Econ 219B
Psychology and Economics: Applications
(Lecture 4)

Stefano DellaVigna

February 16, 2005

Outline

1. Seven Application of Present Bias II
2. Lessons from Self-Control II
3. Self-Control: Summary
4. Reference Dependence: Intro
5. Labor Supply: A Framework
6. Labor Supply: Cab Drivers

1 Seven Applications of Present Bias

- Large number of papers on time preferences/self-control/hyperbolic discounting/present bias

- Two categories:

  1. **Field test (F)**. Use evidence to test theory

  2. **Theory (T).** Applied theory paper

  3. **(Experiments (E).** Laboratory test (Few)**)**

- Some common features in this literature:

  – Puzzling stylized facts

  – Structural or reduced form models

- Sophistication typically assumed

- Some claims that procrastination comes from present bias

5.4 Job Search

- DellaVigna and Paserman (2003)

- Stylized facts:

  - time devoted to job search by unemployed workers: 9 hours/week

  - search effort predicts exit rates from unemployment better than reservation wage choice

- **T.** Model of job search with costly search effort and reservation wage decision:

  - search effort — immediate cost, benefits in near future — driven by β

  - reservation wage — long-term payoffs — driven by δ

- **F.** Correlation between measures of impatience (smoking, impatience in interview, vocational clubs) and job search outcomes:

  - Impatience $\uparrow \Longrightarrow$ search effort $\downarrow$
  - Impatience $\uparrow \Longrightarrow$ reservation wage $\longleftrightarrow$
  - Impatience $\uparrow \Longrightarrow$ exit rate from unemployment $\downarrow$

- Impatience captures variation in β

- Sophisticated or naive – does not matter

- Paserman (2003): structural model estimated by max. likelyhood: $\beta = .40$ (low-wage workers), $\beta = .89$ (high-wage workers)

