Testing Alternative Models of Labor Supply

Evidence from Taxi-Drivers in Singapore

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Abstract

In this paper, we use data from a survey of taxi drivers in Singapore to test two competing labor supply hypotheses: the standard intertemporal model and the income targeting model, where workers set an earnings target over some short time horizon. The former predicts positive wage elasticities of labor supply, while an extreme form of the latter implies an elasticity of -1. The estimated wage elasticities are persistently negative, even after correcting for measurement error using instrumental variables. However, these findings are consistent with those in Camerer et al. (1997)'s study of New York City cab drivers.

1. Introduction

This paper uses panel data on the hours worked and wage rates of taxi drivers in Singapore to test two competing theories of labor supply: the intertemporal formulation of the neoclassical model of labor supply, and the comparatively little-known target income labor supply model. In contrast to the neoclassical model, workers in the target income model set a fixed income target over a short time horizon, adjusting their working hours to meet the target. They therefore work fewer hours when wages rise and more hours when wages fall, generating the prediction of a negative wage elasticity.

The special characteristics of the taxi driving profession affords researchers an opportunity to conduct an unusually clean test of the neoclassical labor supply model. Due primarily to demand shocks (such as weather), taxi drivers face wage rates that are highly correlated within a day, but largely uncorrelated across days. We can therefore test whether labor supply responds positively to transitory wage changes by estimating wage elasticities for drivers using daily observations of wages and hours.

In addition to allowing a clean test of the response of hours worked to transitory wage changes, our survey data of Singapore taxi drivers ensures that our work is uncontaminated by problems that commonly plague labor supply studies. Firstly, unlike other professions, taxi drivers have the luxury of making a relatively unconstrained choice of the number of hours to work each day. The drivers rent their taxis from a fleet for a fixed fee and drive them for as long as they choose to during a continuous 12-hour shift. The flexibility that drivers have in deciding when to quit therefore generates substantial variations in hours worked. Secondly, measurement error in annual hours worked produces a spurious negative correlation between hours and wages, since in most empirical analyses, annual hours are regressed on the hourly wage which has been constructed by dividing yearly income by annual hours. This problem also rears its head in our study, but we can fortuitously correct for the measurement error by using a set of instruments which includes the average wage rate of other drivers who face similar demand shocks on any given day.

Like the pioneering Camerer et al. (1997) study of the labor supply decisions of cab drivers in New York City, the predictions of the standard theory of labor supply, namely that small increases in wages over short horizons will (in the absence of a large income effect making labor supply “backward bending”) generally elicit more working hours, are rejected in our study. Instead, empirical tests of their proposed alternative, the target income theory of labor supply, result in wage elasticities of approximately -0.3 to -0.9 which are significantly different from zero. The wage elasticities become even more negative when instrumental variables are used to ameliorate the effects of measurement error.

2. Alternative Models of Labor Supply

2.1 The Intertemporal Model of Labor Supply

In the intertemporal / life-cycle model of labor supply, utility is defined over lifetime consumption and lifetime hours of work. Similarly, the budget constraint incorporates incomes and expenditures in different periods plus the opportunity to reallocate incomes and expenditures across periods by borrowing and lending.

First proposed by Lucas and Rapping (1969) to account for the observed positive relationship between output and employment, the major obstacle to implementation of intertemporal models of labor supply stems from the fact that, in principle, current labor supply depends on all past and expected future wage rates, while data for these variables are missing for most periods of the lifetime. The problem of missing wage data is compounded by the measurement error in the wage and labor supply variables.

Because of the large number of parameters allowed in intertemporal labor supply models, there is considerable flexibility in the dynamic formulations of these models. However, such models make at least one unambiguous prediction: hours of labor supplied should be positively related to transitory (for example, daily) fluctuations in wages. In a multi-period maximization problem, a transitory change in the wage rate will have a negligible impact on life-cycle wealth, so the implied wealth effect of such a change is minuscule. Since the substitution effect of a wage change on hours worked is positive, a rise in the transitory wage should induce an increase in labor supply.

The labor supply response to a transitory change in the wage therefore provides a solid test of the intertemporal model of labor supply. More than simply rejecting specific assumptions about functional forms or separabilities, a rejection of this prediction casts significant doubt on the fundamental validity of the model. The clean testing of this prediction, however, has proved elusive since wage changes observed in existing data sets are usually not purely transitory. Moreover, changes are often serially correlated, and nominal wages suffer from downward rigidity.

2.2 Estimation of the Life-Cycle Model

Pencavel (1986) has pointed out correctly that the life-cycle model has been characterized without debate as the *maintained* hypothesis and empirical work has taken the form of gauging the parameters describing the presumed life-cycle allocation.

The life-cycle model has been most convincingly estimated when the research makes use of successive observations over time of the same individual (i.e. panel data). The simple correlation between changes over time in the hours worked of individuals and corresponding changes in their wage rates has been shown to be negative at least in the U.S. data. [See, for example, Abowd and Card (1983)]. However, there are potentially serious problems with the accurate measurement of hours and wages. For example, the wage rate variable is often formed by dividing the respondent's annual earnings by hours worked so any error in measuring hours will produce a spurious negative correlation between hours and wage rates (which normally survives first-differencing of the variables). In addition, both the measured hours and the measured wage rate variables do not precisely correspond to their counterparts in the economic model. The wage rate suffers from problems associated with non-linear budget constraints while hours worked are often computed as the product of two variables (average hours worked per week and weeks worked per year) and therefore are unlikely to correspond exactly to the true value of the variable.[1].

In summary, the estimates of the male intertemporal substitution elasticity range from -.07 to .45 with the central tendency of .20. These results span studies that use aggregate data (for example, Mankiw, Rotemberg and Summers (1985)), cohort data (Browning, Deaton and Irish (1985)), and panel data (Altonji (1986)). The estimated standard errors surrounding these point estimates are often large: as often as not, the null hypothesis that life-cycle changes in wages have no effect on hours

[1] The problems concerning measurement error in wage rates and hours worked are prone to be exacerbated by first-differencing because permanent components in these variables are thereby eliminated and "noise" components account for a relatively larger part of the measured total.

worked by prime-aged men cannot be rejected at conventional levels of significance.[2] Pencavel (1986) summarizes these results well: "In other words, the greater part of the variations in male labor supply across workers and over time is left unexplained by this research. A great deal of effort has been brought to bear on what appear to be relationships of second-order of importance."

2.3 The Target Income Hypothesis

The target income hypothesis begins with two fundamentally different assumptions about preferences than are embodied in the standard theory: (i) workers care about levels of income relative to a target (or reference point, or aspiration level); and (ii) workers set a short-horizon (say, daily) income target. Several interesting properties occur if utilities are "reference-dependent". The most important feature that is of relevance to us is that gains (outcomes above the reference point) and losses (outcomes below the reference point) might be treated differently. This gain-loss difference is widely referred to as "loss-aversion". [See Kahneman and Tversky (1979), Tversky and Kahneman (1991)].

Consider a utility function $v(y - t)$, with $v(0) = 0$ where y equals the reference point t. Such a function is usually said to exhibit loss-aversion if $(x) < -v(-x)$ for $x > 0$ - that is, a loss of size x is more painful than a gain of x is pleasurable. As Bowman et al. (1993) point out, this definition is satisfied by any concave function $v(y, t)$ around t as well. Camerer et al. (1997) adopt a different definition: $v(y, t)$ exhibits loss-aversion if the increasing-loss derivative $v'(y, t)$ at $y < t$ is greater than the increasing-gain derivative at $y > t$. Therefore loss-aversion is equivalent to a "kink" or non-differentiability at the reference point t (see Figure 1). These authors offer several reasons to support the existence of the

[2] The presence of capital market imperfections may lead to the rejection of the life-cycle model, but is unlikely by itself to cause the wage elasticity to be as low as the estimates found in this paper.

kink: (1) introspective, (2) historical[3], (3) empirical[4], (4) computational simplicity for boundedly rational agents[5], and (5) theoretical[6].

In the simplest (and highly stylized) case, let the total utility be given by

$$v(y,t)+u(L) \tag{1}$$

where L represents leisure and t is the income reference point or target assuming loss-aversion as described above. In the neighborhood of the kink, the substitution effect of a change in wages is zero: at the kink $y = t$, the slope of the budget line (which is the hourly wage) lies strictly between two different marginal rates of substitution since $v'_+(y) < v'_-(y)$ at $y = t$. That is,

$$\begin{aligned} &w > u'(L)/v'_+(y) && \text{(for increases in income)} \\ &w < u'(L)/v'_-(y) && \text{(for decreases in income)} \end{aligned} \tag{2}$$

In the standard case $v'_+(y) = v'_-(y)$ and L and y are uniquely determined by w because the inequalities in (8) collapse to a single equality, the first-order condition $w = u'(L)/v'(y)$. With income targeting, small wage changes that keep the wage rate between the two marginal rates of substitution (and hold y constant) therefore produce no substitution into more work.

