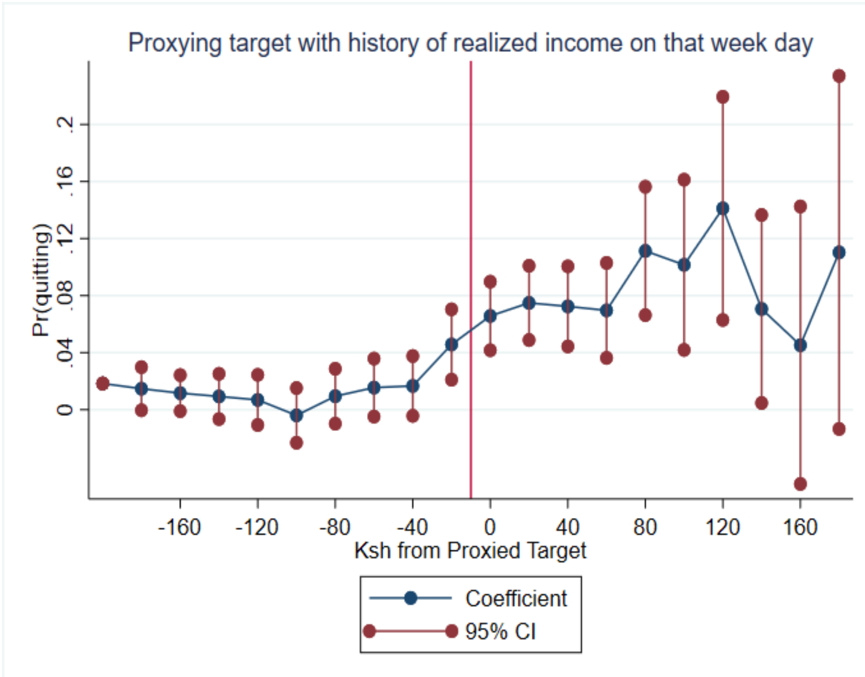
Figure A1b. Variations in the Hourly Wage Rate



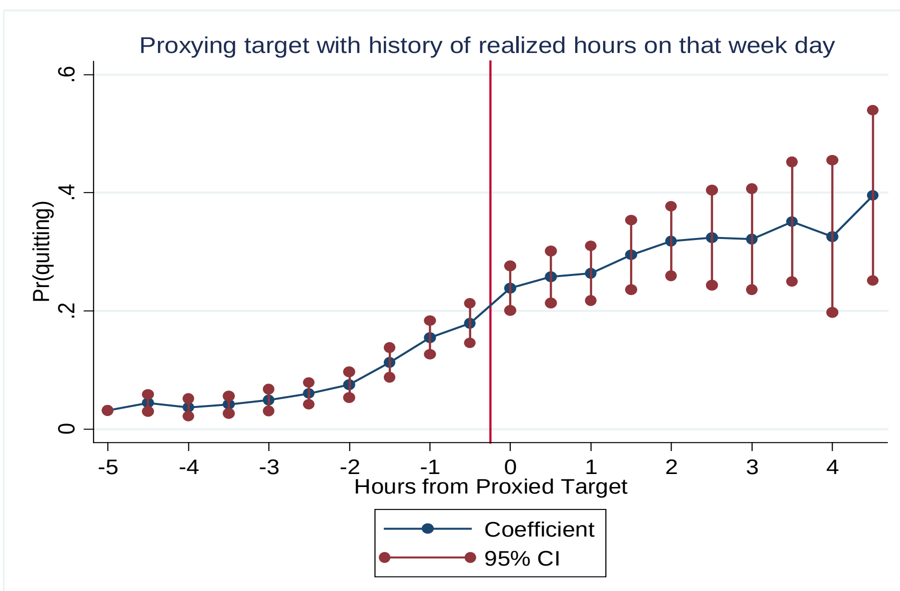
Notes: Figure A1b presents average hourly wage rates at the stage-day level. Results are presented for quartiles of the average wage rate in the morning (7-10 AM).

Figure A2. Proxying Target with Average Past Realized Income/Hours on same Week Day

