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The Daily Grind: Cash Needs, Labor Supply, and Self-Control

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Cash Needs, Labor Supply and Self-Control*

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Abstract

We use detailed observational data constructed from daily passenger-level logbooks and weekly surveys to study the intertemporal labor supply decisions of Kenyan bicycle taxi drivers, while generating variation in cash on hand through randomized cash payouts. We document three key facts: (1) drivers work more in response to both unexpected and expected cash needs; (2) drivers discontinuously increase the probability of quitting once they have reached their day's cash need; but (3) randomized cash payouts have no 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 about 5% more than they would with neoclassical preferences. We propose a model and interpretation of earned income targeting as morphine: it partially numbs the effort cost until the target is reached.

JEL Codes: C93, D12, J22

Keywords: intertemporal labor supply, reference-dependence, income targeting

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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 include 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 discontinuously 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.[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 shoppers on the labor supply choices of vendors in India.

Our findings are not entirely consistent with any existing model of intertemporal labor supply. We consider three standard models: (1) the neoclassical model with functioning savings and credit markets; (2) the neoclassical model without functional version of those markets; and (3) a reference-dependent model where workers have targets over income/consumption (Camerer et al. 1997; Köszegi and Rabin 2006). Model (1) is clearly rejected, since entirely predictable cash needs should not affect labor supply and there should not be daily income effects. Model (2) is not consistent with the data, either – while this model generates a positive response of work hours to needs, it also predicts a response of labor supply to the windfall payments. Model (3) is rejected by the lack of effect of the windfall payment.

What then explains our results? As an alternative, we propose a model in which bike taxi drivers have reference-dependent preferences around an *earned* income target, which itself is a function of the period's cash needs. We write two versions of the model, which differ in how the reference-dependence term appears in the utility function. In our preferred variant, the reference dependence term is embedded in the effort cost function – it mitigates the effort cost proportionally until the target is reached. We call this the morphine or painkiller model. The second variant models the reference dependence term as a level effect, namely, a "boost" in utility if the target is reached.

We calibrate both variants of 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 5.2% less income (this is the case under both variants of the model). 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. The welfare implications of these preferences are less clear-cut than the effect on income, and depend on whether the tendency to react to mental targets reflects true experienced utility or is a mistake (Köszegi, 2010). If the morphine model represents true hedonic utility (such that effort costs are truly less harmful below a target), then welfare is increased.

How are targets themselves set? Our evidence clearly suggests a role for cash needs, but what else matters? The model of Köszegi and Rabin (2006) suggests that targets should depend on expectations about daily income and on expected hours of work. We employ the method of Crawford and Meng (2011) of testing this, which involves proxying for the targets based on behavior on previous (comparable) days. We find evidence that both expectationbased targets (expected hours and expected income) predict quitting behavior, as well as the day's cash need. This implies that the target is a complicated function of expectations and goals. We leave further investigation of need setting to future work.

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. While a number of papers do 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. 2016 for fishermen),[3] others do not. For example, Oettinger (1999) and Goldberg (2016) find positive extensive margin elasticity to wage increases among stadium vendors in the US and day laborers in Malawi, respectively, while a series of papers by Henry Farber raise questions about the original specifications in Camerer et al. (Farber 2005), and whether these hold in a large sample of drivers (Farber 2014) (however, Farber does find some mixed evidence for reference-dependence in Farber 2008).

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 was 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.

[3] 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.

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 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 logs were collected between September and December.[4] 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.

[4]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.

2.3.1 Baseline Survey

Each individual who was enrolled in the study was administered a baseline survey.[5] 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.[6]

2.3.2 Logs

Building on the successful use of logs in previous studies in the same area 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 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.[7]

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.[8] 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."[9] 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.[10]

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

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

[6] 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.

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

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

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

[10] There are several potential problems with people self-reporting needs, which we discuss in Appendix B.

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). The weekly survey also includes more details on health shocks (including symptoms), making it possible to cross-validate the health shock 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]

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% change 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).

Each boda was sampled to participate in at least one and up to four lotteries over the course of two months.[14] If a participant could not be located on a given lottery day, he was

[11]In the interest of time, expenditures were not recorded.

[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, 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, the survey team implemented audit and backchecking procedures.

[14]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.

never told about the lottery he missed.[15]

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 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 2.5 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

[15] As would be expected, almost all respondents who were invited played the lottery that day – only 4% of respondents who were invited chose not to play the lottery.

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).

From Panel A, respondents work on 80% of (non-Sunday) days in our sample. Conditional on working, average income is 145 Kenyan shillings (Ksh), or around $2 per day. Consistent with Table 1, bike taxiing is the primary source of income – respondents received other income on 31% of days.

Conditional on working, bike-taxis work 8.8 hours on average, but 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 consistency 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 truly 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 Correlates of needs

How are needs themselves set? 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), 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 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 cash needs, suggesting that workers report cash needs on the day they bind.

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 further helps to rule out endogenous reporting of needs.

3 Results

3.1 Reduced form: 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. 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 the effort costs of riding with a passenger are likely higher than for waiting for passengers between rides. In the theoretical model section, we take effort costs as being linear in the time without passengers and quadratic in the time with passengers. Here we present results for both the total time spent on the job (total hours) and the effort expended on the job (total passengers, 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 x date fixed effects as in Tables A1 and 3. Unsurprisingly, 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 100% increase 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 completely consistent with such a model: winning a large payout in our experimental lottery has no impact on any measure of labor supply, be it on the day of the lottery or the following day (see rows 3 and 4 in Panels A/B of Table 4).

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 target will be downwardly biased.

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).[16] If the needs serve as targets, 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.[17] 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).[18]

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 but in support of our results, we find a positive and significant effect of cumulative income on quitting behavior.

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 three important conclusions from the coefficient estimates in this specification, shown in column 2 of Table 5: (1) cumulative income matters for quitting behavior even while controlling more flexibly for running hours; (2) as expected, the effort cost of riding with customers appears higher than the effort cost of waiting for customers (see Figure A1a which plots the estimated functions by type of effort); (3) waiting time is positively correlated with quitting – in other words, the opportunity cost of time for workers in our sample is far

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

[17]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.

[18]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).

from zero.

We then estimate the following equation:

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

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 column 3 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 4, we estimate a model where instead of controlling for the lottery win dummy BP_{ipt}, we instead include a dummy for whether cumulative total income (earned income + lottery win earlier that day) has crossed the need threshold. This does not affect γ_1, the coefficient of interest, 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 5 we restrict the sample to rides on lottery days only. This considerably shrinks the sample size 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.

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.[19,20]

3.3 Labor supply responses to earning opportunities

As discussed extensively in Camerer et al. (1997), an important implication of targeting is that the wage elasticity will be reduced compared to the standard inter-temporal labor supply model. In a field experiment where the wage rate for bike messengers was temporarily raised, Fehr and Goette (2007) find a negative elasticity of effort per hour among individuals with loss averse preferences, and show this is consistent with a model of reference dependent preferences in which workers exhibit loss aversion around a target income level.

In this section we discuss our evidence regarding the relationship between labor supply and earning opportunities in our dataset. Since we do not have randomized variation in either expected or unexpected earnings opportunities, our "wage elasticity" results should be seen as at most descriptive – we show them only for comparison with the earlier literature.[21]

In earlier work, authors have constructed a "wage" by dividing income by hours, i.e. average hourly earnings. Though this is not really a wage, we follow the convention of the earlier literature and refer to it as such in this section. Since an individual's own average earnings is endogenous, we follow Camerer et al. (1997) and construct realized average earnings per hour that are potentially exogenous to the individual by taking the average of all of the other taxis in that stage (market center), $\bar{e}^h_{s(i)t}$. The literature estimates a labor supply equation similar to the following:

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

where the dependent variable is a measure of daily labor supply for individual i at date t, the vector X_{it} includes time-variant covariates, and fixed effects for the worker and date are included.

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.

[19] 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.

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

[21] Camerer et al. (1997) and many subsequent papers refer to their estimates as estimates of "wage" elasticities. In our context, however (and in most of these earlier papers), there is no wage. Bike taxis are paid a piece rate (the fare) for a ride, and there is typically no variation in the fare over time – this is akin to a traditional taxi cab in a developed country, where the fare is a time-invariant function of time in the cab and distance traveled, but in contrast to a system such as the "surge pricing" employed in Uber in which fares increase in busy periods (Chen and Sheldon, 2015).

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.[22]

What's more, 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. If the labor supply quickly adjusts to the prevailing wage rate, or if labor demand is negatively correlated across parts of the day, then fluctuations in the wage over the course of a day would make estimating equation (5) meaningless. 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 small. This suggests even more caution when interpreting results of estimating equation (5).

With these caveats in mind, we present some evidence by augmenting equation (5) by adding expected hourly earnings $E(e^h_{s(i)t})$:

$$L_{it} = \beta_1 \bar{e}^h_{s(i)t} + \beta_2 E(e^h_{s(i)t}) + X_{it}\delta + \eta_t + \mu_i + \epsilon_{it} \tag{6}$$

We include the day's cash need in the vector of covariates X_{it}. 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). We construct expected earnings in two ways. First, as above, 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)

Results are presented in Table 7. 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,

[22]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.

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).

Is this negative elasticity with respect to hours meaningful? We argue that it is, but the interpretation depends entirely on the value of a rider's time. 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 more on high-earnings day (which are days with lower waiting times). 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, suggesting that there is still some benefit to taking on more rides in a quicker period of time, since it lowers total hours worked for a given income level. We turn to this issue more formally in the next section.

4 Economic Significance and Rationale

4.1 Time costs of targeting

As discussed in the previous section, while there is no way of reallocating *effort* to increase income while holding total effort constant, workers could still reduce total hours by working more on high earnings days.