In the extreme case, changes in wage rates cause workers to alter labor supply to keep total income equal to the target income level, t. Hence, the labor supply curve is traced out by the relation $h = t / w$ (see Figure 1b) where h is the number of hours worked. This curve implies a constant wage elasticity, $\frac{dh}{dw}\cdot\frac{w}{h}$, of -1.

[3] Antecedents of the notion of income targets may arguably be found in Hicks (1932), among others, who stated that "The expenditure of income is largely a matter of habit…" and concludes therefore that "… a fall in piece rates will be followed immediately by an expansion of output." (p.98)

[4] Experimental evidence on loss-aversion may be found in decision-making under risk (see the two references above), consumer choice and "endowment effects" (Kahneman, Knetsch and Thaler (1990)), contingent values to buy and sell non-market goods, and "status quo biases" (Samuelson and Zeckhauser (1988)). In addition, models using loss aversion have been used to explain phenomena like the excess return of stocks over bonds (Constantinides (1990)), and asymmetric elasticities for price increases and reductions (Hardie et al. (1993)).

[5] Income targeting simplifies the cognitive task of meeting one's spending needs and smooths income flow (trading off some mean level of salary for a reduction in variance), thereby simplifying financial planning.

[6] Kinks of a similar nature are also manifested in economic theory in the form of "first-order risk aversion". Agents who have "ambiguous" set-valued possibilities (see Gilboa and Schmeidler (1989)), Knightian uncertainty with inertia (Bewley (1986)), and are averse to disappointment (see Gul(1991)) will exhibit such kinks. Models possessing this underlying property have been used to study asset pricing (for example, Epstein and Zin (1990)) and insurance (Segal and Spivak (1990)).

Although the existence of a kink generates a wage elasticity of -1, a negative wage elasticity of hours worked with respect to changes in transitory income (that is, a downward-sloping labor supply curve) may be obtained from more conventional utility functions. This is demonstrated below.

Again, let the worker maximize the additively-separable utility function

$$v(C)+u(L) \tag{3}$$

subject to

$$C=y=wh$$

where C is consumption, y is income, L is the number of hours of leisure, and $h=16-L$ is the number of hours worked.

The first-order condition implies that

$$w=\frac{u'(L)}{v'(y)} \tag{4}$$

Differentiating (4) with respect to L, we obtain

$$\frac{dw}{dL}=\frac{u''(L)}{v'(y)}-u'(L)v''(y)\frac{\frac{dy}{dL}}{(v'(y))^2} \tag{5}$$

Noting that $\frac{dy}{dL}=\frac{dw}{dL}(16-L)-w$ and rearranging yields

$$\frac{dh}{dw}\cdot\frac{w}{h}=\frac{1-yR_y}{yR_y+hR_L} \tag{6}$$

where $R_y \equiv -\frac{v''(y)}{v'(y)}$ and $R_L \equiv -\frac{u''(L)}{u'(L)}$ are coefficients of risk-aversion.

Since the concavity of $u(L)$ and $v(y)$ implies that $R_y, R_L > 0$,

$$\frac{dh}{dw}<0 \text{ iff } R_y>\frac{1}{y} \tag{7}$$

A kink in $u(y)$ means that R_y is infinite around the kink so that the elasticity is -1. Logarithmic utility functions deliver zero elasticity. As noted by Camerer et al., other functions that satisfy this inequality either cannot produce sufficiently large negative elasticities or display pathological behavior under certain conditions. For example, strong relative risk-aversion (for example, power functions $u(y)=-y^a$ with $a<0$) allows negative elasticities but behave badly toward income gambles with low outcomes (the certainty equivalent of any gamble with a non-zero probability of a zero outcome is zero).

A very short planning horizon by workers is required to explain negative wage elasticities. As explained in Camerer (1997), if workers have even a two-day decision-making horizon (say, they have a two-day earnings target), estimated elasticities would be positive for a wide range of plausible specifications. Drivers would intertemporally substitute between the two days, working long hours on the first day if it were a high-wage day, and reducing the number of hours in their shift if it were a low-wage day. We can show this using a simple intertemporal version of the model shown above.

Suppose now the worker's objective function is

$$E_1\left[\sum_{t=1}^{2} v(C_t)+u(L_t)\right]=v(C_1)+E\left(v(C_2)\right)+u(L_1)+E\left(u(L_2)\right) \quad (8)$$

subject to

$$C_1+E(C_2)=w_1h_1+E(w_2)h_2$$

where $h_i=16-L_i$, i= 1,2, is the number of hours worked in each period, C_1 is period 1 consumption, $E(C_2)$ is expected consumption in the second period, while $E(w_2)$ is the expected wage in the second period. The components of the utility function, v and u, are both concave with respect to their arguments. We assume certainty-equivalence behavior and a discount rate of zero.

The first-order condition to the above maximization problem implies that

$$\frac{u'(L_1)}{E\left(u'(L_2)\right)}=\frac{E(w_2)}{w_1} \quad (9)$$

If the second day's wage is expected to be greater than the first (say, the driver judges from previous experience that business is really poor on the first day) such that $E(w_2)>w_1$, then from (9), $u'(L_1)>E\left(u'(L_2)\right)$ (and from the certainty-equivalence assumption, $u'(L_1)>u'\left(E(L_2)\right)$). Since we imposed the condition that $u'>0$ and $u''<0$, it must follow that $L_1<E(L_2)$, that is, the driver will substitute his/her labor supply across the two days based on expected relative wages. Therefore, for plausible income utility functions, a *one-day* time horizon for labor supply decisions is needed to explain strongly negative wage elasticities.

Partial empirical support for the target income model of labor supply may be found in Camerer et al. (1997). While the authors reject the hypothesis that the elasticity of hours worked with respect to changes in the wage rate is -1, they show that there is no systematic evidence that elasticities are positive and the evidence for elasticity around -0.5 is consistent across samples and specifications. Since the target income theory suggests that variables which affect the targeting horizon or the target choice could affect elasticities, the researchers investigate the effect of experience on cab drivers. They find that, in two of their three samples, the high-experience drivers do have higher (that is, less negative) elasticities. Indeed, the high-experience results from one of the samples look like typical results from many previous (conventional) studies: there is a slight positive wage elasticity which is very imprecisely estimated. Cameron et al. consider alternative explanations for their results, such as liquidity constraints, increasing disutility of effort, and selection bias arising from endogenous decisions on participation, but ultimately reject them.

3. The Singapore Taxi Driver Study

3.1 Motivations

As explained previously, the taxi driving profession offers an unusual opportunity to study the effects of a purely transitory wage change on the hours of labor supplied, where the choice of hours supplied is (to a large degree) freely made by the taxi driver.

Since the results of previous studies of cab drivers in the US have contradicted the predictions of the standard intertemporal labor supply model and were more consistent with the target income model, it seems natural that a study should be undertaken in the context of a fast-growing Asian economy. There is a common perception that workers in East and South-East Asia are diligent, motivated and shrewd in financial and business affairs.[7] This has been offered as one of the reasons for the high growth rates experienced by many East Asian economies in the past three decades.[8]

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[7] In Singapore, the ethnic Chinese make up about three-fourths of the population. Significant minority groups include the ethnic Malays (about 15%) and the ethnic Indians (less than 10%). Ethnic Chinese are generally thought to be the most concerned about financial success.

[8] Anecdotal evidence frequently support this: in the October 1995 issue of *Travel Holiday*, the writer Laura Stanley recounts a meeting with a Singapore taxi driver, who "had been driving long hours for several years, at a time in life when most men retire, in order to pay for his daughter's education at Dartmouth His whirlwind tour of the United

One would, therefore, expect to find relatively weak support for the target income theory in such a study. After all, income targeting imposes a heavy price in terms of forgone income. It has been estimated that if drivers worked fixed hours each day instead of practicing income targeting, they stand to take home at least 15% more and a tenth of them take home about a third more. The meaning of the simulated increases in take home pay depends on why cab drivers set income targets. If income targeting is a mistake these gains are big financial errors. If targeting is a heuristic shortcut, these gains represent the shadow price of "computational time". If targeting results from quasi-liquidity constraints which are self-imposed (e.g., to keep cab drivers from squandering the extra income from a high wage day) then the gains reveal the price paid for self-control. [9]

Finally, our custom-designed survey means that we can investigate the effects of age, experience, schooling and family composition on the number of hours worked. Previous studies using the static labor supply model have found that the estimated parameters are highly sensitive to the specification of these variables; we can examine if this holds true for our sample of taxi drivers. The custom-designed survey also allows us to investigate in some detail the nature of income targeting as practiced by the taxi drivers.