Panel A. Income



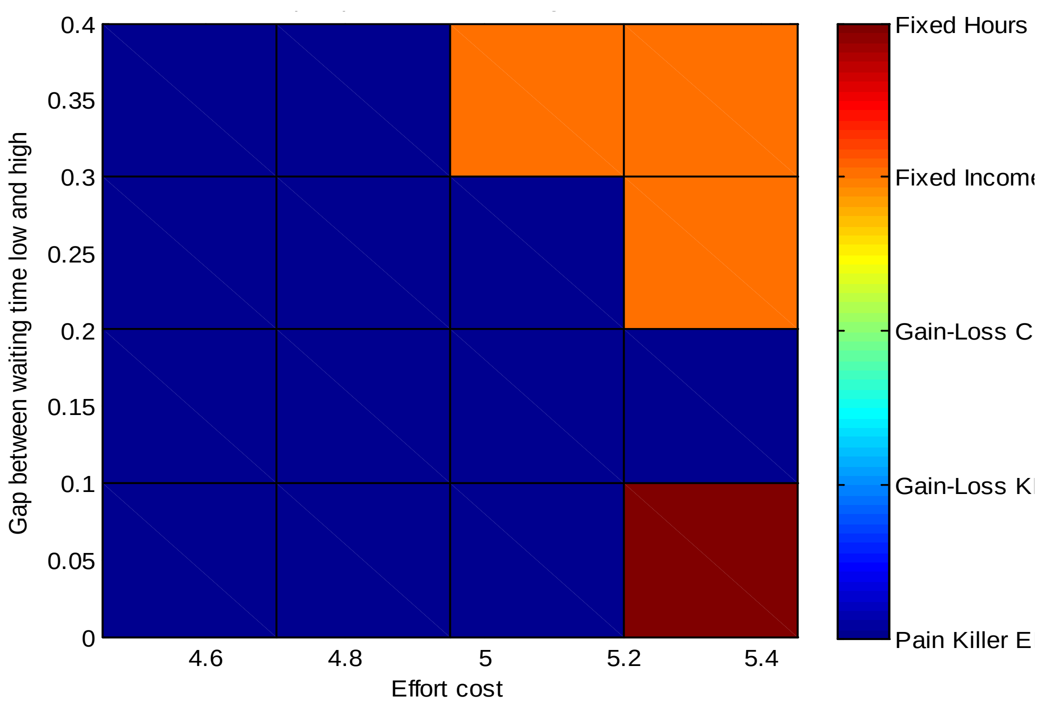
Panel B. Hours



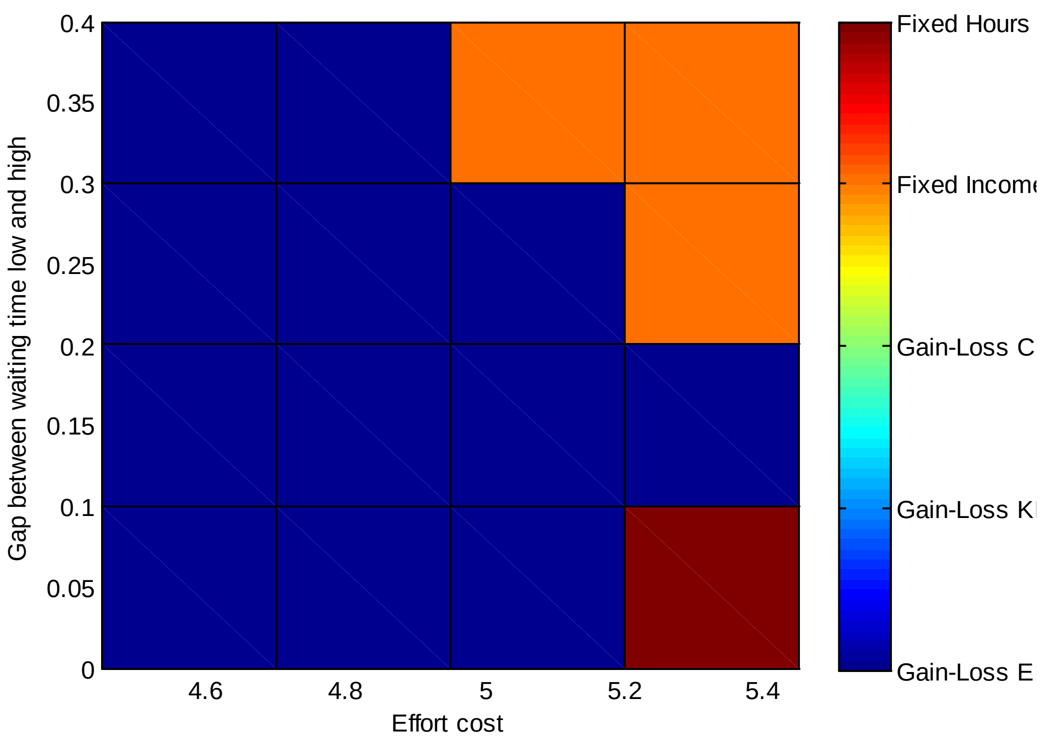
Notes: These estimates follow Crawford and Meng (2011). Proxy targets are estimated as average daily income or hours on days up to but not including the day in question. Proxy targets are estimated by day of the week.

Figure A3. Model that produces highest income for different parameter values

Panel A. Earned income targeting as painkiller



Panel B. Earned income targeting as standard gain-loss utility term



Notes: For each pair (effor cost, "wage" gap) the corresponding cell is colored with the color of the model that produces highest income. The six models considered are: (1) Neoclassical (never highest income so no color assigned); (2) Earned Income (EI) targeting (Painkiller variant in Panel A, Level Gain-Loss variant in Panel B); (3) Gain-Loss KR (ie Koszegi-Rabin(2006), where the income target is expectations-based); (4) Gain-Loss Consumption, with reference dependence over a consumption target; (5) Fixed Income Target; (6) Fixed hours Target.

Figure A4. Simulation Results: Probability of quitting and distance to the need

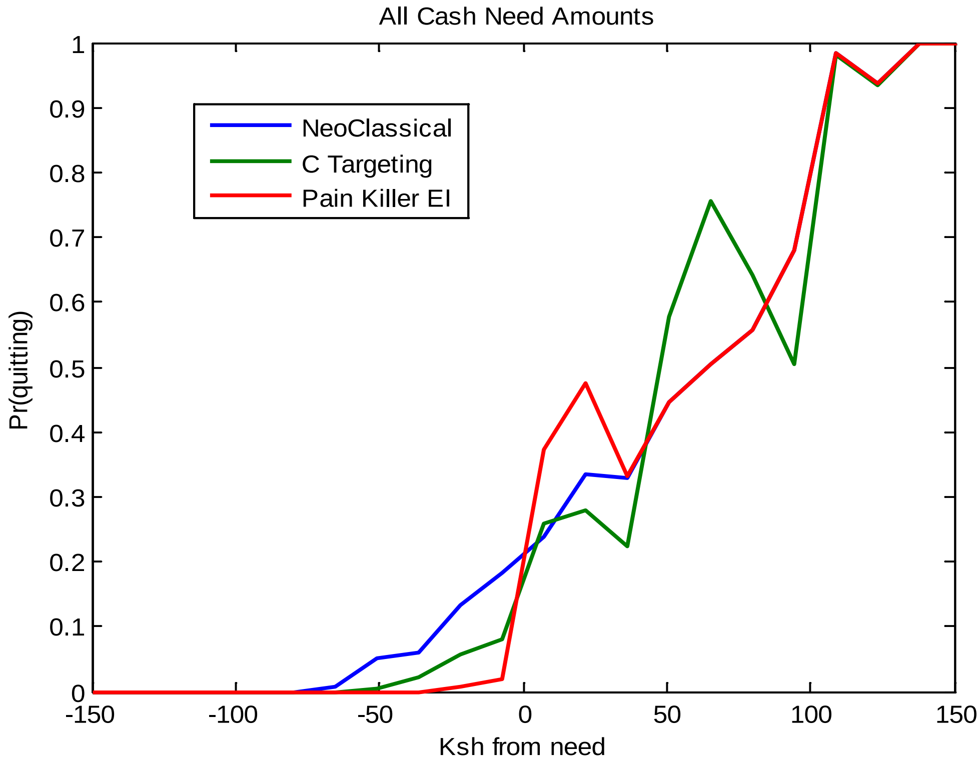


Figure A5. Simulation Results: Probability of quitting by need size Pain Killer EI