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 rules would yield in Figure 3. We find that the mean and median hours reduction would be 2.1% and 1.3%.[23]

[23] 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.

4.2 Proposed Model: Earned Income Targeting as Morphine

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 discontinuously 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 inconsistent with the neoclassical model and suggests an income targeting model may be more appropriate. On the other hand, result (iii) is not aligned with a basic daily income targeting model. Our results can thus only be explained jointly if there is some constraint on the fungibility between earned income and the experimental income shocks. We propose two such models, calibrate them, and use them 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. Specifically, 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. [24] 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.

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:

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

[24] 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 ($h^*(s + fi, c_u, t_w, i) + i$).

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

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

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 $g(c,h,T)$. Thus, in each period the utility function is of the form:

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

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 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 standard CES function:

$$u(c) = \frac{c^{1-\sigma} - 1}{1-\sigma}$$

and for the disutility of labor we use

$$v(h) = \theta_r (ht_r)^2 + \theta_w (ht_w)$$

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.

In our simulations, we present three potential functional forms for the gain-loss utility term,which we compare with each other and with the neoclassical model. 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 because it fits our data well and has a simple, intuitive interpretation, yet it is a departure from earlier interpretations of income targeting, 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. This can be seen easily if we rewrite total utility at each period in its mathematical equivalent of:

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

Formalizing it this way is on par with the psychology literature on goal setting.

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:

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

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

The third model we consider, which we call the "earned income targeting" model (labeled "Gain-Loss EI" in the figures), is a variant of the Köszegi and Rabin (2006) model above that is consistent with our data:

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

Both the painkiller model and the earned income targeting model generate a kink in the marginal utility of an extra ride once earned income has reached the target. We favor modeling the source of this kink as a boost in utility that comes from reduced effort costs below the target thanks to the painkiller effect, rather than as a loss if the target is not reached, because workers in our sample fail to reach their target more often than not. Presumably if they suffered a true utility loss each time they would start revising their targets downwards (i.e. aspiring to a lower consumption path) in order to avoid the loss more often.[25]

[25] The argument does not go both ways: workers cannot strategically set unreachable targets in order to always benefit from the painkiller effect because, as suggested by the psychology literature on goal setting, targets have be reasonable for them to act as reference points.

4.3 Calibration

To calibrate the models, 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) and waiting times (t_w) for our data. We assume that the cash need tomorrow can take two equally likely values $\{c_a, c_a + c_u^H\}$. We assume that the waiting time can take one of two equally likely values $\{t_w^L, t_w^H\}$.

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).

All parameters used in the calibration and their source are shown in Table A5. The only difference in the calibration between the painkiller model and the more standard gain-loss utility models (earned income targeting and consumption targeting) is in the reference-dependence factor λ.

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 four 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 two proposed models with a target on earned income, the painkiller version and the more standard targeting version. We present the simulation results in Figure 4 and A3. Figure 4 compares the painkiller model to the neoclassical and consumption target models. Figure A3 compares the more standard variant of the earned income targeting model to these other models.

In the top panels of both Figures 4 and A3, 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. 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 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, and as discussed in the previous literature, they yield a negative wage elasticity. 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 and A3, panels B1 and B2), as observed in our experimental data.

A direct consequence of having an earned income target is that it increases labor supply for sufficiently high needs, compared to the neoclassical model. This immediately follows from the gain-loss term in the utility function, and it is true whether or not the worker is present-bias. 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 A5).[26]

Another important feature of the simulation results is that, with the calibration that fit the data best, optimal savings levels are very low in 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 savings 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

[26]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 (e.g. below 100 Ksh), we also find no discontinuity.

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 satisfaction of meeting the need with their daily 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 8. For the Painkiller model, we estimate that even exponential discounters would earn 5.16% less income (the standard deviation across the 200 workers in the simulation is 2.82%) if they were in the counterfactual neoclassical world rather than target earners (for present-bias drivers, this figure is almost identical (4.99%), because the optimal savings are close to zero in both cases). The estimate for the Gain-Loss version of the earned income targeting model is a gain in income of 5.29% (with a standard deviation of 2.93%).

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 5% lower for neoclassical workers. This means that the numbing effect of goal setting is akin to a 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 1.8% less if they target consumption rather than income. Figure A4 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 62% of the cases (for needs within the range considered in the simulation), while in our painkiller model the percentage is 66%, suggesting a good fit. We 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.

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 what follows 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.

4.5 Who is a target earner?

Since our hazard analysis is done within-individual, we can run it separately for each individual, and thus estimate an individual-specific jump in the hazard of quitting at the need amount. We show the estimated coefficients in Figure 5. We then classify as "target-earner" anyone with a coefficient on "over need" in equation (4) above 0. With this definition, we find that 54% of the drivers in our sample are target earners. This decreases to 44% if we limit the definition of target earner to those with a coefficient on "over need" of at least 0.03, the estimate over the full sample. It further decreases to 24% if we restrict the definition to those with a coefficient on "over need" that is statistically significantly positive at the 10% in a one-sided test.

In Table A6, 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. These results, as well as the fact more generally that we do not seem to find clear predictors of target earning, 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.

5 Alternate hypotheses

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

5.1 Savings / credit constraints

One alternative is that workers are unable to smooth consumption across days because they lack access to credit or a safe place to save money. The strongest piece of evidence against savings constraints, however, is that such a situation would predict quitting when the lottery was received, which we do not find. Beyond this, it is ambiguous whether savings constraints could cause a discontinuous probability of quitting at the need. If needs were bulky and absolutely required (such as a recommended dosage of medicine for a sick child), reaching such needs would cause a discontinuous increase in quitting. However, many needs appear less bulky – for example, the dominant reported need is "food" and presumably food can be purchased in continuous quantities. Other needs also seem non-urgent, especially the category "nothing special." We re-run our hazard with these need amounts and observe similar results (though with limited precision due to the sample size reduction – results on request).

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. We view this as unlikely given that it is likely hard to observe each others' needs and income, but we check for this by examining how earnings opportunities vary with the cash needs of other workers at the stage. For each driver on each day, we calculate the percentage of other workers in that stage with a need on that day, and the average need amount (this is the same approach used to construct the realized market wage rate). We then regress income on this variable (controlling for the other variables of interest). We find that the coefficients for others' needs are insignificant in nearly all specifications. In any case, to the extent that effort costs are convex, such an insurance scheme would be dominated by simply providing cash payments to each other, rather than priority on rides.

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 A6 and A7).

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. Along those lines, we conjecture that people treat *earning enough for the 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 5% 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 may be able to smooth labor supply by taking on outlay commitments, for example by taking out loans with high-frequency repayment schedules or joining 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, 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 the needs themselves are set. 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.

References

[1] Abeler, Johannes, Armin Falk, Lorenz Götte and David Huffman (2011). "Reference Points and Effort Provision." *American Economic Review* 101 (2): 470-492.

[2] Agarwal, Sumit, Mi Diao, Jessica Pan, and Tien Foo Sing (2015). "Are Singaporean Cabdrivers Target Earners?" Unpublished.

[3] Allen, Eric, Patricia Dechow, Devin Pope and George Wu (2015). "Reference-Dependent Preferences: Evidence from Marathon Runners." Unpublished.

[4] Andersen, Steffen, Alec Brandon, Uri Gneezy, and John A. List (2014). "Toward and Understanding of Reference-Dependent Labor Supply: Theory and Evidence from a Field Experiment." NBER working paper No. 20695.

[5] Augenblick, Ned, Muriel Niederle and Charlie Sprenger (2015). "Working Over Time: Dynamic Inconsistency in Real Effort Tasks". *Quarterly Journal of Economics* 130 (3): 1067-1115,

[6] Bénabou, Roland and Jean Tirole (2004). "Willpower and Personal Rules." *Journal of Political Economy* 112 (4): 848-886.

[7] Camerer, Colin, Linda Babcock, George Loewenstein, and Richard Thaler (1997). "Labor Supply of New York City Cabdrivers: One Day At A Time." *Quarterly Journal of Economics* 112 (2): 407-41.

[8] Chen, M. Keith and Michael Sheldon (2015). "Dynamic Pricing in a Labor Market: Surge Pricing and Flexible Work on the Uber Platform". Mimeo, UCLA.

[9] Crawford, Vincent and Juanjuan Meng (2011). "New York City Cab Drivers' Labor Supply Revisited: Reference-Dependent Preferences with Rational-Expectations Targets for Hours and Income." *American Economic Review* 101 (5): 1912-1932.

[10] Chang, Tom and Tal Gross (2014). "How Many Pears Would a Pear Packer Pack if a Pear Packer Could Pack Pears at Quasi-Exogenously Varying Piece Rates?" *Journal of Economic Behavior and Organization* 99: 1-17.

[11] Chou, Yuan K (2002). "Testing Alternative Models of Labour Supply: Evidence from Taxi Drivers in Singapore." *Singapore Economic Review* 47 (1): 17–47.

[12] Dalton, P., S. Ghosal and A. Mani (2016), "Poverty and aspirations failure", *The Economic Journal* 126, 165-188.

[13] de Mel, Suresh, Christopher Woodruff and David McKenzie (2010). "Who are the Microenterprise Owners?: Evidence from Sri Lanka on Tokman v. de Soto. In *International Differences in Entrepreneurship*, J. Lerner and A. Schoar (eds.), pp. 63-87.

[14] Dupas, Pascaline and Jonathan Robinson (2013). "Savings Constraints and Microenterprise Development: Evidence from a Field Experiment in Kenya." *American Economic Journal: Applied Economics* 5 (1): 163-92..

[15] Farber, Henry (2005). "Is Tomorrow Another Day? The Labor Supply of New York City Cabdrivers." *Journal of Political Economy* 113 (1): 46-82.