3.2 Data Collection

Taxi drivers in Singapore keep a log book which records the number of miles driven, and the log-in and log-off time for each shift, but not the driving time or fare of each trip. This means that we cannot accurately record the number of hours worked per day by each taxi driver. On a day when business is slow and the hourly "wage rate" low, a taxi driver may simply elect to take a longer lunch break, stop to watch a movie, or even take a short nap at home. The log-off time may therefore be uncorrelated with the briskness of business or the lack thereof.

States had coincided with her graduation last year, a proud moment that had cost his family more than Singapore $120,000 (about US$84,000) … Energy like [this] is typical."

[9] Why taxi drivers do not over a longer horizon requires an explanation. Given the low correlation of wages across days, income targeting with a weekly target guarantees a regular weekly income and raises total leisure and income by allowing substitution across days. However, targeting over a longer horizon requires increased self-control. Given the monotony of driving, drivers face a big temptation to quit early on any given day. A daily target wage limits temptation by providing a "bright-line" rule which is less susceptible to self-decision (see Shefrin and Thaler (1992)).

A conversation with the head of the taxi operations branch of the Land Transport Authority (LTA), the government agency responsible for regulating all modes of land transportation, indicated that the LTA had not requested detailed hours worked per shift in their routine surveys of taxi drivers. It was therefore necessary to custom-design a special survey to elicit the desired information for our study.

3.3 Methodology of Survey

The objective of the survey was to elicit information of average hourly wage rates and daily hours worked of taxi drivers in Singapore. The public relations manager of the largest taxi company in Singapore, Comfort Taxi (with more than 10,000 licenses), was contacted. She indicated that a random survey would likely generate a poor response. Worse still, if a reward was offered to increase the response rate, many would probably concoct figures so that they would receive the reward without having to take time to keep proper records. It was suggested that the survey be instead administered to 200 drivers who were participating in a newly-introduced scheme where customers could telephone for a taxi and be guaranteed one within 15 minutes for a surcharge of S$3 (about US$2). Since the taxi drivers had been in contact with the taxi company recently, it was felt that they would be more likely to be truthful in their responses.

To qualify for the newly-introduced scheme, these drivers had to satisfy several criteria, of which the most important were the ability to converse in English and the absence of customer complaints made against them. The sample bias that these selection criteria generate, as far as daily hours worked and the prevalence of income targeting, are unclear. However, we have no reason to believe that they are of a large magnitude.

The survey form was sent to 150 drivers in four batches over a period of a month, and 114 responses (a 76% response rate) were received. Each driver was rewarded with a payment of S$20 (about US$14). The form comprised three sections. In the first section, the participant was asked to provide personal particulars, including their race, previous occupation, the number of children in the household, educational qualification, and their daily rental fee. The second consisted of three short, open-ended questions: “Do you set a *target* as to how much you want to earn every day? If so, what is the target?”, “What things make business *good* or *bad* each day (e.g. weather)?”, and “Do you drive *longer* or *shorter* hours when business is good that day?” The last section contained a table, in which respondents were asked to fill in the dates, shifts (day or night), starting and ending times, breaks taken, and total fares collected for five consecutive days.

Out of the 114 responses, 22 were discarded because the table in the third section was incorrectly filled out. Most of these respondents had simply filled in the exact same starting and ending times, and indicated identical breaks taken for each of the five days.

3.4 Sample Characteristics

Table 1 shows means, standard deviations, minimum and maximum values of the key variables used in our analysis. Taxi drivers in Singapore work about 9 hours a day and collect approximately S$14 per hour in revenues (before paying their lease fees and buying diesel fuel). The standard deviation of mean daily earnings across drivers was $33.15, while the mean standard deviation of daily earnings ‘within’ drivers was $20.02. That is, daily earnings showed greater variation across drivers than between days for a given driver, suggesting the appropriateness of including a fixed effects estimator. The average driver surveyed was 46 years old, had 2-3 children, and 9 years of formal schooling. Of the 92 valid driver responses, 12 were Malay (13.04%) while the rest were ethnic Chinese. Among the spoilt responses, however, 6 were Malay (27.27%) and 16 were Chinese.

Table 2 summarizes the responses of the drivers to the short questions on whether they practiced income targeting and whether they would drive longer or shorter hours when business was good. These results are surprising since income targeting is associated with driving shorter hours when business was good. However, we believe that the results do not indicate irrationality on the part of the respondents, but rather the possibility that many took the target to be the *minimum* income they expected to earn each day, so that they would not stop driving if the target was *not* met, but would possibly continue driving even if the target was surpassed.

We estimate labor supply curves using the daily number of hours as the primary dependent variable and the average wage the driver faced during that day as the main explanatory variable (both in log form). The average wage is calculated by dividing daily total revenue by daily hours (ending minus starting times, subtracting breaks taken). As Camerer et al. point out, this assumes that the decision the driver makes regarding when to stop driving depends on the average wage during the day, rather than fluctuations of the wage rate during the day. Their analysis, however, suggests that wages are strongly and positively serially correlated, so that they can rule out the spurious consistency with the target income theory arising from the fact that on a day with low early wages drivers will drive long hours expecting the wage to rise. However, we cannot perform a similar test for autocorrelation of daily wages since our data is not disaggregated into hours within a shift.

3.5 Qualitative Responses

As noted in Table 2, when asked if they set a daily target income, about half responded affirmatively. Their targets varied fairly widely, ranging from S$50 (net of rental and diesel costs) to above S$200 (presumably gross earnings).

In response to Question 2 on "Short Question" segment of the survey, most taxi drivers wrote that business was good on very hot days, rainy days, public holidays, and bad during the school examination period (when students ride taxis to malls and movie theaters less frequently), in heavy rain, and near the end of the month (when workers are low on cash and are awaiting their next pay check). Many cited luck as a very important factor. Presumably, much of the variation in business was felt to be unsystematic and not attributable to recurrent factors or conditions.

When asked if they drive longer or shorter hours when business is good on a certain day, about half of the respondents indicated that they would drive longer hours, while the other half claimed that they would drive the "normal" number of hours. Many cited the fixed times in which they have to hand over their taxis to the relief driver as a constraint on driving more hours on a good day. However, this constraint is not usually binding since breaks taken constitute a significant part of their 12-hour shifts. Only three respondents said that they would drive shorter hours when business was good.

4. Empirical Analyses

4.1 Estimation Issues

Before reporting the regression results, we make a preliminary pass at the data by checking if drivers behave differently on days/nights when the average hourly wage (obtained by dividing the total earnings for a shift by the number of hours worked during that shift) is high when compared to days/nights when the average hourly wage is low. We designate the former as "high wage" observations, defining them as ones in which the driver's average hourly wage on that shift is above the mean value of his/her average hourly wage across all (five) observations. Observations in which the average hourly wage is below the driver's mean value are classified as "low wage" observations. For example, if a certain driver earned the following average hourly wages over the course of a week - $11 per hour on Monday, $12 on Tuesday, $13 on Wednesday, $14 on Thursday and $15 on Friday, so that the mean value is $13 - Monday and Tuesday are classified as "low wage" observations while Thursday and Friday are "high wage" observations. We then compare the number of hours he/she drives on *each* of the days against the *average* number of hours worked over the 5 observations. Table 3 displays the results of this exercise in matrix form.

We see that with most "high wage" observations, drivers tend to drive shorter than average hours (this being the case on 119 such occasions, against 77 in which they drive longer than average hours). The numbers for the "low wage" observations are even more striking – on these days/nights when business is worse than usual, drivers work longer than average hours on 160 occasions against 75 instances in which they drive shorter than average hours.

Moving on to our formal estimations of labor supply elasticities, we first run OLS regressions of log hours against log wage (again using each driver's average hourly wage from that day). For daily decisions, the standard theory of labor supply predicts a positive elasticity (assuming that the substitution effect is positive and that the income effect is negligible). The target income theory, on the other hand, predicts a region in which elasticity is -1.[10]

[10] Short-horizon income targeting may be tested more rigorously if data on hourly wages are available. Then, utilizing a hazard specification, the probability that a driver quits for the day at any point in time may be parameterized as a function of the cumulated income and the expected marginal wage (given a specification of the wage expectation formation process). Short-horizon targeting predicts that quitting is related to cumulative same-day income, while the neoclassical theory predicts that quitting is related only to expected wages.

As noted earlier, measurement error in the hours worked may lead to predictable biases in the estimated wage elasticities. Since the average hourly wage is derived by dividing daily income by reported hours, inflated hours produces high hours-low wage observations while deflated hours produces low hours-high wage observations, leading to spurious negative elasticities. Conversely, measurement error in income causes the wage elasticity to be biased towards zero. The two sources of bias will either reinforce and counteract each other, depending on whether the true wage elasticity is positive or negative, so the net effect is ambiguous.

To control for measurement error (and thus the endogeneity of the wage rate), we use an instrumental variable approach. The instruments used in the first stage regression are the average wage of other drivers working on the same day[11] (who face similar underlying demand shocks), the experience of the driver, the experienced squared, the number of years of education received by the driver, as well as day and night shift dummies.[12]

In addition, we include driver fixed effects in some of our estimations to control for the possibility that drivers vary systematically in their hours worked or their daily income target.