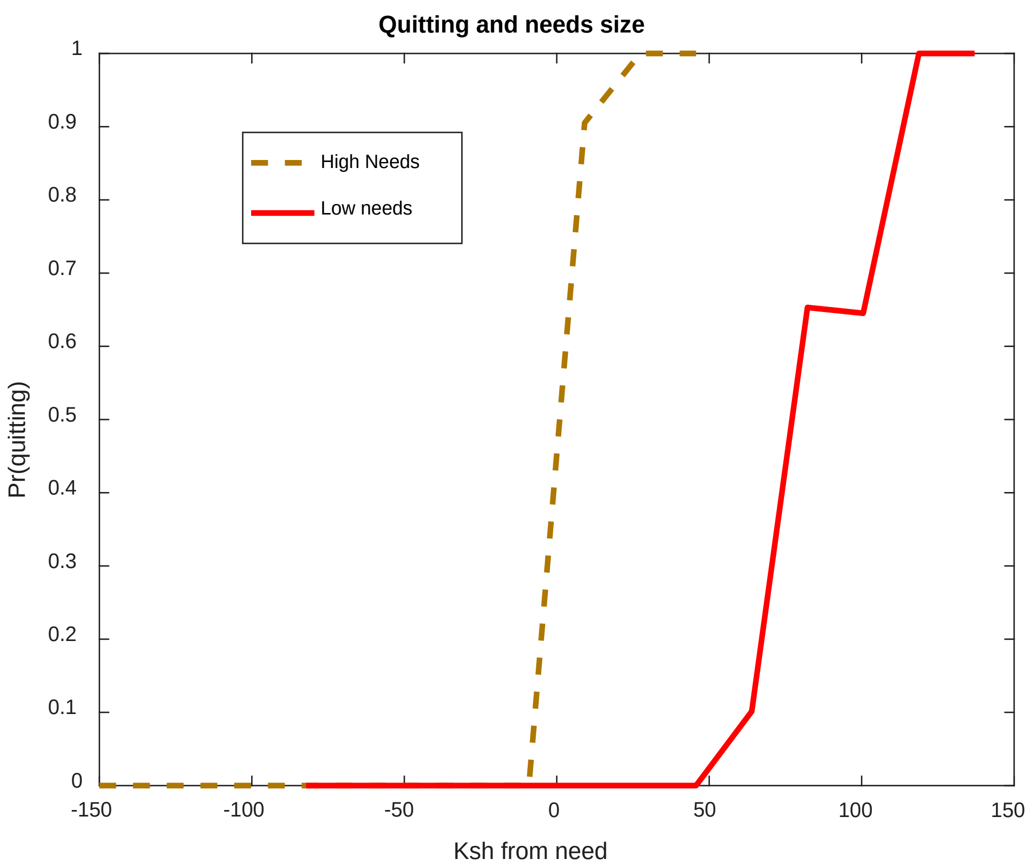


Figure A5. Simulation Results: Hours worked with varying borrowing constraint

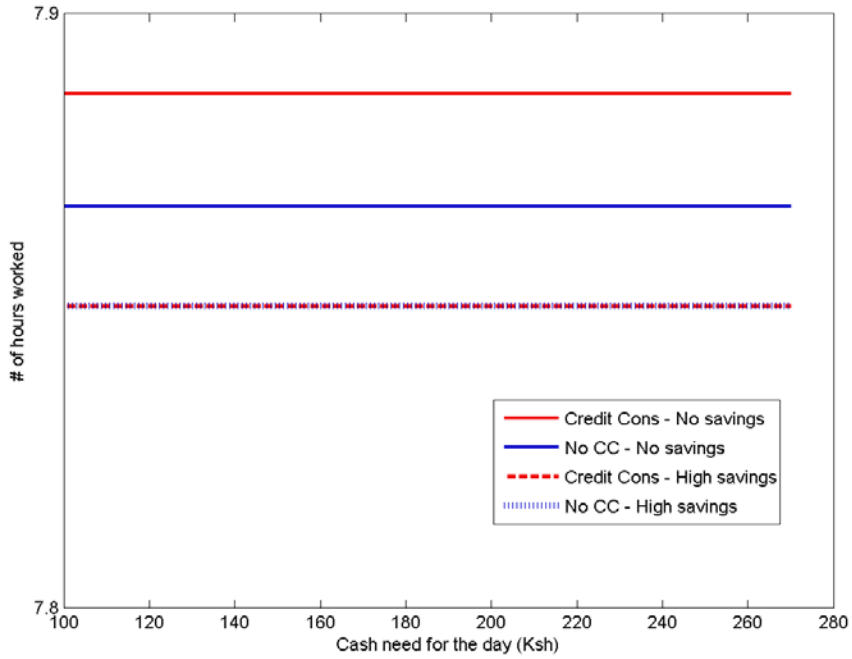


Table A1. Demands on Income and Reported Cash Need for the Day

	(1)	(2)	(3)	(4)	(5)	(6)
	Reports cash need today		Amount of cash need (0 if none reported)		If reports need: Cash amount	
ROSCA contribution due today	0.0633***		-0.0145		-0.1380	
	(0.0127)		(0.1040)		(0.1090)	
ROSCA contribution amount due (0 if none)		0.0223***		0.228**		0.190*
		(0.0058)		(0.1080)		(0.1050)
School fees due today	0.102***		0.617***		0.475*	
	(0.0188)		(0.2370)		(0.2460)	
School fees amount due (0 if none)		-0.0023		0.1070		0.262**
		(0.0039)		(0.0838)		(0.1200)
Bike repairs needed today	0.0908***		0.173***		0.0214	
	(0.0130)		(0.0540)		(0.0590)	
Bike repairs costs (0 if none)		0.0460***		0.545***		0.470***
		(0.0098)		(0.1100)		(0.1270)
Funeral to attend and contribute to	0.0477***		0.969*		0.922*	
	(0.0140)		(0.5030)		(0.5390)	
Funeral contribution amount (0 if none)		0.00916**		1.711		1.718
		(0.0044)		(1.066)		(1.077)
Somebody in household is sick today	0.0384***	0.0372***	0.529***	0.479***	0.514***	0.462***
	(0.0098)	(0.0097)	(0.1120)	(0.088)	(0.118)	(0.091)
Respondent sick today	0.0141	0.0120	0.1270	0.149	0.122	0.154
	(0.0113)	(0.0111)	(0.1380)	(0.142)	(0.153)	(0.155)
Observations (individual-days)	10863	10863	10530	10530	9406	9406
R-squared	0.134	0.126	0.106	0.219	0.109	0.226
Number of IDs	259	259	259	259	258	258
Mean of Dep. Var.	0.90	0.90	1.83	1.83	2.04	2.04
Std. Dev. of Dep. Var	0.30	0.30	3.22	3.22	3.34	3.34

Notes: Standard errors are in parentheses, clustered at both the individual and date level. All monetary values in 100s Ksh. Regressions include individual fixed effects, and stage-date fixed effects. ***, **, * indicates significance at 1, 5 and 10%.