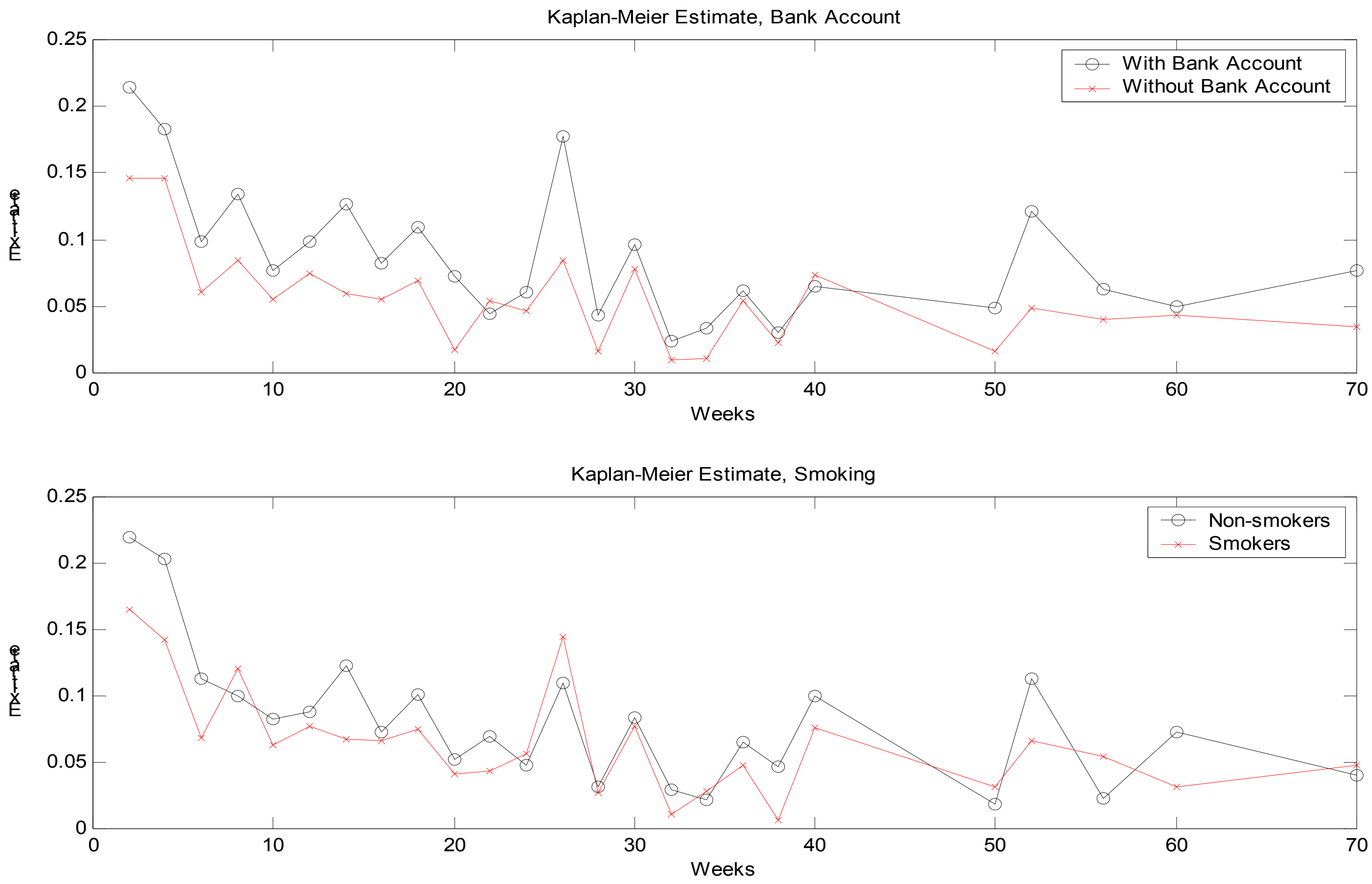

FIGURE 2: Exit Rates in the PSID

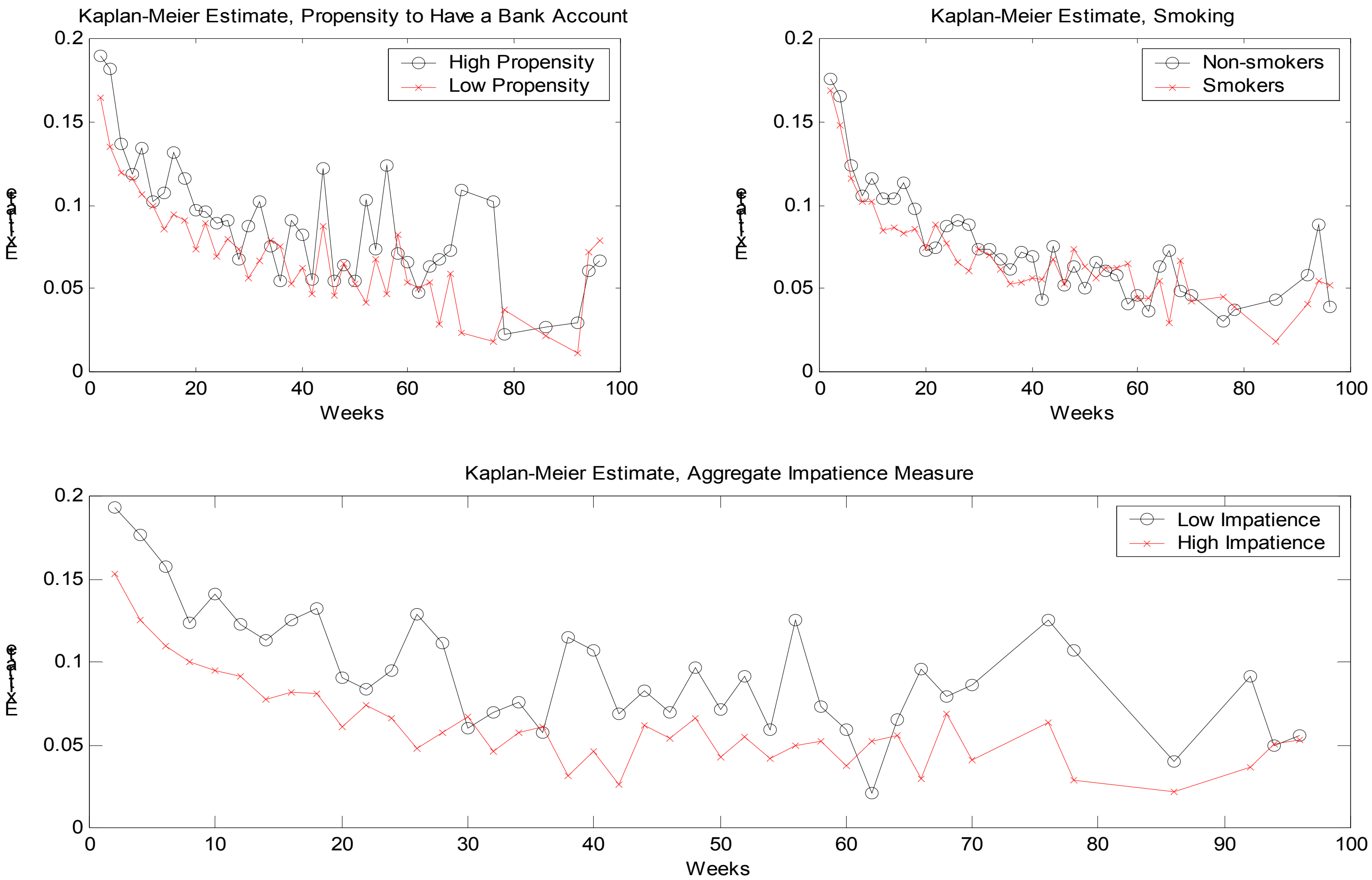

Figure 3: Exit Rates in the NLSY

Table 4: Benchmark Models †

	NLSY Sample	
	(1)	(2)
Controls	No	Yes
Aggregate Impatience Measure	-0.1501**	-0.089**
	(.0159)	(.0177)
	[5664]	[5664]
1. NLSY Assessment of Impatience	-0.0552**	-0.0431**
Measure of impatience during	(.0138)	(.0135)
Interview	[8778]	[8778]
2. Bank Account	-0.135**	-0.0793**
Did not have a bank account	(.0131)	(.0141)
	[8532]	[8532]
3. Contraceptive Use	-0.0827**	-0.0243
Had unprotected sex	(.0141)	(.0148)
	[6696]	[6696]
4. Life Insurance	-0.0456**	-0.0131
Did not have life insurance	(.0146)	(.0150)
At job	[7671]	[7671]
5. Smoking	-0.0484**	-0.0294**
Smoked before	(.0136)	(.0136)
Unemployment spells	[8594]	[8594]
6. Alcohol	-0.0044	-0.0115
Average number of hangovers	(.0140)	(.0140)
In past 30 days	[8764]	[8764]
7. Vocational Clubs	-0.0438**	-0.0320**
Measure of non-participation	(.0130)	(.0126)
In vocational clubs in HS	[8400]	[8400]
	PSID Sample	
Controls	No	Yes
1. Bank Account [1]	-0.1974**	-0.1622**
Did not have a checking account	(.0336)	(.0383)
	[1426]	[1409]
2. Smoking	-0.1149**	-0.0964**
Smoked before	(.0283)	(.0288)
Unemployment spells	[1649]	[1639]

† **Notes:** Entries in the table represent the coefficient on the relevant variable from *separate* Cox proportional hazard models. Robust standard errors in parentheses. Number of spells used in each regression is in brackets. Observations with missing values for any of the control variables were discarded. All measures of impatience are standardized (see Notes to Table 3). All the impatience variables (with one exception specified below) are measured prior to the occurrence of the unemployment spells. The aggregate impatience measure is constructed using factor analysis (see Appendix for details).

Control Variables in the NLSY: age, education, marital status, race, dummy for kids, self-reported health status, AFQT score, father's occupation/presence (4 dummies), parental education, received magazines while growing up, received papers, had a library card, urban dummy, SMSA dummy, central city dummy, local unemployment rate (5 dummies), dummy for receipt of UI benefits, region (3 dummies), 8 occupation dummies, 12 industry dummies, log (hourly wage) before unemployment spell, tenure on last job.