4.2 Wage Elasticities and Ethnicity

Tables 4a and 4b summarize results for the entire sample, as well as results disaggregated by ethnicity. We first report (in column 1 of Table 4a) the results of the "between regression" (n = 90), where we regress the average (log) hours worked by drivers against their average (log) wage. The estimated elasticity is –0.2625, which is statistically significant at the 5% level. In column 2, the results from panel data estimation using OLS on the full sample (n = 445) indicate a highly significant negative elasticity of -.3987 (t-ratio = -8.18). The estimated elasticity for the Chinese sub-sample (n = 394) is -0.4622 (t-ratio = -8.79); the estimated elasticity for the Malay sub-sample (n = 51) is considerably higher at -0.1904, although it is statistically insignificant (t-ratio = -1.22) because of the small sample

[11] The average wage of the other drivers working on the same day summarizes the "wage" for the day, and should be uncorrelated with a particular driver's measurement error.

[12] Conceptually, we can also use weather (say, rainfall) as an additional instrument. However, we only have data from one meteorological station; as rainfall varies considerably across different parts of the island for any given day, our limited meteorological data may hurt rather than help our estimations.

size. A *t*-test test indicates that this difference between the two ethnic sub-samples is significantly differently from 0 at the 95% confidence level. This result is surprising in light of the stereotypical view that the ethnic Chinese are more "business-minded"[13]. To the extent that income targeting is non-optimal since rearranging hours worked could yield both greater income and leisure over a period of time, our results indicate otherwise. [14]

In the instrumental variable (IV) specification, the wage elasticity estimate for all drivers falls to -0.5623 (*t*-ratio = -5.00), as does the estimate for the Chinese sub-sample (with a point estimate of -0.7494 and *t*-ratio = -5.58). Conversely, in the Malay sub-sample, the IV estimate is less negative than its OLS counterpart at -0.1644 (*t*-ratio = -0.54). The fact that some of the IV estimates are *more* negative than the OLS estimates is surprising. Candidate explanations are that measurement error in income biased the original estimates toward zero (although the implied degree of recording error appears implausibly large), and that the mean of several drivers' wage on any given day is a more reliable estimate of the daily wage than a single driver's wage.

Figure 2 shows scatter plots of wages and hours (both on log scales) for the full sample as well as the sub-samples by race. In the plots for the entire sample and the Chinese sub-sample. the negative relation between wages and hours is apparent. The plots indicate that the negative elasticity estimates are not unduly influenced by outliers, and show little evidence of heteroskedasticity or other misspecifications. In fact, they look very similar to those obtained by Camerer et al. In the plot for the Malay sub-sample, however, the fit is considerably worse. A visual inspection suggests the presence of heteroskedasticity. To correct for this, Feasible Generalized Least Squares (FGLS) was used, and the results are reported in Column 7 of Table 4a. The estimated elasticity decreases somewhat in magnitude (from -0.1904 to -0.0997), and it remains statistically insignificnt (*t*-ratio = -0.62).

A scrutiny of the survey forms indicated that wages tended to be high on Sundays while hours worked tended to be short. A possible explanation is that the taxi drivers' desire to work longer hours when business was good was tempered by the desire to spend leisure time with their families. If that were so, then the estimated elasticities would have been biased downwards (that is, more negative than

[13] Ethnic Chinese minorities dominate the business communities of Malaysia, Indonesia and the Philippines, arousing resentment and occasional violence. In Malaysia, affirmative action policies designed to increase Malay participation in economic life have been in place for the last 30 years.

[14] Since the discarded responses were disproportionately from ethnic Malay drivers, there is a possibility of a sample selection bias for the valid responses, although the direction of bias is uncertain.

they should be). Table 5 reports the estimated elasticity for all taxi drivers but excluding the Sunday observations. The elasticity is found to be -0.3239 (t-value = -6.01), which is only slightly lower than that for the full sample. The explanation postulated above appears to be true but the overall effect is not very important.

In their study of New York cab drivers, Camerer et al. found that regressions which included a squared log wage term increased the fit of their model substantially. Although the fit of our model does not improve with the inclusion of this term (the R^2 statistic increases only marginally from 0.4009 to 0.4079), the coefficients on the log wage and log wage squared terms (1.9063 and -0.4328) are both statistically significant at the 5% level (the t-ratios are 2.05 and -2.48 respectively). The relationship between log hours and log wage suggested by these estimated coefficients (which are reported in the right half of Table 5) is one that is concave with respect to the origin.

The alternate columns in Table 4a, Table 4b and Table 5 report the estimates of wage elasticities accounting for the presence of fixed effects. Driver-specific characteristics not captured in the specification of the estimation equation are expected to be numerous. A Hausman test for the full sample confirms this intuition (chi-squared statistic = 59.8). Using the fixed effects estimator, the wage elasticity for the full sample rises to -0.5127 and is highly significant. Moreover, the combined IV-fixed effects specification yields an even more negative elasticity estimate of -0.8525 which is again highly significant (t-ratio = -6.13). This is somewhat surprising since the fixed effects estimator only utilizes the variance of the data within each driver and therefore tends to lower the signal-to-noise ratio for any given set of measurement errors, causing the estimates to be biased towards zero.[15] The estimate for the Chinese sub-sample also rises in magnitude, to -0.5850 while that of the Malay sub-sample decreases in magnitude to -0.1313 respectively. These estimates confirm the presence of driver-specific factors influencing his hours of work response to changes in wage rates. Moreover, the fixed effect estimates provide strong evidence for some degree of income targeting being practiced by Singapore taxi drivers, especially in the combined IV-fixed effects specification. Lastly, the fixed effects estimates reinforce the earlier observation that, contrary to expectations, the evidence for income targeting is much stronger for Chinese drivers than Malay drivers.

[15] However, fixed effects estimates are less subject to omitted variable bias problems due to unobserved driver heterogeneity, and are preferred in our analyses.

In summary, the results reported in this section clearly do not support the predictions of the standard intertemporal model of labor supply. Except for the small ethnic Malay sub-sample, all estimates of the wage elasticity of hours worked are significantly different from zero. In many cases, these elasticities come fairly close to -1, especially those obtained with the IV-fixed effects estimator. It is obvious, then, that the evidence presented thus far favor the target income labor supply model.

4.3 The Effect of Age, Experience, Education and Family Size

In the tradition of many labor supply studies, we now include several non-budget constraint variables in the hours of work equation. These studies on male labor supply often differ from each other in the set of control variables entered in the hours of work regression equation. For instance, some studies include a measure of the individual's educational attainment. When such a variable is included, its estimated coefficient is almost always positive and significant by conventional criteria suggesting that, other things equal, more formally educated men work longer hours. Of course, in most of these studies, the workers are drawn from different occupations. As another example, a measure of the number of dependents in the household is sometimes included. When included, it tends to reveal a significantly positive (partial) association with hours of work. As Pencavel (1986) points out, researchers have been somewhat cavalier in their choice of non-budget constraint variables to be included in an hours of work equation, but unfortunately, Da Vanzo et al. (1983)'s experiment with their schooling variable indicates that the presence or absence of certain non-budget constraint variables may profoundly affect the inferences about the wage elasticity of hours of work. Most researchers seem to believe that variables such as education or family size are systematically associated with differences in tastes for work (or equivalently, differences in non-market productivity).

Table 6 reports the results from regressions including various combinations of the following non-budget constraint variables: education, experience, experience squared, and number of children in the household. The age of the taxi driver was excluded because of multicollinearity (with experience). In the OLS regressions, only experience squared is statistically significant at the 5% level, and barely at that (t-ratio = -2.02 in column 2 and 2.00 in column 3). In the IV regressions, experience is significant at the 10% level (t-ratio = 1.93 in column 5 and 1.92 in column 6), while experience squared is significant at the 5% level (t-ratio = 2.49 in both columns 5 and 6). However, even these *t*-ratios are swamped by those of the coefficients on log wage and the day and night shift dummies.

When the sample is disaggregated by race, the coefficients on all the non-budget variables in the full specification (using OLS or IV estimation techniques) become statistically insignificant, with the largest *t*-ratio at 1.53 (results not reported).

In the OLS regressions, the wage elasticity estimates are robust to the addition of the various combinations of non-budget constraint variables (staying in the range of -0.42 to 0.44). In the IV estimations, the inclusion of experience and experienced squared as explanatory variables substantially decreases the estimated coefficient on log wage, lowering it from -0.5623 to -0.7273 (see column 6). In the analyses that follow, we therefore choose to include these variables in all our estimations.