Table A2. Relationship Between Reported Cash Needs and Actual Expenditures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	On daily log, reported needing cash for [ ] on date *t*							
	ROSCA payment		School Fees		Funeral Expenses		Bike Repair	
On weekly survey, reported...								
Making ROSCA deposit at *t*	0.53***	0.54***						
	(0.03)	(0.03)						
Making ROSCA deposit at *t+1*		-0.04**						
		(0.02)						
Making ROSCA deposit at *t+2*		-0.04***						
		(0.01)						
Paying school fees at *t*			0.57***	0.57***				
			(0.04)	(0.04)				
Paying school fees at *t+1*				0.04				
				(0.03)				
Paying school fees at *t+2*				0.02				
				(0.02)				
Contributing to funeral at *t*					0.49***	0.49***		
					(0.03)	(0.03)		
Contributing to funeral at *t+1*						0.02		
						(0.02)		
Contributing to funeral at *t+2*						0.00		
						(0.02)		
Making bike repairs at *t*							0.70***	0.70***
							(0.02)	(0.02)
Making bike repairs at *t+1*								-0.01
								(0.01)
Making bike repairs at *t+2*								0.00
								(0.01)
Observations	8,429	8,429	7,616	7,616	7,647	7,647	7,562	7,562
Number of IDs	256	256	255	255	255	255	255	255
R-squared	0.22	0.22	0.21	0.21	0.21	0.21	0.46	0.46
Mean of dependent variable	0.18	0.18	0.03	0.03	0.06	0.06	0.26	0.26

Notes: Regressions include individual fixed effects, as well as controls for the day of the week and the week of the year. Standard errors in parentheses, clustered at both the individual and date level. *, **, and *** indicate significance at 10%, 5%, and 1% respectively.

Table A3. Effect of Need, and Lottery Payment on Daily Labor Supply (including Sundays)

	(1)	(2)	(3)	(4)
	Worked Today		Total Income	
Panel A. Extensive Margin				
Has a need	0.18***		21.02***	
	(0.02)		(4.35)	
Log (cash need)		-0.01		12.24***
		(0.01)		(1.99)
Won big lottery prize today	0.04	0.04	4.19	2.52
	(0.03)	(0.03)	(6.31)	(7.05)
Won big lottery prize yesterday	0.03	0.01	0.47	-3.06
	(0.02)	(0.03)	(4.71)	(5.59)
Observations (individual-days)	12,582	10,654	12,385	10,501
Number of IDs	259	258	259	258
R-squared	0.28	0.26	0.20	0.19
Mean of Dep. Var.	0.75	0.78	107.40	111.80
Std. Dev. of Dep. Var	0.43	0.41	102.60	100.60

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Log (Total Income)		Number of passengers		Total hours		Passengers per hour		Total time spent carrying		Average fare per hour carrying	
Panel B. Intensive Margin (conditional on working)												
Has a need	-0.02		-0.01		-0.16		0.00		-0.05		-1.67*	
	(0.02)		(0.10)		(0.12)		(0.01)		(0.05)		(1.00)	
Log (cash need)		0.11***		0.21***		0.28***		0.00		0.20***		1.05*
		(0.01)		(0.04)		(0.06)		(0.01)		(0.03)		(0.60)
Won big lottery prize today	-0.01	-0.02	-0.17*	-0.20**	-0.22	-0.33**	0.00	0.01	0.10**	0.04	-2.37	-1.94
	(0.04)	(0.05)	(0.09)	(0.10)	(0.17)	(0.15)	(0.01)	(0.02)	(0.05)	(0.07)	(1.68)	(1.67)
Won big lottery prize yesterday	-0.01	-0.02	0.04	-0.01	0.35*	0.21	0.00	0.00	0.07	0.01	0.26	0.45
	(0.03)	(0.04)	(0.15)	(0.15)	(0.18)	(0.18)	(0.02)	(0.02)	(0.05)	(0.05)	(2.42)	(2.73)
Observations (individual-days)	9,196	8,157	9,399	8,315	9,289	8,240	9,289	8,240	9,190	8,152	9,193	8,155
Number of IDs	259	258	259	258	259	258	259	258	259	258	259	258
R-squared	0.16	0.18	0.16	0.18	0.17	0.18	0.12	0.13	0.14	0.15	0.12	0.13
Mean of Dep. Var.	4.81	4.81	4.35	4.36	8.78	8.78	0.55	0.55	2.34	2.34	68.94	68.68
Std. Dev. of Dep. Var	0.59	0.58	2.20	2.19	2.89	2.87	0.36	0.35	1.32	1.32	25.79	25.46

Notes: This table replicates Table 4 but including Sundays. See Table 4 notes.

Table A4. Effect of Week's Need and Lottery Payment on Week's Labor Supply

	(1)	(2)	(3)	(4)
	Log (Total Income)	Number of passengers	Total hours	Total time spent carrying passengers
Log (cash need)	0.29***	2.84***	5.80***	1.80***
	(0.04)	(0.58)	(0.92)	(0.34)
Won big lottery prize in the week	0.00	-0.09	0.78	0.03
	(0.03)	(0.54)	(0.74)	(0.18)
Observations (individual-weeks)	2,015	2,095	2,093	2,089
Number of IDs	258	258	258	258
R-squared	0.48	0.40	0.44	0.36
Mean of Dep. Var.	6.15	17.65	35.16	9.30
Std. Dev. of Dep. Var	0.76	11.38	18.94	6.32

Notes: Regressions are at the worker-week level. Sundays excluded from week totals. We exclude days from weekly totals for which either the cash need information or the dependent variable information is missing (not reported). The average week in the sample has data for 4.95 days. All regressions include individual fixed effects and stage-week fixed effects. Regressions also control for whether the respondent reports being sick that week. Standard errors are in parentheses, clustered at both the individual and week level. ***, **, * indicates significance at 1, 5 and 10%.