[16] Farber, Henry (2008). "Reference-Dependent Preferences and Labor Supply: The Case of New York City Taxi Drivers." *American Economic Review* 98 (3): 1069-82.

[17] Farber, Henry (2014). "Why You Can't Find a Taxi in the Rain and Other Labor Supply Lessons from Cab Drivers." NBER working paper No. 20604.

[18] Fehr, Ernst and Lorenz Goette (2007). "Do Workers Work More if Wages Are High? Evidence from a Randomized Field Experiment." *American Economic Review* 97 (1): 298-317.

[19] Frankenberg, Elizabeth, James P. Smith and Duncan Thomas (2003). "Economic shocks, wealth and welfare." *Journal of Human Resources* 38 (2): 280-321.

[20] Giné, Xavier, Monica Martínez-Bravo, and Marian Vidal-Fernández (2016). "An Empirical Investigation of Daily Labor Supply: Evidence from South Indian Boat-owners." Unpublished.

[21] Goldberg, Jessica (2016). "Kwacha Gonna Do? Experimental Evidence about Labor Supply in Rural Malawi." *American Economic Journal: Applied Economics* 8(1): 129–149.

[22] Guth, W. and Yaari, M. (1992), "An Evolutionary Approach to Explain Reciprocal Behavior ¨ in a Simple Strategic Game, in: *Explaining Process and Change—Approaches to Evolutionary Economics*, U. Witt, Ed., Ann Arbor, 23–34.

[23] Jayachandran, Seema (2006). "Selling Labor Low: Wage Responses to Productivity Shocks in Developing Countries." *Journal of Political Economy* 114 (3): 538-575.

[24] Kaur, Supreet, Michael Kremer and Sendhil Mullainathan (2010). "Self-Control and the Development of Work Arrangements." *American Economic Review* 100 (2): 624-628.

[25] Kaur, Supreet, Michael Kremer and Sendhil Mullainathan (2015). "Self-Control at Work". *Journal of Political Economy* 123(6): 1227-1277

[26] Keniston, Daniel (2011). "Bargaining and Welfare: A Dynamic Structural Analysis of the Autorickshaw Market." Unpublished manuscript, Yale University.

[27] Kremer, Michael, Jean Lee, Jonathan Robinson and Olga Rostapshova (2013). "Behavioral Biases and Firm Behavior: Evidence from Kenyan Retail Shops." *American*

Economic Review (Papers and Proceedings Issue) 103 (3): 362-368.

[28] Kremer, Michael, Jean Lee, Jonathan Robinson and Olga Rostapshova (2015). "Rates of Return, Optimization Failures, and Behavioral Biases: Evidence from Kenyan Retail Shops." Unpublished.

[29] Kochar, Anjini (1995). "Explaining Household Vulnerability to Idiosyncratic Income Shocks." *American Economic Review* 85(2): 159-164.

[30] Kochar, Anjini (1999). "Smoothing Consumption by Smoothing Income: Hours-of-Work Responses to Idiosyncratic Agricultural Shocks in Rural India." *The Review of Economics and Statistics*, 81(1): 50-61.

[31] Köszegi, Botond (2010). "Introduction to Reference-Dependent Preferences: Economics for Neuroscientists Lecture". Last accesssed 2/23/2016 at: http://neuroeconomics.org/documents/Koszegi_Workshop2010.pdf

[32] Köszegi, Botond and Matthew Rabin (2006). "A Model of Reference-Dependent Preference." *Quarterly Journal of Economics* 121 (4): 1133-1165.

[33] Kyllo, L.B., & Landers, D.M. (1995). "Goal setting in sport and exercise: A research synthesis to resolve the controversy." *Journal of Sport and Exercise Psychology*, 17, 117-137.

[34] Oettinger, Gerald (1999). "An Empirical Analysis of the Daily Labor Supply of Stadium Vendors." *Journal of Political Economy* 107 (2): 360-92.

[35] Pope, Devin and Maurice Schweitzer (2011). "Is Tiger Woods loss averse? Persistent bias in the face of experience, competition, and high stakes." *American Economic Review* 101 (1): 129-157.

[36] Rabin, Matthew (2000). "Risk Aversion and Expected-Utility Theory: A Calibration Theorem." *Econometrica* 68 (5): 1281-1292.

[37] Robinson, Jonathan (2012). "Limited Insurance Within the Household: Evidence from a Field Experiment in Kenya." *American Economic Journal: Applied Economics* 4 (4): 140–164.

[38] Robinson, Jonathan and Ethan Yeh (2011). "Transactional Sex as a Response to Risk in Western Kenya." *American Economic Journal: Applied Economics* 3 (1): 35-64.