In Table 7, we report the results of regressions for sub-samples divided by experience and education (around the means). The importance of experience is explained in Camerer et al. Suppose that drivers use target income behavior as a heuristic device before they learn that driving more on high-wage days and less on low-wage days produces more income (*and* more leisure). If learning varies monotonically with driver experience, then more experienced drivers will have larger (that is, less negative, or more positive) wage elasticities. The standard theory of labor supply, by contrast, does not predict an experience effect unless the magnitudes of the income and substitution effects differ by age or experience.

The fixed effects estimates of wage elasticities contradict the prediction that more experienced drivers will have less negative elasticities than less experienced drivers (-1.1737 against -0.6423). (The hypothesis that both groups have the same wage elasticity is also easily rejected.) These rankings are also preserved in estimations using OLS, although the difference shrinks to an insignificant level (results not reported). In the IV specification, the difference virtually disappears (-0.5883 for more experienced drivers versus -0.5534 for less experienced drivers). The significance of these results should not be overstated, however, as the variation in the experience of drivers in our sample is relatively small (with a mean of 10 years and a standard deviation of 2.7 years).

The results obtained from separating observations by the years of schooling of drivers (more highly-educated versus less-highly educated) indicate that the group of drivers with greater number of years of schooling exhibit a less negative wage elasticity than the less educated drivers (-0.5146 against

-0.8750), a difference which is statistically significant at conventional levels. In the fixed effects estimation, this difference is again apparent (-0.7253 versus -0.9523). Since income targeting is sub-optimal, one expects that drivers who are more educated will exhibit a lower tendency to practice it, a prediction borne out by our results.

4.4 Targeters Versus Non-Targeters

Our next set of results (reported in Table 8) investigates the differences in wage elasticities of hours worked for drivers who claimed to practice income targeting and those who claimed that they did not. In addition, we separated the full sample into those who wrote that they drive longer hours when business was good from those who wrote that they would drive "normal" hours.[16]

The IV estimates show that professed targeters, in accordance with the target income theory, have a more negative wage elasticity (-0.7631 against -0.6080), with the ranking preserved in the fixed effects estimations (-0.9602 against -0.7710). In both cases, the differences are statistically insignificant, although the elasticity estimates themselves are highly significant (with *t*-ratios between -3.53 and -5.02).

In comparing those that claim they drive longer hours when business is good with those who claim they drive the usual number of hours, the IV estimates confound the intuition that, since driving *shorter* hours when business is good accords with income targeting, those who claim to drive longer hours should have a *less negative* wage elasticity. Instead the opposite is true: the estimated elasticities using the IV approach are -0.9750 for those who claim to drive longer hours when business is good against -0.6105 for those who claim to drive normal hours in the same situation. With the fixed effects specification, however, the difference in the magnitudes of the estimates are reduced considerably (-0.8554 compared to -0.8339). The IV estimates indicate that sometimes economic agents do not practice what they claim they do or want to do. Perhaps social or cultural norms dictate how agents respond in a survey in ways that are antithetical to those actually practiced in their particular profession.

5. Summary of Results and Alternative Explanations

In this section, we evaluate several plausible explanations for the empirical results obtained. To summarize, the following are the most important findings of the study:

1. The OLS wage elasticity estimate for the entire sample was -0.40, the IV estimate was -0.56, while the fixed effects estimate was -0.51. All were highly statistically significant.
2. Contrary to expectations, the wage elasticity was more negative for the Chinese sub-sample (OLS: -0.46, IV: -0.75 fixed effects: -0.59) compared to the Malay sub-sample (OLS: -0.14, IV: -0.16, fixed effects: -0.13).
3. Non-budget constraint variables such as schooling, age, and family size did not have much explanatory power in a regression of log hours against log wages. This may be attributed to the very small variations in these variables found in our sample. Experience and experience squared possessed some explanatory power.
4. The evidence for income targeting is stronger for the less educated and more experienced drivers.
5. Drivers who claim that they practice daily income targeting do indeed have a more negative wage elasticity than those do claim they do not. By contrast and unexpectedly, drivers who claim that they drive longer hours when business is good have a significantly more negative wage elasticity than those who claim they drive the "usual" number of hours, although the difference evaporates when driver fixed effects are included in the regressions. The negative point estimates of the wage elasticities for professed non-targeters, and the fact that they are significantly more negative for those who profess to want to drive longer hours when business is good indicates a significant dichotomy and contradiction between *desired* behavior and *actual*, realized behavior. This suggests that the issue of self-control on the part of economic agents in decision-making is worthy of deeper exploration.[17]

What *precisely* does an estimated elasticity of -0.40 (OLS), -0.56 (IV) or -0.51 (fixed effects) for the entire sample mean? Because our study uses survey data, we are able to probe this question more deeply than the researchers in the earlier New York study were able to. One possible explanation is that part of the sample practices income targeting while the rest do not. Suppose we

[16] As noted in an earlier section, only three respondents answered that they drive shorter hours when business is good. These were discarded in this section's analyses.

multiply the fraction of the sample which claimed that they income-target (45.9%) by -1, and the fraction that do not (54.1%) by a small positive elasticity (say, 0.10), then the elasticity for the entire sample will be approximately -0.40. Unfortunately, this neat explanation is refuted when we look at the estimated wage elasticities (approximately -0.6) of those who claim they *do not* set income targets.

An alternative explanation is that most drivers implicitly set income "targets" (including those that claim not to) which are only binding when daily earnings are below the target. That is, the "target" is really a minimum below which they will continue driving even when business is slow. If this is true, then our estimated elasticities are biased upwards since both observations for good-business days and bad-business days are included.

To test this hypothesis, we retain only the observations in our data set recorded by drivers who stated numerical daily earnings targets in the qualitative section of our survey form. We then separate the observations in which the daily target was exceeded from those in which the driver was unable to or barely attained the earnings target. As can be seen in Table 9, the results (again using IV estimation techniques to account for the endogeneity of the wage rate arising from reporting errors) are inconclusive. The rankings of the coefficients on the log wage wage are reversed when the driver fixed effects are included in the regressions; the differences between the two groups in either case are very small anyway. This ambiguity can probably be attributed to the drivers' vague understanding of the income target concept. For example, when asked for an explicit income target in the Section II of the survey form, some drivers responded in terms of a range (say "$80-$100") or produced contradictory answers such as "I do not set a target; I just aim to earn $90 a day".

The next logical step then is to run separate regressions for observations in which wages were relatively high and those in which wages were relatively low. In practice, we took the two highest wage observations for each driver to be those in which wages were relatively high and the two lowest wage observations to be those in which wages were relatively low. This meant that the middle observation was dropped for the majority of drivers who had five complete observations. Interesting results emerge from this stratification, especially from those regressions estimated using the fixed effects estimator (see Table 10). The IV estimates are -0.8928 for the high-wage observations and -0.6224 for the low-wage observations. The differences between the two groups are considerably more striking for the

[17] As explained earlier, the estimates may also be revealing confusion about the concept of daily income targeting in

fixed effects estimates: -1.094 (t-value = -8.13) for the high-wage observations compared to -0.1135 (t-value = -0.92) for the low-wage observations. One cannot help but notice the striking similarity that the low-wage estimate (both it its point value and its imprecision) bears to the results commonly obtained in the labor supply literature. In addition, the hypotheses that the labor supply elasticities are -1 and 0 for the respective wage groupings cannot be rejected at conventional levels of significance. The significant differences in the slopes of the two regressions are, however, consistent with the concave relationship between log hours and log wages implied by the non-linear model in Table 5.[18]

These estimated labor supply elasticities suggest a special variant of the income targeting model in which drivers work shorter hours on high-wage days when they attain their targets more quickly, while on low-wage days they behave in a manner closer to that predicted by the neoclassical labor supply model. These estimated labor supply elasticities also suggest that there is an asymmetry in the behavior of drivers between that exhibited on high-wage days (days with good business) and that on low-wage days. On days when business is good, the temptation to quit upon reaching the target is very great (so that a higher wage rate will in fact lead to even fewer hours of driving). However, on days when business is poor, drivers are relatively less willing to continue driving even if their targets have not been met (that is, an even lower wage rate will not induce much more driving). This mode of behavior is probably unsurprising, given the monotony and drudgery of the job.[19]

Clearly, then, income targeting is not a mistake nor a heuristic shortcut, but probably a reflection of the battle for self-control that drivers face every day. On the one hand, drivers will strive to earn more to provide a better tomorrow for their families, while on the other, they are always tempted to quit when the takings are already relatively high. There appears to be a tug-of-war between fulfilling long-term objectives and the temptation to satisfy immediate, very short-term desires.

Given the negative wage elasticities obtained in our study which clearly reject the implications of the intertemporal labor supply model, what other factors can they be explained by? It has been suggested in the literature on labor supply that negative estimated labor supply elasticities may arise for

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the minds of some drivers.

[18] The two results are not strictly equivalent since some of the "low wage" observations in the Table 9 regression may in fact be "above-average wage" observations in the non-linear regression. A "low wage" for a driver with very high wages may still be greater than the overall mean wage for the full sample.