Table A5. Parametric Hazard Regressions (with hour of the day fixed effects)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent variable: Quit after dropping off passenger							
	Farber (2005)	Farber +Over Need	Separating time carrying/ waiting	Adding Needs and Lottery Payouts				Only lottery days/players
Cumulative Earned Income (Units = Ksh / 1000)	0.06	-0.03	0.11	0.03				
	(0.07)	(0.06)	(0.08)	(0.07)				
Cumulative Hours Worked (Units = Hours / 10)	0.08***	0.08***						
	(0.02)	(0.02)						
Cumulative Carrying Hours (Units = Hours / 10)			-0.13***	-0.12**	-0.10**	-0.10**	-0.10**	0.17
			(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.14)
Cumulative Carrying Hours Squared			0.08	0.06	0.04	0.04	0.04	-0.34
			(0.11)	(0.15)	(0.15)	(0.15)	(0.15)	(0.33)
Cumulative Waiting Hours (Units = Hours / 10)			0.10***	0.09**	0.09**	0.09**	0.09**	0.26**
			(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.12)
Cumulative Waiting Hours Squared			-0.01	0.01	0.01	0.01	0.01	-0.17
			(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.11)
Earned Income - Need					0.00	0.00	0.00	-0.23
					(0.07)	(0.07)	(0.07)	(0.17)
Dummy if Earned Income > Need		0.03***		0.03***	0.03***	0.03***	0.03***	0.06**
		(0.01)		(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
(Dummy if Earned Income > Need) * (Income - Need)					0.04	0.04	0.04	0.14
					(0.10)	(0.10)	(0.10)	(0.34)
Lottery Day * Won big lottery prize earlier in the day					-0.01	-0.01	0.00	0.01
					(0.01)	(0.01)	(0.02)	(0.03)
(Dummy if Earned Income > Need) * Lottery Day * Won big lottery prize earlier in the day						0.02		
						(0.04)		
Lottery Day * Lottery pushed total cumulative income over need							-0.01	-0.02
							(0.03)	(0.04)
Observations	38,107	33,810	38,107	33,810	32,854	32,854	32,854	1,772
Number of IDs	259	259	259	259	259	259	259	196
R-squared	0.23	0.23	0.23	0.24	0.24	0.24	0.24	0.25
Mean of Dep. Var.	0.0877	0.0864	0.0877	0.0864	0.0862	0.0862	0.0862	0.0697

Notes: This table replicates Table 5 but including hour of the day fixed effects. See Table 5 notes.

Table A6. Responses to Wage variation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Extensive margin		Intensive margin					
	Worked Today	Total Income	Log (Total income)	Number of passengers	Total hours	Passengers per hour	Total time spent carrying passengers	Fare per hour carrying
Panel A. Expectations of wage based on prior realizations								
Log (cash need)	-0.01	10.44***	0.10***	0.20***	0.25***	0.01	0.17***	1.24**
	(0.01)	(2.39)	(0.01)	(0.04)	(0.06)	(0.01)	(0.03)	(0.59)
Won big lottery prize today	0.01	4.38	0.03	0.03	0.06	-0.01	0.05	-1.03
	(0.02)	(5.24)	(0.04)	(0.12)	(0.15)	(0.01)	(0.05)	(1.21)
Won big lottery prize yesterday	-0.01	-4.60	-0.02	0.04	0.07	0.02	-0.01	-0.41
	(0.02)	(4.79)	(0.03)	(0.10)	(0.09)	(0.02)	(0.05)	(1.85)
Expected wage: (Log) Average hourly earnings	0.08*	38.86***	0.27***	0.42*	-0.66*	0.10***	0.43***	7.59**
on similar days in the past	(0.04)	(11.25)	(0.05)	(0.25)	(0.34)	(0.04)	(0.14)	(3.18)
Gap: Realized wage[a] - Expected wage	0.10***	47.94***	0.20***	0.38**	-0.84***	0.13***	0.31***	5.69***
	(0.03)	(9.12)	(0.05)	(0.19)	(0.27)	(0.03)	(0.11)	(2.10)
Observations (individual-days)	8,241	8,130	6,676	6,791	6,739	6,739	6,674	6,677
Number of IDs	257	257	257	257	257	257	257	257
R-squared	0.12	0.07	0.05	0.04	0.03	0.02	0.03	0.01
Mean of Dep. Var.	0.82	119.04	4.81	4.42	8.78	0.55	2.36	68.38
Std. Dev. of Dep. Var	0.38	101.83	0.58	2.20	2.82	0.35	1.33	25.26
Panel B. Using "market days" as proxy for expected higher-wage days								
Log (cash need)	-0.01*	11.97***	0.12***	0.23***	0.30***	0.00	0.20***	1.17*
	(0.01)	(2.26)	(0.01)	(0.04)	(0.06)	(0.01)	(0.03)	(0.62)
Won big lottery prize today	0.00	2.12	0.02	0.01	0.02	-0.01	0.05	-1.10
	(0.02)	(4.81)	(0.04)	(0.11)	(0.14)	(0.01)	(0.05)	(1.20)
Won big lottery prize yesterday	0.00	-3.26	-0.01	0.09	0.16	0.01	0.02	-0.33
	(0.03)	(4.84)	(0.03)	(0.11)	(0.12)	(0.02)	(0.05)	(1.85)
Market day	0.02	11.09***	0.06***	0.31***	0.44***	-0.01	0.14***	0.39
	(0.01)	(2.66)	(0.02)	(0.07)	(0.08)	(0.01)	(0.04)	(0.52)
Log (realized wage[a])	0.09***	55.53***	0.29***	0.56***	-0.81***	0.14***	0.42***	5.16***
	(0.03)	(8.48)	(0.06)	(0.20)	(0.22)	(0.03)	(0.11)	(1.95)
Observations (individual-days)	9,362	9,234	7,594	7,727	7,669	7,669	7,589	7,591
Number of IDs	258	258	258	258	258	258	258	258
R-squared	0.10	0.07	0.05	0.04	0.03	0.02	0.03	0.01
Mean of Dep. Var.	0.83	119.12	4.81	4.40	8.84	0.55	2.35	68.57
Std. Dev. of Dep. Var	0.38	100.55	0.58	2.20	2.83	0.35	1.32	25.34

Notes: Regressions are OLS regressions at the individual-day level. All regressions include individual fixed effects and control for week and day of the week fixed effects. Regressions also control for whether it rained in the area around the stage, separately for the morning and afternoon, and whether the respondent reports being sick that day. We have fewer observations for the hour variables since the stopping time was left blank in some cases. Standard errors are in parentheses, clustered at both the individual and date level. ***, **, * indicates significance at 1, 5 and 10%.