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

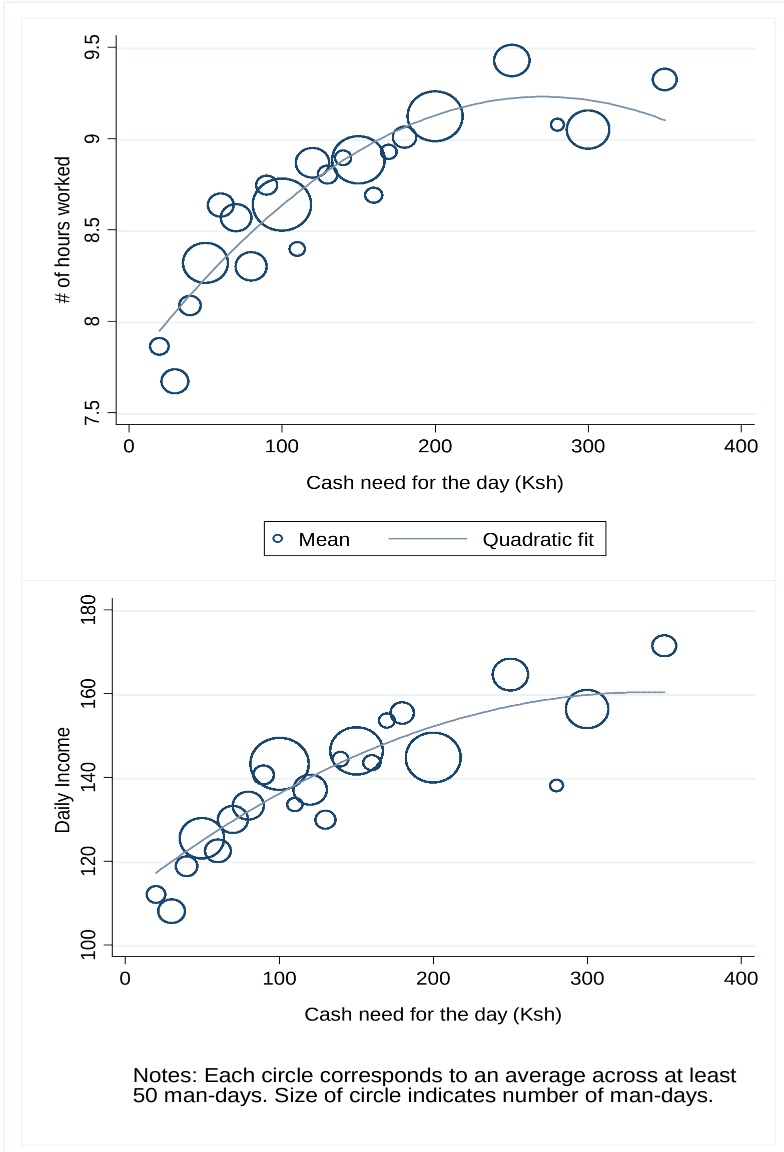


Figure 1B. Quitting behavior: Daily Cash Need vs. Running hours

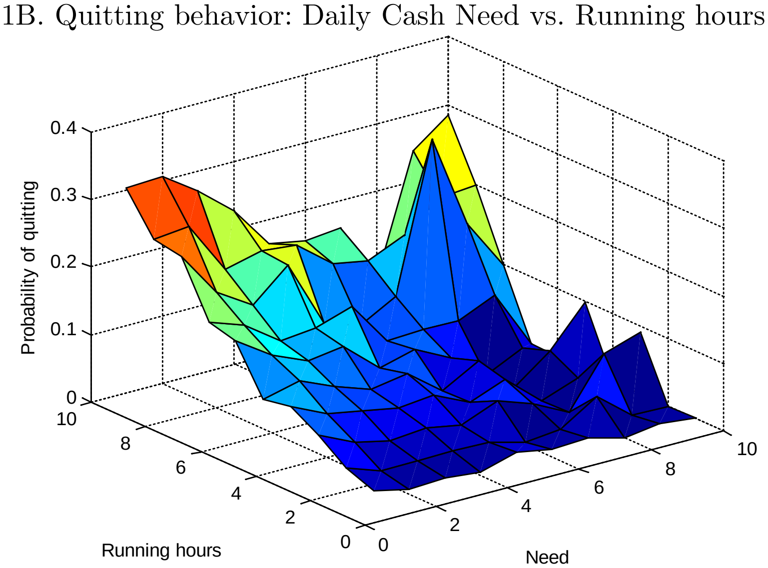
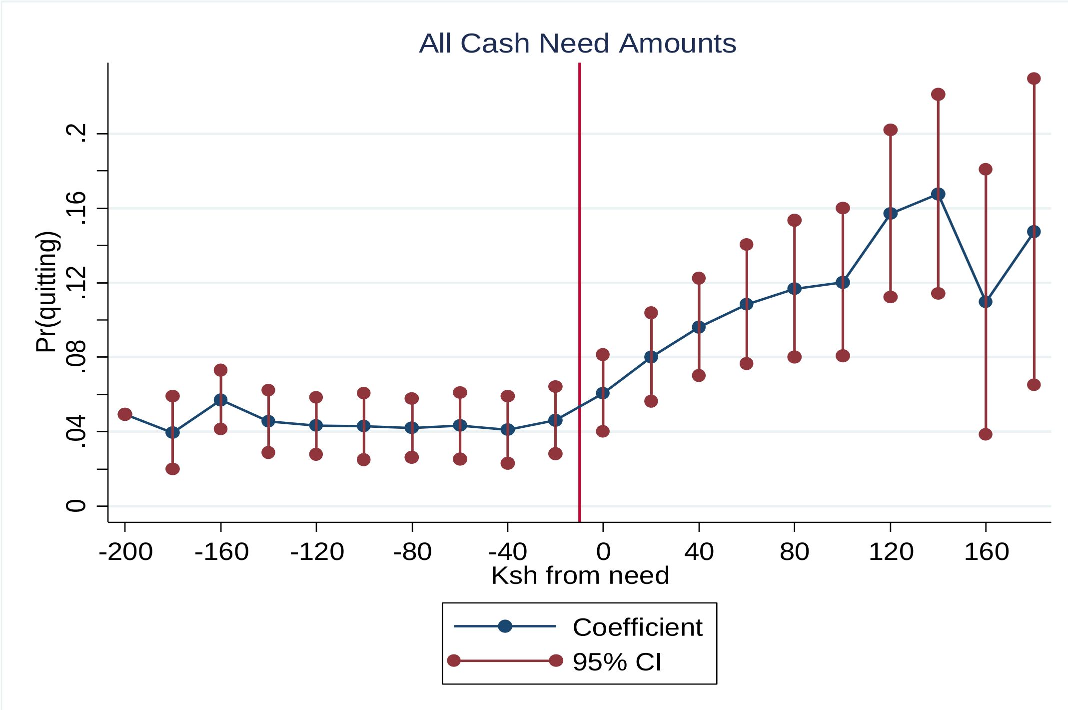
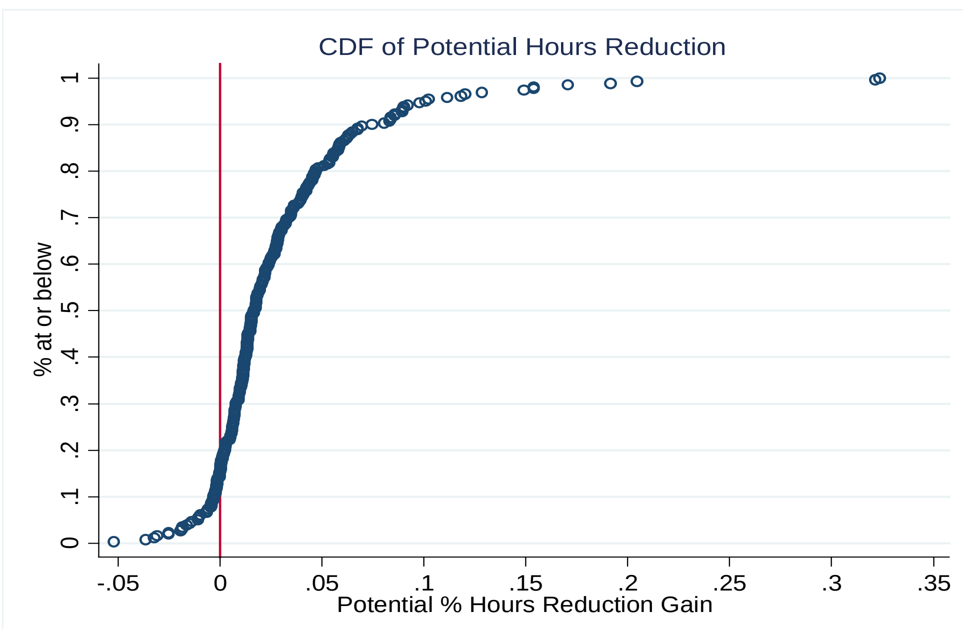


Figure 2. Coefficients from Hazard Regressions



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

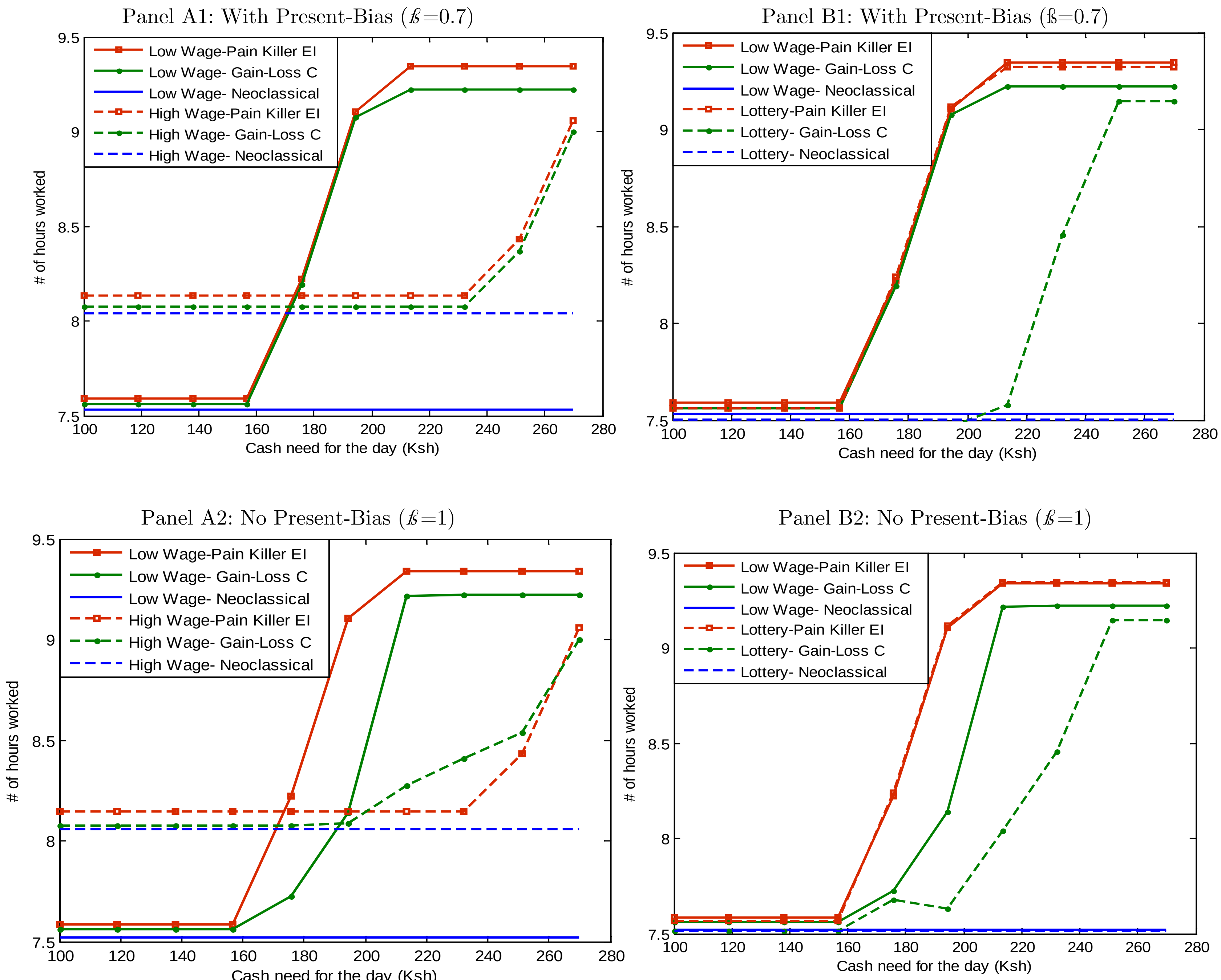


Notes: This graph shows the cumulative distribution function of the counter-factual hours reduction (as a percentage) workers could achieve by working a fixed hours schedule. For each individual, we calculated the number of hours they would have to work to earn the same income working a set number of 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)

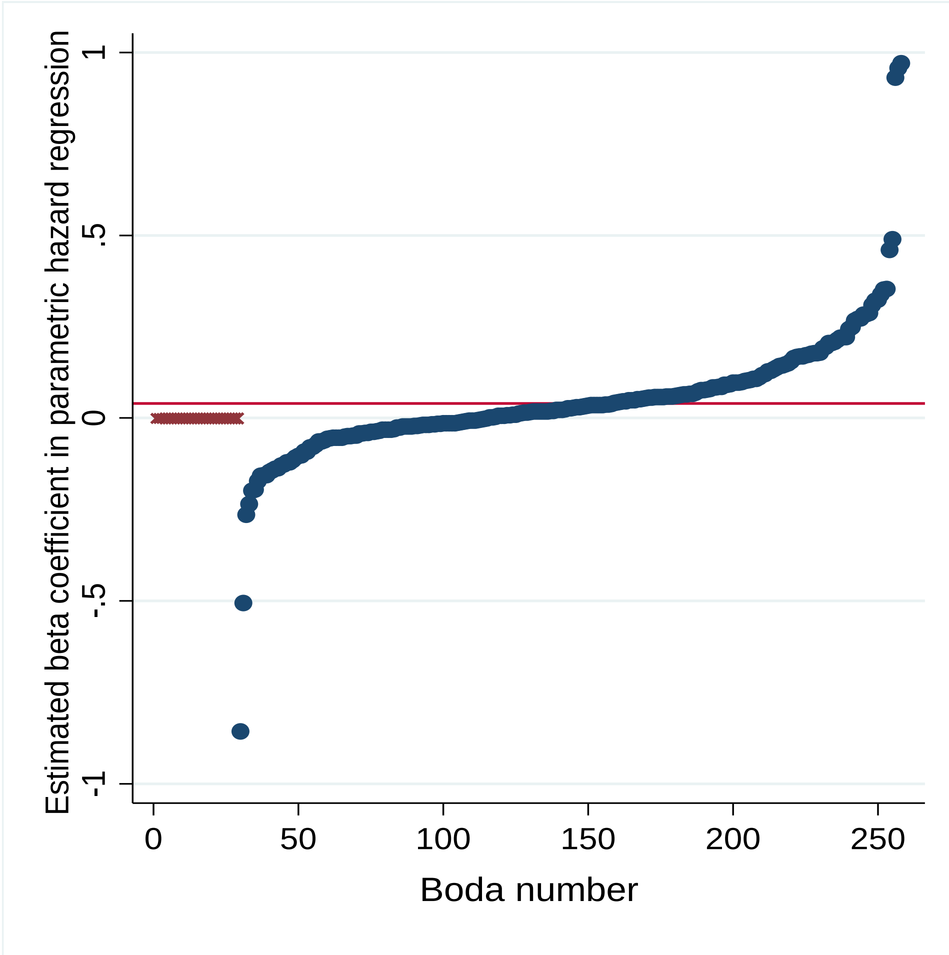
Panel A: Relation between Cash Need and Labor Supply

Panel B. Labor Supply and Cash Windfalls (Lottery Wins)



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).