[19] Another possible interpretation of the estimated labor supply elasticity for low-wage days is that perhaps drivers would like to drive longer hours on these days but are constrained by the number of hours for which they have

other reasons than short-horizon income targeting. These include capital market imperfections that limit smoothing possibilities, severe liquidity constraints (such that drivers lack the savings or credit to pay for their daily operating expenses except out of current-day's earnings), progressive taxes and non-linear budget constraints, and sample selection bias (arising from the fact that the hours equation is estimated using days in which cab drivers worked positive hours). We believe that their effects are of second-order importance in our study. Firstly, most Singaporean workers have considerable savings (the private savings rate in Singapore is among the highest in the world) so that severe liquidity constraints unlikely to be binding. Secondly, taxes are not very progressive at the income level of most taxi drivers. Finally, the sample selection bias problem appears to be of a very small magnitude in our study. Among the 91 drivers sampled, only 8 reported not working for one day out of the five consecutive days for which they provided earnings and hours data. These were apparently their scheduled off-days.

6. Conclusion

The intertemporal model of labor supply predicts that a transitory increase in the wage rate will lead to greater hours worked, since the substitution effect dominates the very small income effect. Previous studies using aggregate data from many industries have reported unsatisfactory results, with imprecisely estimated wage elasticities that are often of the "incorrect" sign. However, these studies are plagued by numerous practical problems, as discussed earlier, so that their findings do not constitute solid proof against the empirical validity of the intertemporal model.

The taxi driving profession, by contrast, provides an unique opportunity to conduct a clean test of the intertemporal labor supply model. Taxi drivers face wages that are highly correlated within days but weakly correlated across days, and are relatively unconstrained in choosing the number of hours to work on any given day. A previous study of cab drivers in New York City yielded surprising estimates of the wage elasticity of hours worked -- they were unfailingly negative -- and suggested that they could be explained by the target income hypothesis. In this paper, we studied the labor supply behavior of taxi drivers in Singapore, chosen as a representative of the Asian "growth miracles", a dynamic

access to the taxi. This interpretation is refuted when we find that the mean number of hours worked on low-wage multi-racial (and highly materialistic) society known for its shrewd competitiveness and business acumen. The expectation, then, was to find relatively weak evidence for the sub-optimal practice of income targeting.

The results we obtain clearly reject the predictions of the intertemporal labor supply model, and provides considerable evidence for short-horizon income targeting. In our full sample, wage elasticities are negative and significantly different from zero. When instrumental variables are used to correct for measurement error in wages, the estimated wage elasticity becomes even more negative. Accounting for driver heterogeneity by the use of the fixed effects estimator also fails to reverse the negative elasticities. In addition, the empirical estimates indicate that income targeting is more prevalent among ethnic Chinese drivers than ethnic Malay drivers, debunking the belief that the ethnic Chinese are more business-oriented and "money-minded", and highlights the dangers of simplistic ethnic stereotyping. Other stratification of the data also yield surprising and counter-intuitive results. For example, we find that more experienced drivers tend to exhibit more pronounced income targeting behavior than do their less experienced colleagues.

In the final analysis, our results are consistent with a variant of income targeting in which drivers quit early on high-wage days when their earnings targets are attained more quickly, while on low-wage days they behave much like what the standard model of labor supply predicted they would. There appears to be a conflict between long-term objectives and short-term desires - the driver fights a constant battle for self-control as he endures the numbing monotony of his job. Clearly, the behavior of economic agents is at once less mechanical and therefore less mathematically tractable than that suggested by standard optimizing models, and that to ignore this paradoxical complexity is a grievous error if we are truly serious in modeling the actual workings of the economy and the decision-making of economic agents.

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days was 9.54 (each shift lasts for 12 hours) and the standard deviation is a large 2.576 hours.

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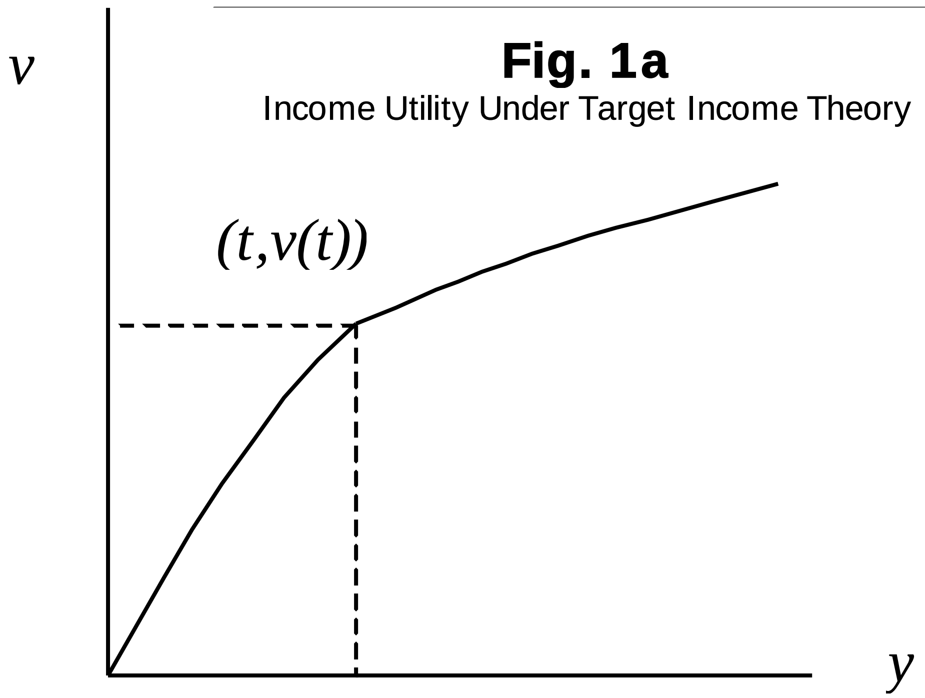