[a] The realized wage is the average hourly earnings that day for all stage drivers but self.

Table A7. Elasticity of labor supply with respect to earnings opportunities

	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)	OLS (7)	IV (8)
	Log (hours)		Log (Number of passengers)		Log (Passengers per hour)		Log (time spent carrying passengers)	
Log (wage)	-0.31***	-0.29***	0.25***	0.33***	0.55***	0.62***	0.49***	0.52***
	(0.02)	(0.07)	(0.02)	(0.09)	(0.02)	(0.06)	(0.03)	(0.10)
Log (cash need)	0.01***	0.01***	0.01**	0.01**	-0.00	-0.00	0.02***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Won big lottery prize today	0.03	0.03	0.03	0.03	-0.00	-0.00	0.05*	0.05*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Won big lottery prize yesterday	-0.01	-0.01	0.01	0.01	0.03	0.03	-0.01	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
Observations (individual-days)	8,286	8,283	8,254	8,251	8,254	8,251	8,281	8,278
Number of IDs	259	259	259	259	259	259	259	259
R-squared	0.18	0.18	0.12	0.12	0.42	0.41	0.24	0.24
Mean of Dep. Var.	2.11	2.11	1.38	1.38	-0.73	-0.73	0.69	0.69
Std. Dev. of Dep. Var	0.44	0.44	0.51	0.51	0.54	0.54	0.60	0.60

Notes: Regressions are at the worker-date level. Wage instrumented with the wage of other drivers in the same stage. Log (cash need) is measured in Log(Ksh). All regressions include individual fixed effects and date fixed effects. Regressions also control for whether it rained and the respondent reports being sick that day. Standard errors are in parentheses, clustered at both the individual and date level. ***, **, * indicates significance at 1, 5 and 10%.

Table A8: Model Calibration: Parameter values and source

Parameter	Value	Source
δ	0.957^(1/365)	Angeletos et al (2001)
β	0.7	Angeletos et al (2001) (β = 1 no hyperbolic)
t_r	0.5	Average ride length in the data
t_w		Drawn from data distribution
r	0.01 %	Daily equivalent of a yearly 5% Standard Chartered Bank Kenya
f	30	Average fare in the data for rides around t_r
T		Drawn from data distribution
ϑ_r	5	Jointly chosen to match average daily hours of Neoclassical drivers
ϑ_w	17	
λ	0.12	Chosen to match hours of drivers exhibiting earned income targeting

Table A9. Covariates of Earned Income Targeting Behavior

Dep. Var:	Dummy =1 if β_{hat} >0.07 & one-sided p-val<0.1 in total hours analysis (Table 4 col 6)
More loss averse: Refuses the 50-50 gamble	-0.086
(win 30 or lose 10)	(0.074)
Less risk averse: Amount invested (out of 100 Ksh)	-0.002*
in Risky Asset	(0.001)
Impatience measure: Amount needed in 2 days	0.084
in order to forego payment today	(0.063)
Present-Bias	0.104
	(0.099)
Future-Bias	0.199**
	(0.095)
Extremely impatient in both present and future	-0.011
	(0.086)
Age in years (/10)	-0.027
	(0.054)
Self-reported health level (1-5 scale)	0.009
	(0.044)
Experience working as boda (in years)	0.004
	(0.008)
Does not own bike, rent one	0.249***
	(0.084)
Has other source of regular income	-0.026
	(0.091)
Number of children in household	-0.011
	(0.019)
Number of adults in household	0.028
	(0.063)
Years of education	-0.008
	(0.015)
Share of days report need	0.261
	(0.311)
Average amount of daily need (/100)	0.054**
	(0.022)
Std. Dev. of need (/100) across days	-0.047**
	(0.020)
Observations	235
R-squared	0.126
Dep. Var. Mean	0.328

Notes: See text section 4.5 for definitions of the dependent variables and notes to Table 1 for definitions of independent variables. All those drivers with an estimated beta that is significantly greater than zero at the 10% level in a one-sided test turn out to have a beta greater than 0.07.

Table A10. Effect of Personal and Household Cash Needs on Daily Labor Supply

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
			If worked:									
	Worked Today		Log (Total income)		Number of passengers		Total hours		Passengers per hour		Total time spent carrying	
Has a personal need	0.13***		0.02		0.09*		0.10*		0.01		0.07**	
	(0.01)		(0.01)		(0.05)		(0.05)		(0.01)		(0.03)	
Has a household need	0.13***		0.01		0.08		0.25***		-0.01		0.01	
	(0.01)		(0.02)		(0.06)		(0.09)		(0.01)		(0.04)	
If has a personal need:		0.000		0.11***		0.23***		0.30***		0.000		0.21***
log (cash need)		(0.01)		(0.01)		(0.04)		(0.06)		(0.01)		(0.03)
If has a household need:		-0.01*		0.11***		0.22***		0.30***		0.000		0.19***
log (cash need)		(0.01)		(0.01)		(0.04)		(0.06)		(0.01)		(0.03)
p-value for test personal = shared	0.90	0.00	0.69	0.75	0.86	0.34	0.07	0.63	0.03	0.16	0.16	0.09
Observations (individual-days)	10,862	8,486	8,542	7,099	8,719	7,225	8,626	7,169	8,626	7,169	8,536	7,096
Number of IDs	259	258	259	258	259	258	259	258	259	258	259	258
R-squared	0.21	0.21	0.15	0.18	0.16	0.19	0.16	0.18	0.11	0.13	0.13	0.15
Mean of Dep. Var.	0.80	0.85	-2.10	-2.10	4.38	4.41	8.83	8.86	0.55	0.55	2.36	2.35
Std. Dev. of Dep. Var	0.40	0.36	0.59	0.58	2.21	2.21	2.85	2.82	0.36	0.35	1.33	1.32

Notes: Personal needs include bicycle repairs and ROSCA contributions. Households needs include food and school fees. Regressions are at the individual-day level. All regressions include individual fixed effects and stage-date fixed effects. Regressions also control for whether the respondent reports being sick that day, and whether he won the lottery that day. Standard errors are in parentheses, clustered at both the individual and date level. ***, **, * indicates significance at 1, 5 and 10%.