Figure 5. Individually estimated effect of crossing the need on probability of quitting



Notes: See main text section 4.6.
The red line represents the estimated beta on the full sample.
The red Xs represent bodas for which no beta can be individually estimated because they never reach their need.

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. Small-Stakes Risk Aversion and Loss Aversion		
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 2. Day-Level Summary Statistics from Diaries (excluding Sundays)

	(1) Mean	(2) Std. Dev.
A. Labor Supply		
Worked today	0.80	0.40
If yes, total income (Ksh)	145	95
If yes, total hours	8.83	2.85
If yes, hours spent carrying a customer	2.35	1.33
Rented bike	0.17	0.38
Worked if Sunday	0.39	0.49
Received income from other activity	0.31	0.46
If yes, amount earned (Ksh)	71.53	472.52
B. Cash Needs as reported in Daily Log (Is there something in particular that you need money for today?)		
Yes	0.90	0.30
If yes, amount (Ksh)	204	334
Has need if Sunday	0.78	0.41
If has need: day's income exceeds need amount	0.41	0.49
If has need: day's income exceeds need amount by 20 Ksh or less	0.09	0.28
If has need: reported need (listed in the same order as survey options):		
Bicycle repairs	0.26	0.44
Medical expenses	0.11	0.31
Housing	0.01	0.10
Loan payment	0.02	0.12
School expenses	0.03	0.18
Funeral to contribute to	0.06	0.24
ROSCA contribution	0.18	0.39
Food	0.60	0.50
Make up for recent big expense	0.01	0.09
Nothing special	0.07	0.26
C. Cash outflows		
Respondent Sick	0.18	0.38
Somebody in household sick	0.10	0.30
School fees due	0.02	0.14
If yes, amount spent on fees (Ksh)	306	662
Contributed to funeral	0.05	0.21
If yes, amount spent (Ksh)	142	252
Had to make repairs to bike	0.22	0.41
If yes, amount spent on repairs (Ksh)	78	93
Made a ROSCA contribution	0.14	0.35
If yes, amount contributed (Ksh)	101	121
D. Other Cash Flows		
Somebody outside household asked for money	0.02	0.15
Got money from somebody outside household	0.02	0.14
Got money from spouse	0.01	0.10
Gave money to spouse	0.12	0.33
Made withdrawal from home savings	0.04	0.20
Made withdrawal from bank savings	0.01	0.09
Received lump sum payment from regular customer	0.01	0.11
Received a ROSCA payout	0.01	0.11

Notes: There are 259 respondents and 10,870 respondent-days in the sample (excluding sundays), though the exact number for each question varies due to reporting errors. Exchange rate was roughly 75 Ksh to $1 US during the sample period.

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	0.0591***	12.15***	0.518***	0.196***
	(0.0161)	(4.093)	(0.179)	(0.0565)
School fees due today	0.0599*	2.473	0.526	0.0531
	(0.0310)	(8.114)	(0.365)	(0.106)
Bike repairs needed today	0.0623***	10.23***	0.633***	0.223***
	(0.0113)	(2.719)	(0.122)	(0.0431)
Funeral to attend and contribute to	-0.108***	-15.63**	-0.895***	-0.198**
	(0.0292)	(6.232)	(0.313)	(0.101)
Somebody in household is sick today	-0.00709	3.033	-0.0678	-0.0238
	(0.0125)	(3.299)	(0.130)	(0.0469)
Respondent sick today	-0.356***	-56.89***	-3.349***	-0.900***
	(0.0276)	(5.131)	(0.267)	(0.0769)
Won big lottery prize today	0.0331	3.691	0.0720	0.0946
	(0.0306)	(6.135)	(0.249)	(0.0782)
Observations (individual-days)	10,863	10,692	10,752	10,662
R-squared	0.191	0.145	0.192	0.156
Number of IDs	259	259	259	259
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)	10863	9406	10692	9272
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-hours)	8543	7596	8720	7735	8627	7672	8627	7672	8537	7591	8540	7594
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. All monetary values in Ksh, or the indicated transformation. All regressions include individual fixed effects and stage-date fixed effects. 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 5. Parametric Hazard Regressions

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Quit after dropping off passenger				
	Farber (2005)	Separating time carrying/waiting	Adding Needs and Lottery Payouts		Only lottery days
Cumulative Earned Income (Units = Ksh / 1000)	0.16**	0.22**			
	(0.08)	(0.11)			
Cumulative Hours Worked (Units = Hours / 10)	0.30***				
	(0.02)				
Cumulative Carrying Hours (Units = Hours / 10)		0.28***	0.26***	0.26***	0.19
		(0.09)	(0.09)	(0.09)	(0.32)
Cumulative Carrying Hours Squared		0.21	0.30*	0.30*	0.73
		(0.15)	(0.16)	(0.16)	(0.47)
Cumulative Waiting Hours (Units = Hours / 10)		-0.05	-0.10**	-0.10**	-0.06
		(0.04)	(0.05)	(0.05)	(0.13)
Cumulative Waiting Hours Squared		0.39***	0.45***	0.45***	0.41***
		(0.05)	(0.06)	(0.06)	(0.14)
Earned Income - Need			0.05	0.05	-0.19
			(0.09)	(0.09)	(0.34)
Dummy if Earned Income > Need			0.03***	0.03***	0.06**
			(0.01)	(0.01)	(0.03)
(Dummy if Earned Income > Need) * (Income - Need)			0.13	0.13	0.25
			(0.12)	(0.12)	(0.40)
Won big lottery prize			-0.01		
			(0.01)		
Won lottery prize * lottery pushed cumulative income over need				0.02	0.02
				(0.05)	(0.06)
Observations	38,132	38,132	32,867	32,867	1,772
Number of IDs	259	259	259	259	196
R-squared	0.13	0.14	0.15	0.15	0.17
Mean of Dep. Var.	0.0882	0.0882	0.0865	0.0865	0.0697

Notes: An observation is at the worker-passenger-date level (i.e. if a worker has three passengers at date t, there are three observations for this worker on that date). All regressions include individual fixed effects and controls for week and day of the week fixed effects. Standard errors clustered at both the individual and date level in parentheses. Columns 3, 4 and 5: analysis restricted to worker-days where a cash need is reported. Column 5 restricted to lottery days

*, **, and *** indicate significance at 10%, 5%, and 1% respectively.

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	259	259	259	259
Number of bodas	38132	33826	38132	33826
R-squared	0.15	0.16	0.15	0.16
Mean of dependent variable	0.0882	0.0868	0.0882	0.0868

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. 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)	8241	8130	6676	6791	6739	6739	6674	6677
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 known 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)	9362	9234	7594	7727	7669	7669	7589	7591
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%.

Table 8: Main simulations results

Model	Pain-killer EI	Gain-loss EI
Exp. Discounting: Average income change if no targeting (λ=0)	-5.16%	-5.29%
Std. Dev. of income change across 200 drivers	*2.82%*	*2.93%*
Hyp. Discounting: Average income change if no targeting (λ=0)	-4.99%	-5.10%
Exp. Discounting: Average income change if target consumption	-1.82%	-1.79%
Percentage of driver days the target is met	66%	66%
Percentage of driver days the target is met if target consumption	91%	92%