Fig. 1a
Income Utility Under Target Income Theory

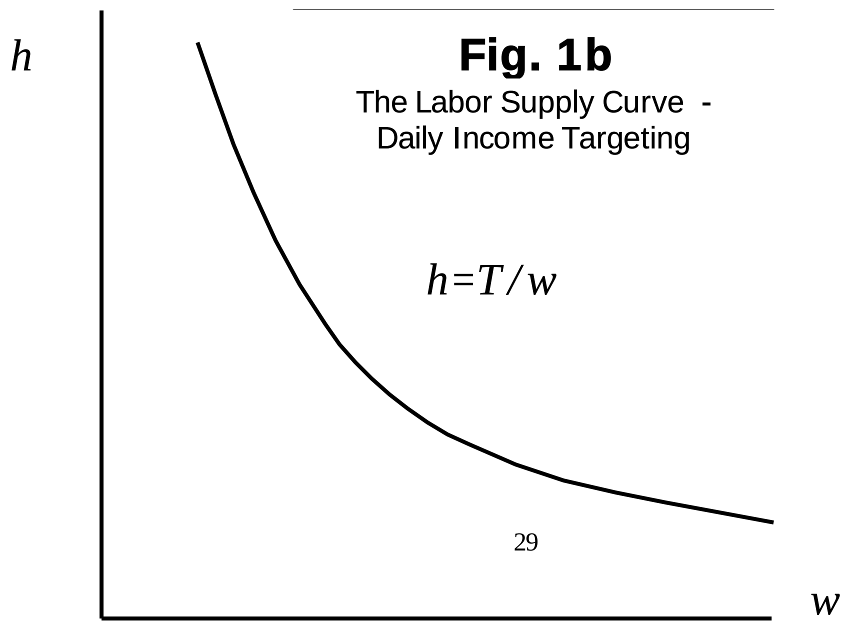


Fig. 1b
The Labor Supply Curve -
Daily Income Targeting

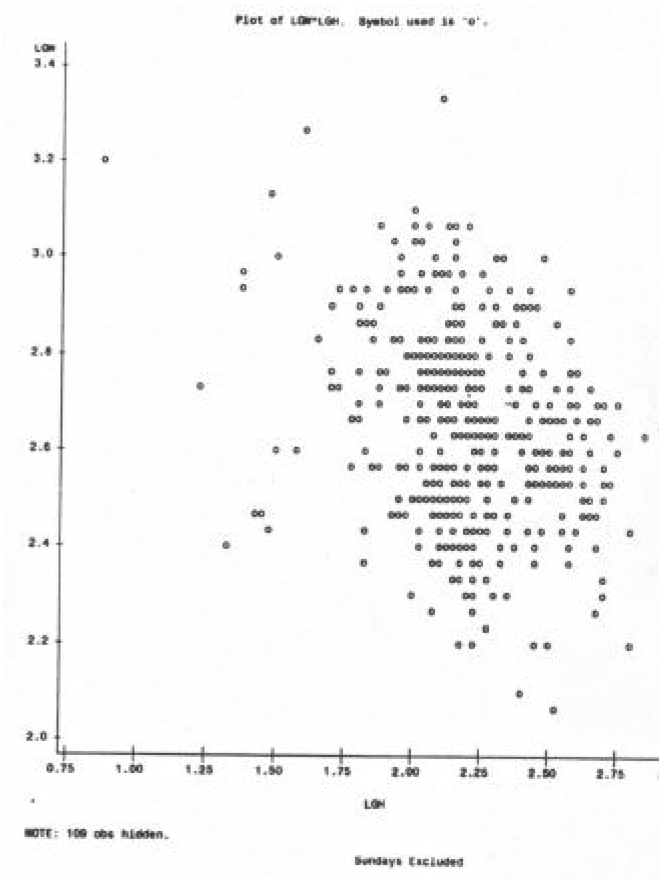
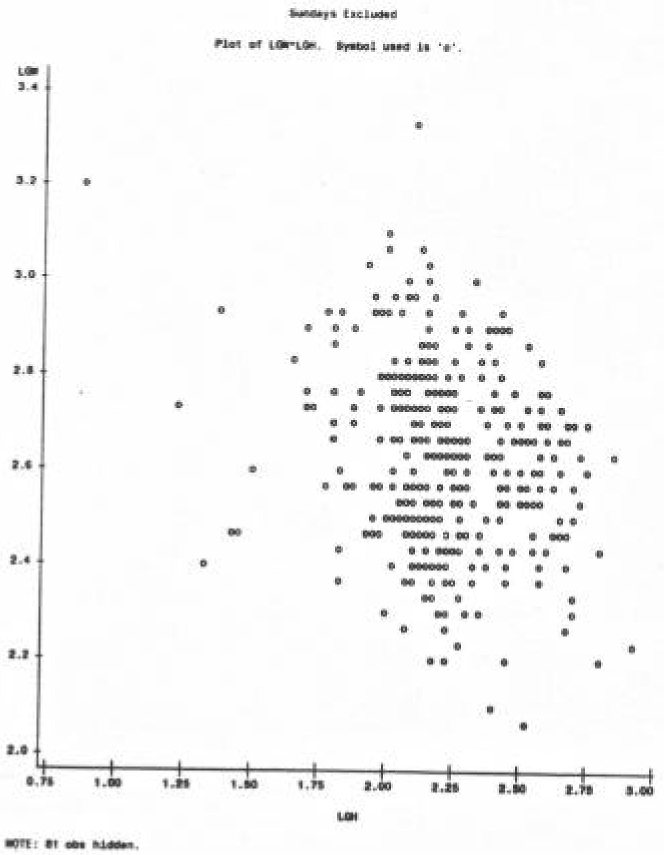
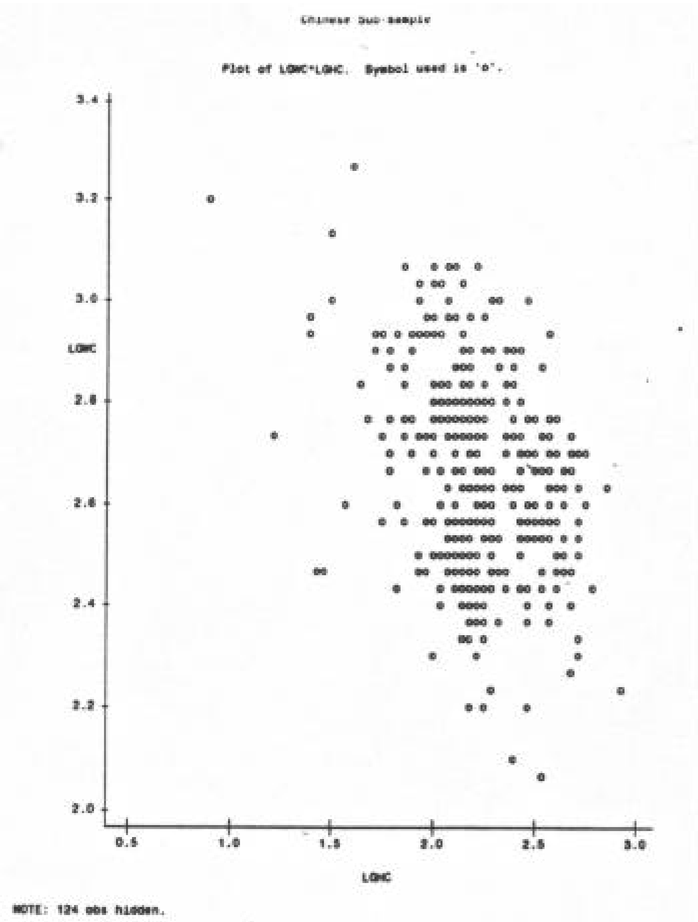


Fig. 2
Plot of log wage against log hours

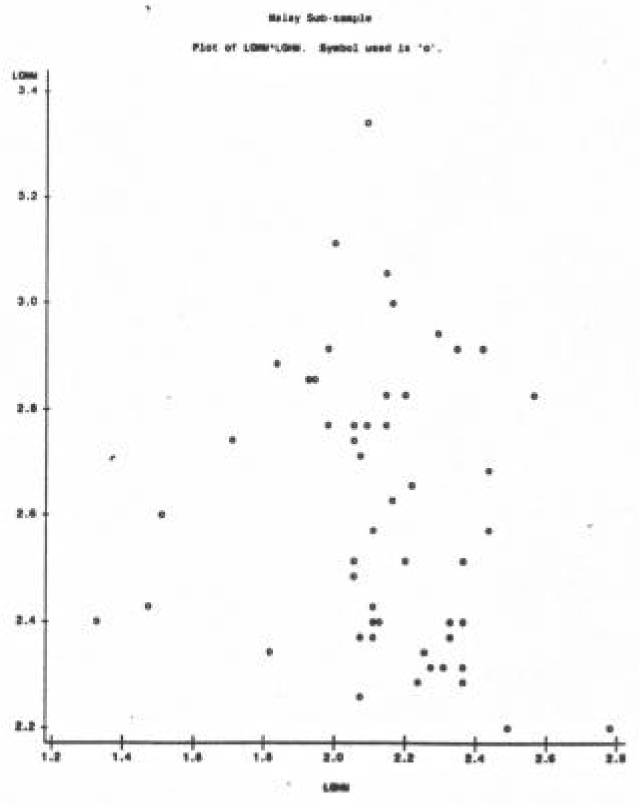
All



All – Sundays Excluded



Chinese Sub-Sample



Malay Sub-Sample

Table 1: Sample Characteristics

Variable	*Number of Observations*	*Mean*	*Std Dev*
Malay	442	0.1146067	0.3189053
Age	442	46.0921345	4.1441434
Experience (Yrs)	442	10.0640449	2.6942233
# of children	442	2.4494382	1.1291713
Education (Yrs)	400	9.0750000	1.4764299
Target (Y/N)	442	0.4921348	0.5005008
Drive Longer	431	0.4129930	0.4929438
Drive Shorter	431	0.0348028	0.1834930
Wage	442	14.4222472	3.0199361
Hours	442	9.4319708	2.5018628

Table 2: Resonses to Short Questions on Income Targeting

	Target	*No Target*
Drive Longer	17	21
Drive As Usual	22	25

Table 3: A preliminary Look at Wages and Hours Worked

	"High" Wage	*"Low" Wage*
Drive longer than average	77	160
Drive shorter than average	119	75

Table 4a: Estimated Wage Elasticities (Basic Model - OLS)

	All			Chinese		Malay		
	"Between" Regression	*OLS*	*Fixed Effects*	*OLS*	*Fixed Effects*	*OLS*	*Fixed Effects*	*GLS*
Intercept	2.9222 (7.88)	2.8773 (21.27)	--	3.0400 (21.11)	--	2.2814 (4.31)	--	1.9640 (3.34)
log w	-0.2625 (-1.88)	-0.3987 (-8.18)	-0.5127 (-8.63)	-0.4622 (-8.79)	-0.5850 (-9.52)	-0.1904 (-1.22)	-0.1313 (-0.66)	-0.0997 (-0.62)
Day	------	0.2903 (8.62)	0.2674 (3.59)	0.3040 (8.99)	0.2636 (3.29)	0.3057 (1.40)	0.3615 (1.32)	0.3798 (1.36)
Night	------	0.3836 (15.22)	0.3063 (6.48)	0.3753 (14.94)	0.3078 (6.76)	0.4815 (2.65)	0.3438 (0.97)	0.5089 (2.05)
Adj R^2	0.0279	0.4009	0.2212	0.4352	0.2672	0.1310	0.0013	0.0528
n	90	442	442	392	392	50	50	50

(*t*-ratios in parenthesis)

Note: The R^2 statistic for the FE estimator is not comparable to that for the OLS estimator.