Table A11. Parametric Hazard Regressions for Personal and Shared Needs

	(1)	(2)
	Dependent variable: quit after dropping off passenger	
	Personal needs	Shared needs
Cumulative Carrying Hours (Units = Hours/10)	0.25**	0.26***
	(0.11)	(0.09)
Cumulative Carrying Hours Squared	0.44**	0.28*
	(0.21)	(0.16)
Cumulative Waiting Hours (Units = Hours/10)	-0.15***	-0.11**
	(0.05)	(0.05)
Cumulative Waiting Hours Squared	0.52***	0.46***
	(0.07)	(0.06)
Earned Income - Need	0.01	0.02
	(0.10)	(0.10)
Dummy if Earned Income > Need	0.04***	0.04***
	(0.01)	(0.01)
Dummy if Earned Income > Need * (Income - Need)	0.03	0.12
	(0.14)	(0.15)
Won big lottery prize	-0.01	0.01
	(0.02)	(0.02)
Observations (individual-days)	16,601	23,873
Number of IDs	257	256
R-squared	0.15	0.15
Mean of Dep. Var.	0.08	0.08

Personal needs include bicycle repairs and ROSCA contributions. Households needs include food and school fees. All regressions include individual fixed effects and controls for week and day of the week fixed effects. Standard errors clustered at the individual level in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% respectively.

Appendix B: Relationship between reduced form results and prior literature

The most striking and controversial result in prior work is the finding by Camerer et al. (1997) of a *negative* wage elasticity among taxi cab drivers – because of income targeting, workers worked less on days with more earnings opportunities. This result has been re-examined in several papers, including Farber (2005, 2008, 2015). In this section, we replicate these results and discuss how our findings relate. We stress that the specifications in this section raise some concerns, so we interpret them only as supportive evidence.

To start, we follow the convention of constructing a "wage" as income divided by hours, i.e. average hourly earnings. Since an individual's own average earnings is endogenous, we follow the literature and use the average "wage" of other workers at the same market on the same day (which we denote $\bar{e}^h_{s(i)t}$). We also augment the specifications used by previous authors to include *expected* hourly earnings $E(e^h_{s(i)t})$, which we construct in 2 ways. First, we use own realizations on the same day in prior weeks, à la Crawford and Meng (2011). Second, we use market days (during which realized wage rates are empirically higher, suggesting the supply does not fully adjust to the increased demand for ride from market customers). Putting this all together, we run the following regression:

$$L_{it} = \beta_1 \bar{e}^h_{s(i)t} + \beta_2 E(e^h_{s(i)t}) + X_{it}\delta + \eta_t + \mu_i + \epsilon_{it} \tag{5}$$

where the dependent variable is a measure of daily labor supply for individual i at date t, and the vector X_{it} includes time-variant covariates. We include fixed effects for the worker and date are included, and cluster standard errors at the individual level.[32]

As discussed extensively in Farber (2005), estimating an equation like (5) only makes sense if the average hourly earning are sufficiently autocorrelated within the day: the current rate should only influence quitting behavior if it meaningfully predicts expected earnings going forward. We examine the autocorrelation in earnings opportunities in Figure A1b, in which we plot hour-by-hour average imputed wages, by quartile of the wage distribution between 7 and 10 am (these are averaged at the stage level). We find that days that are in the top quartile of earnings potential in the first three hours of the morning have on average a higher earnings potential throughout the day, though the magnitude of the gaps is fairly

[32] Identification of this equation rests on the assumption that variations in $\bar{e}^h_{s(i)t}$ are exogenous to individual labor supply. There are reasons to be concerned that this is not true. For example, if there is a correlated negative supply shock, aggregate supply will fall, and the "wage" will rise. To address these sorts of issues, we would ideally have a shock to the supply of other drivers. Unfortunately, as in most of the prior literature, there is no such instrument available here. One possible instrument would be the needs of other drivers. This is too weak for use here, as we have data on only a subset of all the drivers in any given stage.

small. This raises further caution when interpreting results.

Based on the predictions of Köszegi and Rabin (2006), we expect $\beta_2 > 0$ (people should work more when they expect the wage rate to be higher) and $\beta_1 < 0$ (earlier quits when hourly earnings are higher than expected).

Results are presented in Table A6. Panel A presents the results using rational expectations based on prior experience and Panel B using the market day dummies. There are three main results. First, our earlier findings with respect to the impact of the cash need on labor supply are unchanged when controlling for the wage rate (both expected and realized). Second, workers are more likely to work on days when expected earnings are higher, a result similar to Oettinger (1999) and Fehr and Goette (2007). Third, evidence on the intensive margin is mixed. Conditional on working, workers earn more income, have more passengers, and spend more time riding when earnings opportunities are higher. However, they quit earlier on such days, supplying less total hours. On the intensive margin, then, the elasticity of hours with respect to earnings opportunities is negative (replicating the negative "wage elasticity" in Camerer et al. and others). In Table A7 we include the instrumental variable regression like Farber (2015), and also obtain a negative "wage elasticity".

Appendix C: Robustness of need measures

This section discusses two potential threats to the analysis above. First, there may exist experimenter effects, given the high frequency and nature of the data collected. Second, it might be possible that the timing of cash needs is endogenous.

Experimenter effects

The log asked individuals to record their cash need at the beginning of every day. Besides the potential goal setting effect discussed in Section 5, one may worry that simply asking this question made that specific amount salient in respondents' minds. It is also possible that respondents felt an experimenter demand effect, i.e. that respondents believed that the researchers expected them to work up to the need, and then quit thereafter. In this section we argue that these two types of experimenter effects are unlikely to be driving our results.