Appendix A: Appendix Figures and Tables

Figure A1a. Estimated Effort Costs

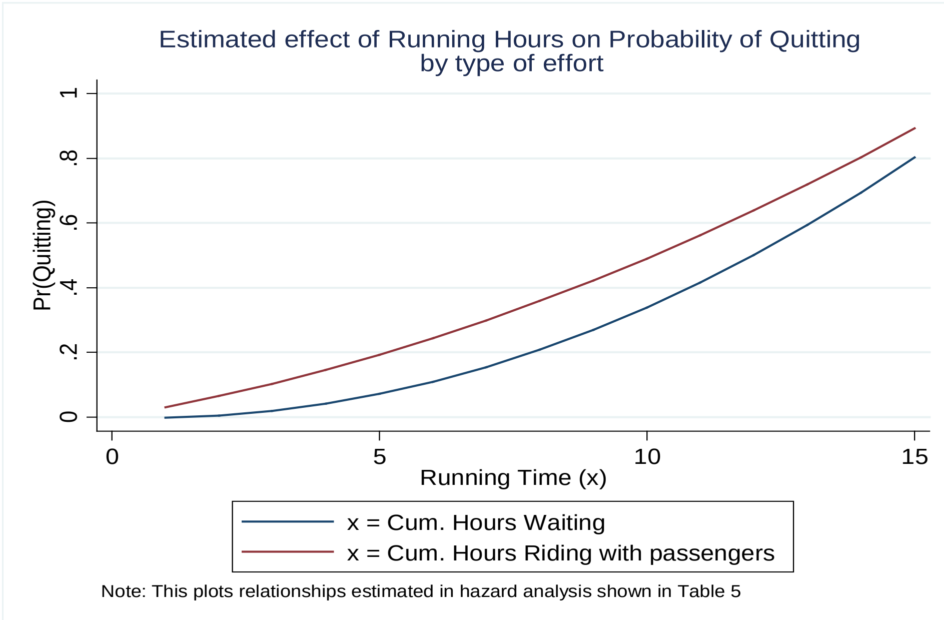
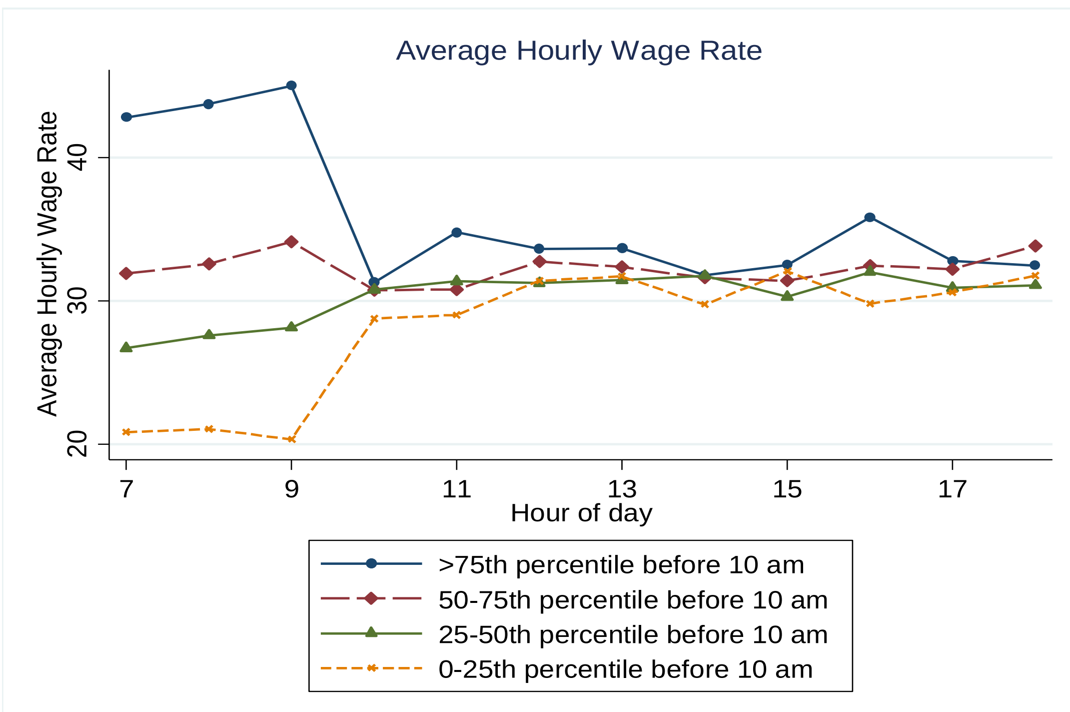


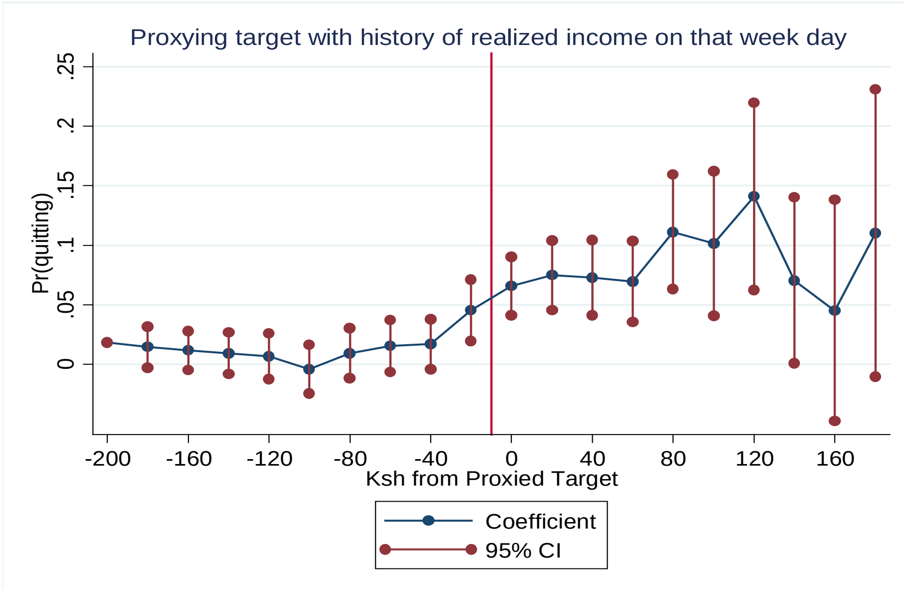
Figure A1b. Variations in the Hourly Wage Rate



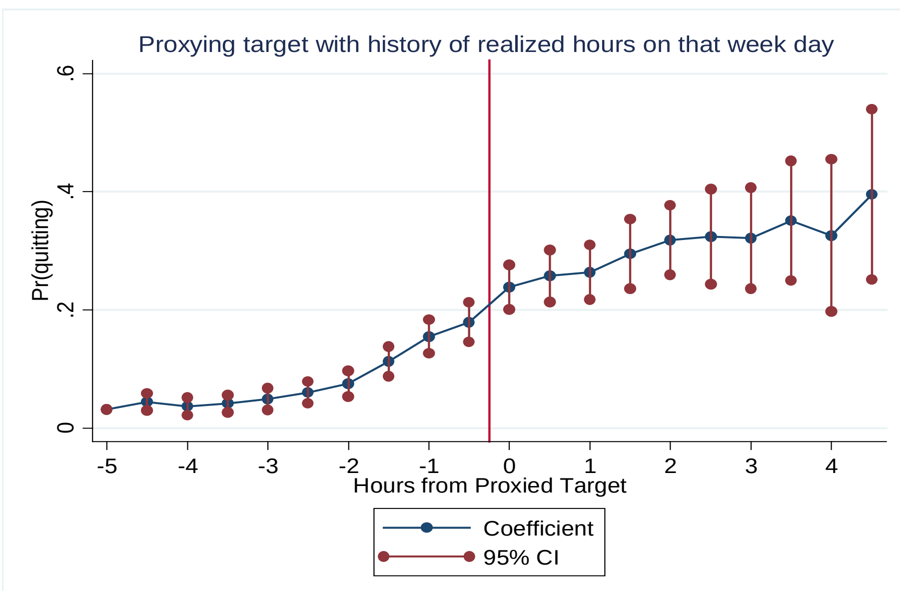
Notes: Figure A1b presents average hourly wage rates at the stage-day level. Results are presented for quartiles of the average wage rate in the morning (7-10 AM).

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

Panel A. Income



Panel B. Hours

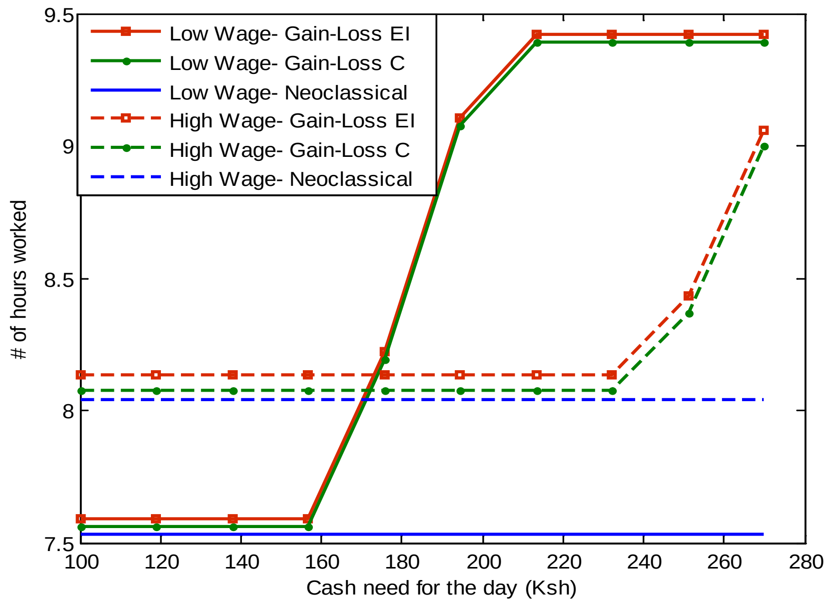


Notes: These estimates follow Crawford and Meng (2011). Proxy targets are estimated as average daily income or hours on days up to but not including the day in question. Proxy targets are estimated by day of the week.