Table 4b: Estimated Wage Elasticities (Basic Model - IV)

	All		Chinese		Malay	
	2SLS	*Fixed Effects*	*2SLS*	*Fixed Effects*	*2SLS*	*Fixed Effects*
Intercept	3.3492 (11.09)	--	3.8343 (10.79)	--	2.1998 (2.25)	--
log w	-0.5623 (-5.00)	-0.8525 (-6.13)	-0.7494 (-5.58)	-0.8939 (-6.50)	-0.1644 (-0.54)	-0.3850 (-0.70)
Day	0.2530 (7.22)	0.1804 (2.16)	0.2767 (7.68)	0.1906 (2.17)	0.3206 (1.21)	-0.2515 (0.71)
Night	0.3809 (14.99)	0.2973 (6.05)	0.3685 (14.30)	0.3024 (6.42)	0.4863 (2.58)	0.2734 (0.70)
Adj R^2	0.3831	0.1613	0.2672	0.1887	0.1120	0.0004
n	396	396	346	346	50	50

(*t*-ratios in parenthesis)

Note: The R^2 statistic for the FE estimator is not comparable to that for the OLS estimator.

Table 5: Estimated Wage Elasticities (Excluding Sundays and Non-Linear Model)

	All Drivers (Excluding Sundays)		**Non-Linear Model (All Days)**	
	OLS	*Fixed Effects*	*OLS*	*Fixed Effects*
Intercept	2.6752 (18.04)	--	-0.1639 (-0.13)	--
log w	-0.3239 (-6.01)	-0.3220 (-4.92)	1.9063 (2.05)	3.4395 (4.62)
$(log\ w)^2$	--	--	-0.4328 (-2.48)	-0.7406 (-5.32)
Day	0.3078 (8.44)	0.2923 (3.38)	0.2801 (8.30)	0.2643 (3.65)
Night	0.3988 (14.73)	0.2941 (5.59)	0.3805 (15.16)	0.2697 (5.80)
Adj R^2	0.4118	0.1203	0.4079	0.2668
N	371	371	445	445

(t-ratios in parenthesis)

Table 6: Estimated Wage Elasticities for Model with Non-Budget Constraint Variables

	All					
	OLS			*IV*		
Interecept	2.9277 (17.76)	2.9035 (14.84)	2.9301 (14.76)	3.2703 (9.27)	3.6807 (9.20)	3.6875 (9.17)
Log w	-0.4158 (-8.03)	-0.4411 (-8.44)	-0.4455 (-8.47)	-0.5373 (-4.40)	-0.7260 (-5.28)	-0.7273 (-5.28)
Education	0.0045 (0.61)	0.0035 (0.46)	0.0038 (0.49)	0.0024 (0.31)	-0.0019 (-0.23)	-0.0018 (-0.22)
Experience	--	0.0277 (1.55)	0.0277 (1.54)	--	0.0367 (1.93)	0.0367 (1.92)
Experience^2	--	-0.0016 (-2.02)	-0.0016 (-2.00)	--	-0.0022 (-2.49)	-0.0022 (-2.49)
No. of Children	--	--	-0.0076 (-0.79)	--	--	-0.0018 (-0.18)

Day	0.2562 (7.09)	0.2586 (5.15)	0.2596 (7.17)	0.2536 (6.95)	0.2538 (6.76)	0.2540 (6.75)
Night	0.3696 (13.96)	0.3620 (13.65)	0.3612 (13.61)	0.3707 (13.89)	0.3620 (13.16)	0.3618 (13.13)
Adj R^2	0.3985	0.4066	0.3487	0.3514	0.3502	0.3487

(t-ratios in parenthesis)

Table 7: Estimated Wage Elasticities (Stratified by Experience and Education)

	More Educated		**Less Educated**		**More Experienced**		**Less Experienced**	
	IV	*Fixed Effects*	*IV*	*Fixed Effects*	*IV*	*Fixed Effects*	*IV*	*Fixed Effects*
Intercept	3.2997 (8.46)	--	4.1938 (6.98)	--	3.1982 (7.10)	--	3.3744 (8.45)	--
log w	-0.5146 (-3.53)	-0.7253 (-3.98)	-0.8750 (-4.35)	-0.9523 (-4.67)	-0.5583 (-3.35)	-1.1737 (-4.32)	-0.5534 (-3.77)	-0.6423 (-4.48)
Experience	-0.0108 (-0.46)	--	0.0286 (0.75)	--	--	--	--	--
Expr^2	0.0007 (0.54)	--	-0.0022 (-1.39)	--	--	--	--	--
Day	0.2546 (6.63)	-0.0688 (0.59)	0.1595 (1.94)	0.1904 (1.38)	0.3721 (4.14)	0.0221 (0.11)	0.2236 (5.98)	0.2735 (3.43)
Night	0.3191 (11.10)	0.1765 (2.50)	0.4389 (9.32)	0.3981 (5.03)	0.4637 (8.65)	0.3329 (2.07)	0.3414 (11.13)	0.3168 (7.32)
Adj R^2	0.4090	0.1361	0.3568	0.1701	0.3298	0.0998	0.4045	0.2614

(t-ratios in parenthesis)

Note: Those who are classified as less educated had fewer than 10 years of formal schooling, while those classified as less experienced had worked for fewer than 10 years as taxi drivers.

Table 8: Estimated Wage Elasticities (Targeters vs Non-Targeters)

	Target		**No Target**		**Drive Longer Hours**		**Drive Normal Hours**	
	IV	*Fixed Effects*	*IV*	*Fixed Effects*	*IV*	*Fixed Effects*	*IV*	*Fixed Effects*
Intercept	3.8622 (9.62)	--	3.2732 (7.01)	--	4.3984 (7.32)	--	3.2907 (8.60)	--
Log w	-0.7631 (-4.74)	-0.9602 (-5.02)	-0.6080 (-3.53)	-0.7710 (-3.86)	-0.9750 (-3.99)	-0.8554 (-3.24)	-0.6105 (-4.14)	-0.8399 (-5.70)
Experience	0.0328 (1.47)	--	0.0275 (0.71)	--	0.0585 (1.27)	--	0.0320 (1.62)	--
Expr^2	-0.0024 (-2.39)	--	-0.0014 (-0.73)	--	-0.0032 (-1.49)	--	-0.0020 (-2.18)	--
Day	0.2614 (5.67)	0.0163 (0.12)	0.2955 (4.96)	0.3306 (3.15)	0.0906 (1.44)	0.3078 (2.56)	0.3286 (6.41)	0.0598 (0.57)
Night	0.3622 (9.81)	0.1955 (2.33)	0.3824 (10.30)	0.3717 (6.33)	0.3192 (8.04)	0.4781 (5.02)	0.4020 (9.70)	0.1942 (3.60)
Adj R^2	0.3822	0.1511	0.4198	0.1845	0.3952	0.1335	0.3190	0.1890

(*t*-ratios in parenthesis)

Note: The sub-samples are classified according to the taxi driver's responses to Question 1 and Question 3 in the Part II (Short Questions) section of the survey. The questions were "Do you set a target as to how much you want to earn every day? If so, what is the target?", and "Do you drive longer or shorter hours when business is good that day?" respectively.

Table 9: Estimated Wage Elasticities (Under-Target Days vs Above-target Days)

	Under/On Target		**Above Target**	
	IV	*Fixed Effects*	*IV*	*Fixed Effects*
Intercept	3.6523 (7.79)	--	3.4771 (5.57)	--
Log w	-0.6589 (-3.61)	-0.4664 (-2.00)	-0.6022 (-2.31)	-0.5268 (-1.77)
Experience	0.0113 (0.46)	--	0.0066 (0.22)	--
Expr^2	-0.0010 (-0.83)	--	-0.0013 (-1.05)	--
Day	0.3014 (5.73)	0.2700 (1.67)	0.3500 (5.25)	0.1499 (0.71)
Night	0.3878 (8.32)	0.2723 (3.51)	0.3541 (8.13)	0.1360 (0.85)
Adj R^2	0.4263	0.1504	0.4804	0.0414
N	116	116	92	92

(*t*-ratios in parenthesis)

Table 10: Estimated Wage Elasticities (High-Wage Days vs Low-Wage Days)

	High-Wage Observations		**Low-Wage Observations**	
	IV	*Fixed Effects*	*IV*	*Fixed Effects*
Intercept	4.0857 (7.40)	--	3.5178 (5.11)	--

Log w	-0.8928 (-4.41)	-1.0943 (-8.13)	-0.6224 (-2.20)	-0.1135 (0.92)
Experience	0.0676 (2.14)	--	-0.0048 (-0.17)	--
Expr^2	-0.0040 (-2.69)	--	0.0000 (0.015)	--
Day	0.2000 (3.30)	0.1519 (1.92)	0.2640 (4.70)	0.0839 (1.09)
Night	0.2961 (6.27)	0.0141 (1.88)	0.4103 (10.24)	0.1077 (2.00)
Adj R^2	0.3108	0.2813	0.3876	0.0098
n	182	182	183	183

(*t*-ratios in parenthesis)