The most convincing test of the presence of such experimenter effects would be if we had a comparable group of bicycle taxi drivers who were asked to fill logs similar to those we used, except for the question on the daily cash need. We could then check whether workers who were not asked to state their cash need still exhibit a positive relationship between expected demands on income (e.g. ROSCA payments due) and labor supply. Though we cannot test this directly since all of the workers in our study were asked about the need, we can compare the variance in hours we observe in our sample to that of bicycle taxi drivers followed in Dupas and Robinson (2013). While that data was collected between 2006 and 2008 (i.e. 1 to 3 years earlier than the present study), it was collected using almost identical logbooks except that they did not include the question on the day's needs. Interestingly, we find comparable (and if anything, *larger)* within-worker variance in hours worked across days in that earlier sample: 2.74 compared to 2.16 in the sample considered in the present paper. This at least suggests that the large within-individual variance in daily labor supply observed in the present study is not an artifact of our data collection protocol.[33]

A second way to test whether the data collection made needs particularly salient is to check how persistent the effects are. If people were not income targeting at all before the study, but then began to do so after keeping the logs since the cash needs became salient, then such respondents would eventually have switched back to their previous behavior after some time. When we run the hazard analysis separately for the first and last month during which individuals were keeping the logs, however, we find the exact same pattern of results, with the same magnitude, for both time periods, suggesting no fading out.

[33] One question which we cannot answer is whether keeping any type of log in the first place affects behavior.

Endogenous timing of needs

While many of the determinants of the cash needs reported by our study participants are almost certainly exogenous and unexpected (e.g. health shocks, funerals), some can be anticipated (e.g. food for the household). For such anticipated needs, workers may choose the days in which they decide to "deal" with those – for example, they may decide to purchase food on the day they expect to make more money, or they may decide to pay school fees on the day they wake up feeling in particularly good health. If that is the case, workers would mechanically report higher needs on days in which they expect to make more money, explaining the positive correlation we observe between needs and labor supply. While this may be the case on the extensive margin – on Sundays, which is much less likely to be a work day than other days, respondents typically report smaller cash needs – this does not appear to be the case on the intensive margin. What's more, as shown in Table A2, people report needs such as savings club payments exactly on the days in which these are paid (and these savings club payments are on fixed schedule that workers cannot unilaterally decide on). Finally, if we restrict the sample to individual-days with only unexpected needs, we see the same pattern of results.

Ex-post rationalization of labor supply

Another concern is that people may have felt that they were "supposed to" make at least as much as the need, and therefore filled in the needs at the end of the day to match whatever they made that day. There are several pieces of evidence against this. First, respondents were of course instructed to fill the log in order. During weekly recall surveys we checked whether the logs were correctly filled (i.e. whether the log had been filled up to the current time) and only paid respondents who had done so, building incentives to fill the log in order throughout the day. Second, reported needs are highly correlated with shocks reported in the weekly survey. Third, the reduced form relationship between shocks and labor supply exists, and this analysis does not rely on the reported need amount. Fourth and most important, while the amount that people earn is correlated with the need, it is not the case that people often report earning just barely enough to cover the need. In fact, people only make enough for the need on 41% of days, and only make 20 Ksh or less over the need 8% of the time. This is consistent with the model predictions – if the need is sufficiently low or the wage is sufficiently high, people will continue to work beyond the need level.

Appendix D: Model

We present in this section the equations and details of the proposed theoretical model. The pay-off for the driver is:

$$E_t \left[U(c_t, h_t) + \beta \sum_{i=1}^{\infty} \delta^i U(c_{t+i}, h_{t+i}) \right]$$

where c is consumption, h the number of rides, δ is the discount factor and β represents the present-bias discount factor. We allow for present-bias in the model to be as general as possible, but we simulate the model under both the nested case of no present bias ($\beta = 1$) and the present-bias case in the simulation exercise.

We assume the bike-taxi driver starts the day with some savings from the previous days (s), and given level of anticipated cash need (c_a). He learns the unanticipated cash need for the day (c_u), and observes the waiting time between rides for the day (t_w). He sets a target $T = c_a + c_u$ for the day (and knows he will set targets every day after that), and decides optimally the number of rides to do that day, or equivalently when to quit, given his expectations on the needs (hence targets) and waiting time realizations in the future.[34] The evolution of the savings variable is given by $s' = (s + hf - c)(1 + r)$ where f is the fare per ride and r is the interest rate. To solve numerically and include credit constraints we assume $s_{min} \leq s \leq s_{max}$.

The driver is naive about his present-bias and thinks that tomorrow he will decide optimally the number of rides h' to do that day:

$$V(s', c'_u, h') = \max_{h', c'} U(c', h') + \delta E \left[V(s'', c''_u, h'') \right]$$

But today (and when tomorrow arrives) he uses a different decision function due to the presence of the present bias discount factor β:

$$W(s, c_u, h') = \max_{h, c} U(c, h) + \beta\delta E \left[V(s', c'_u, h') \right]$$

Recall from above that the target T is a function of the day's need: $T = c_a + c_u$, thus while the worker is a "broad bracketer" for all other aspects, the target is set under narrow bracketing: workers anticipate tomorrow's cash needs in today's labor supply decision, but not in today's target. Narrow bracketing for goal setting (which we observe empirically) may

[34] Allowing for spontaneous reoptimization within the day does not change things, because we do not allow the wage rate to change in an observable fashion within the day, thus the optimal number of rides planned at the begining of the day ($h^*(s, c_u, t_w, 0)$), is equal to the optimal number of rides he plans to do after i rides ($h^*(s + fi, c_u, t_w, i) + i$).

work well because the day's cash needs are exogenous from today's perspective, hence offer a readily available target that cannot be strategically manipulated or revised downwards as fatigue sets in.

For the utility of consumption we use a linear function:

$$u(c) = c$$

and for the disutility of labor we use

$$v(h) = \theta_{1r}(ht_r) + \theta_{2r}(ht_r)^2 + \theta_{1w}(ht_w) + \theta_{2w}(ht_w)^2$$

where t_r represents the average time a ride takes, and recall t_w represents the average waiting time between two rides (so a high t_w means a low wage rate that day). The reason for not using the standard disutility of labor is that we want to allow the physical effort of riding to have a different cost from that of waiting idle for the next ride, as evidenced by our findings above.