Figure A3. Calibration: Comparison of Gain-Loss EI targeting, C targeting and neo-classical model

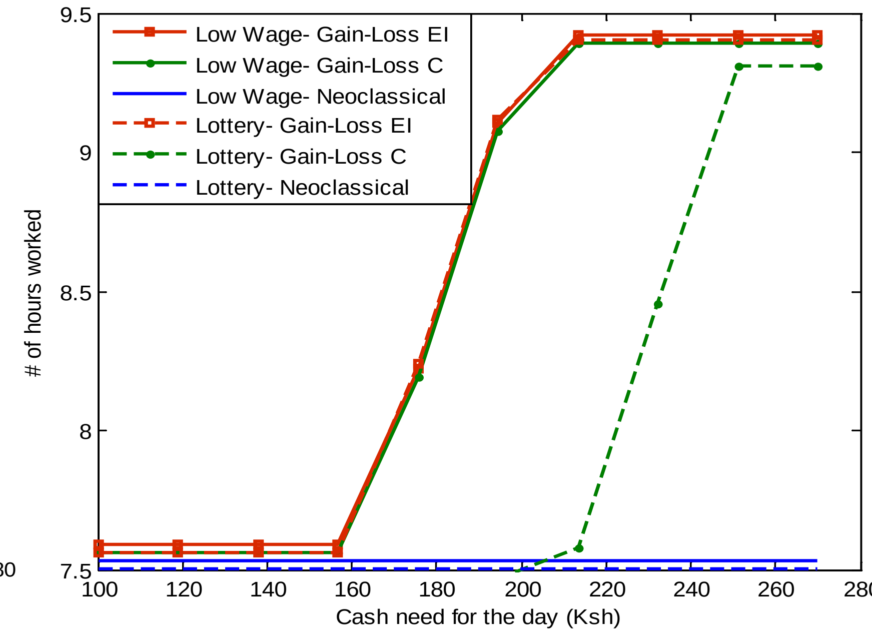
Panel A: Relation between Cash Need and Labor Supply

Panel A1: With Present-Bias (ß=0.7)

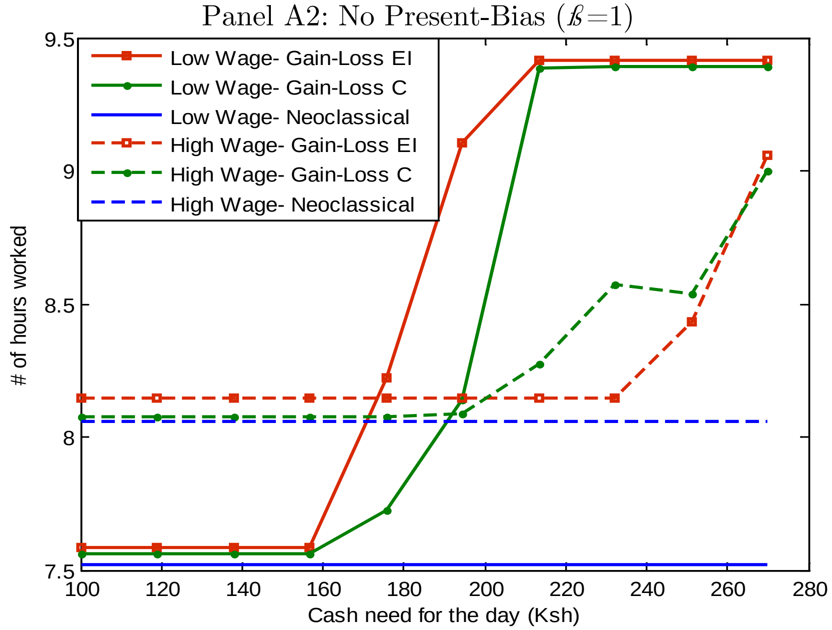


Panel B. Labor Supply and Cash Windfalls (Lottery Wins)

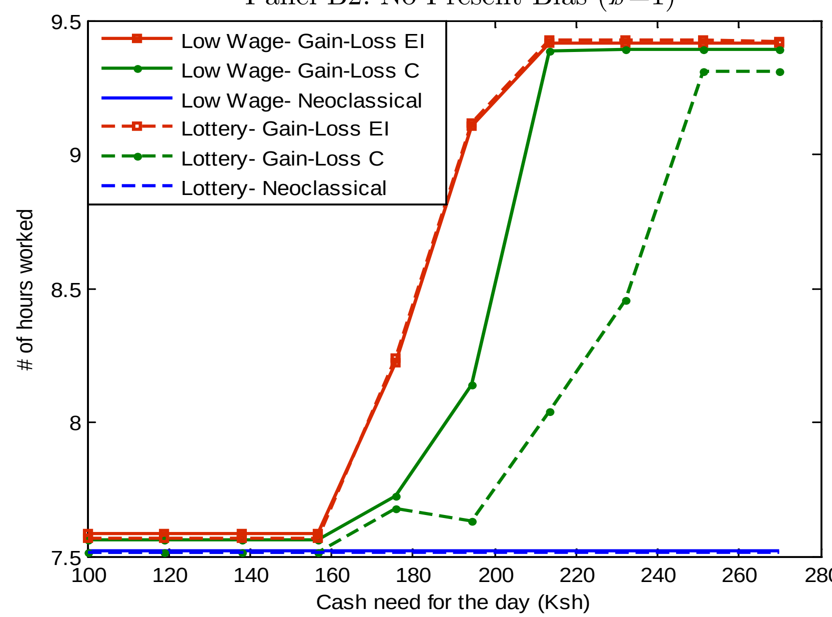
Panel B1: With Present-Bias (ß=0.7)



Panel A2: No Present-Bias (ß=1)



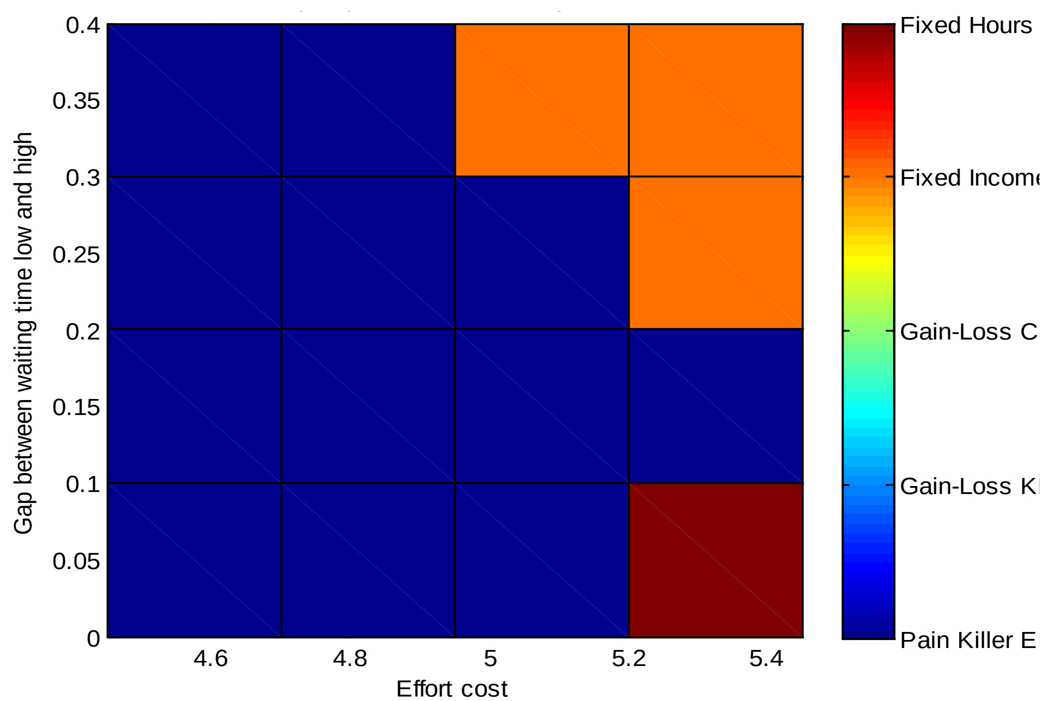
Panel B2: No Present-Bias (ß=1)



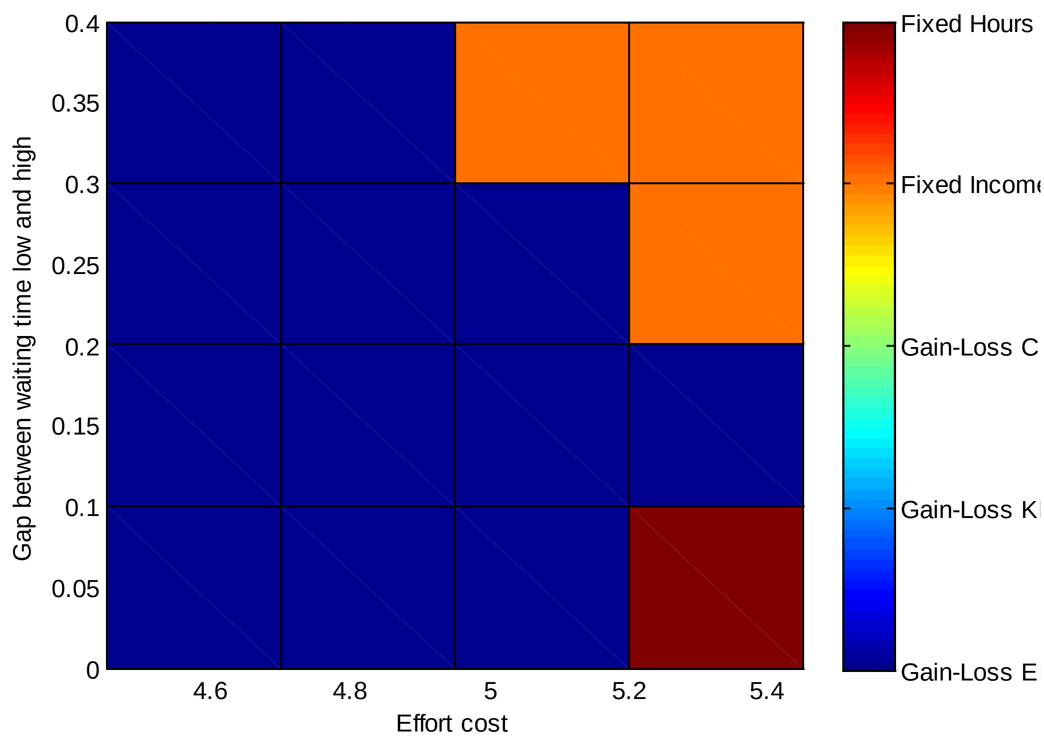
Notes: We compare three models -- the standard neo-classical model (blue lines), a model of reference dependence with a target over consumption (C, green lines) and the standard gain/loss variant of our earned income targeting model (red lines).

Figure A4. 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 A5. Simulation Results: Probability of quitting and distance to the need

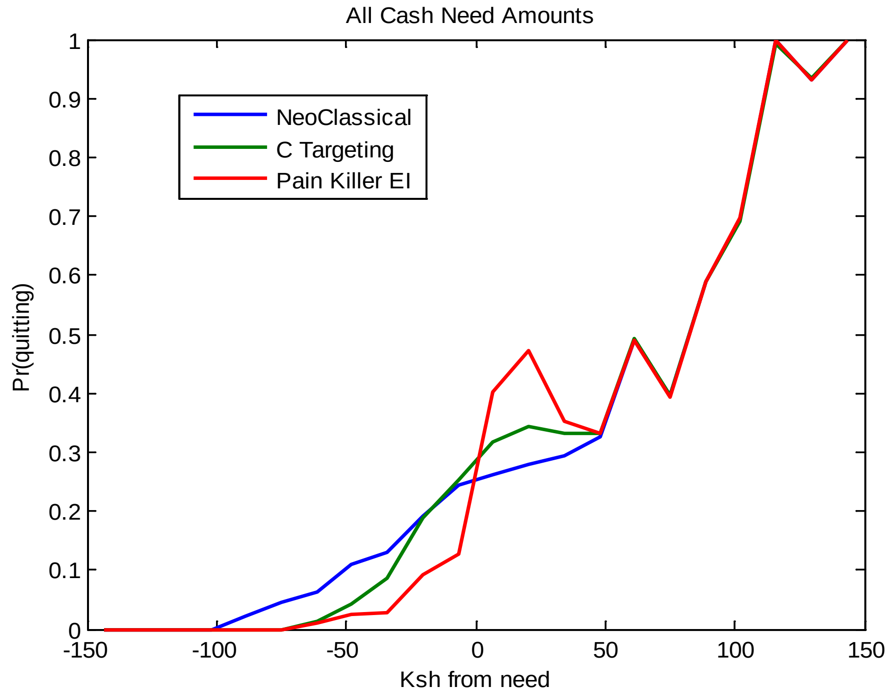
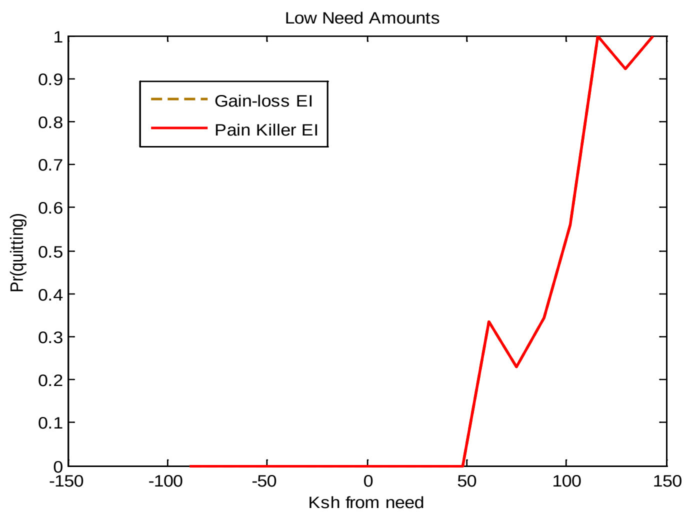


Figure A6. EI Targeting Simulations: Probability of quitting and distance to the need, by need level



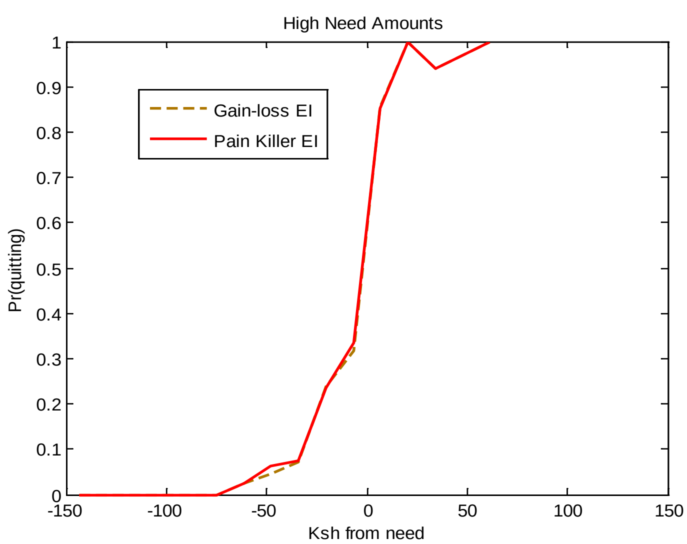


Table A1. Demands on Income and Reported Cash Need for the Day

	(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	8429	8429	7616	7616	7647	7647	7562	7562
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%

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)	12582	10654	12385	10501
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-hours)	9196	8157	9399	8315	9289	8240	9289	8240	9190	8152	9193	8155
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)	2015	2095	2093	2089
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: Model Calibration: Parameter values and source

Parameter	Value	Source
Panel A: parameters common to painkiller and gain/loss models		
δ	0.957	Angeletos et al (2001)
β	0.7	Angeletos et al (2001) ($\beta = 1$ no hyperbolic)
σ	0.01	Andersen et al (2014)
t_r	0.5	Average ride length in the data
$\mathrm{t}_w{}^L$	0.5	Percentile 40 of implied wage distribution
$\mathrm{t}_w{}^H$	0.9	Percentile 60 of implied wage distribution
r	0.01 %	Daily equivalent of a yearly 5% Standard Chartered Bank Kenya
f	30	Average fare in the data for rides around tr
c_a	100	Percentile 40 of needs of target earners
c_u	0-170	Span needs of target earners
ϑr	5	Jointly chosen to match average daily hours of Neoclassical drivers
ϑW	17	
Panel B: Reference-dependence parameter, by model variant		
λ_{GL}	0.11	(Gain-Loss EI model). Chosen to match hours of drivers exhibiting earned income targeting
λ_{PK}	0.10	(Painkiller EI model). Chosen to match hours of drivers exhibiting earned income targeting

Table A6. Covariates of Target Earning behavior

	(1)	(2)	(3)
Dep. Var:	Dummy =1 if individual has β_{hat} >0 in hazard analysis	Dummy =1 if individual has β_{hat} >0.03 in hazard analysis	Dummy =1 if individual has β_{hat} >0.03 & one-sided p-val<0.1 in hazard analysis
More loss averse: Refuses the 50-50 gamble	-0.004	0.017	-0.001
(win 30 or lose 10)	(0.077)	(0.077)	(0.066)
Less risk averse: Amount invested (out of 100 Ksh)	0.001	0.001	0.002
in Risky Asset	(0.001)	(0.001)	(0.001)
Impatience measure: Amount needed in 2 days	-0.006	0.037	0.046
in order to forego payment today	(0.049)	(0.048)	(0.042)
Time consistent	0.002	0.048	-0.111
	(0.114)	(0.113)	(0.098)
Age in years (/10)	-0.003	0.002	-0.048
	(0.057)	(0.057)	(0.049)
Poor health index (out of 8 questions)	-0.018	-0.007	-0.029
	(0.063)	(0.062)	(0.054)
Experience working as boda (in years)	-0.007	-0.010	-0.001
	(0.008)	(0.008)	(0.007)
Does not own bike, rent one	-0.018	-0.09	-0.052
	(0.089)	(0.088)	(0.077)
Has other source of regular income	0.054	0.062	0.168**
	(0.096)	(0.096)	(0.083)
Number of children in household	0.013	0.012	0.024
	(0.020)	(0.020)	(0.017)
Number of adults in household	0.062	0.100	-0.009
	(0.065)	(0.065)	(0.056)
Years of education	0.009	0.006	0.009
	(0.016)	(0.015)	(0.013)
Share of days report need	-0.809**	-0.754**	-0.236
	(0.328)	(0.327)	(0.283)
Average amount of daily need (/100)	-0.004	0.017	0.026
	(0.023)	(0.023)	(0.020)
Std. Dev. of need (/100) across days	-0.03	-0.038*	-0.028
	(0.021)	(0.020)	(0.018)
Observations	235	235	235
R-squared	0.132	0.134	0.107
Dep. Var. Mean	0.553	0.438	0.234

Notes: See text section 4.6 for definitions of the dependent variables and notes to Table 1 for definitions of independent variables. The distribution of the estimated beta coefficients is shown in Figure 5. All those 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 0.04.

Table A7. 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)	10862	8486	8542	7099	8719	7225	8626	7169	8626	7169	8536	7096
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 A8. 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.	0.0832	0.0825

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: 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. One may worry that simply asking this question made that specific amount salient in respondents' minds, especially those with a lower level of education. 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.[27]

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 should 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. This further suggests that experimenter effects are unlikely explanations for our results.

[27] 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. While there is no way of checking they did this, there is no obvious reason not to – it is not clear why people would feel that earning enough for a need was socially desirable. What's more, during weekly recall surveys we checked whether the logs were correctly filled (i.e. whehter the log had been filled up to the current time) and only paid respondents who had done so, building incentives to fill the logs correctly. Second, reported needs are highly correlated with shocks reported in the weekly survey. Third, the reduced form relationship between shocks and labor supply exists without any reliance on the reported need amounts. 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.