Control variables in the PSID: age, education, race, marital status, self-reported health in 1986 (2 dummies), father's occupation (2 dummies), parental education (2 dummies), county unemployment rate, dummy for receipt of UI benefits, 7 industry dummies, 4 occupation dummies, log (hourly wage) before the unemployment spell.

[1] The bank account proxy in the PSID is measured after the occurrence of the spells.

5.5 Welfare programs

- Fang, Silverman (2002, 2003)

- Stylized Facts:

  - limited transition from welfare to work

  - (more importantly) large share of mothers staying home and not claiming benefits

- Examines decisions of single mothers with kids. Three states: Welfare (leisure + benefits), Work (wages), Home (leisure)

- Mothers stay home because of one-time social disapproval of claiming benefits

- Naiveté crucial here

Table 2: Transition Matrix, Never-married Women with at Least One Child

Choice (t-1)	Choice (t) Welfare	Work	Home
Welfare			
Row %	84.3	3.5	12.3
Column %	76.7	6.3	17.9
Work			
Row %	5.3	79.3	15.3
Column %	2.6	76.4	12.1
Home			
Row %	28.3	12.0	59.7
Column %	20.7	17.3	70.0

of those who chose welfare in period t, 76.7% had chosen welfare in the previous period. Of those who chose work in period $t-1$, 79.3% went on to choose it again in period t. Decisions to remain at home are considerably less persistent. Of those who chose to stay home in period $t-1$, 59.7% chose it again in period t.

6 Results

6.1 Estimates of Θ'

The parameters of the government benefits and fertility functions (Θ'), estimated in the first stage, are presented in Tables 9 and 12 of the appendix, respectively. As has been often noted, there is considerable variation in benefits levels across states. In our sample, the estimated average annual benefit for a mother with two children ranges from $4,856 (1987 dollars) to $9,490. Patterns of welfare participation vary with the level of benefits in ways consistent with optimizing behavior. In our sample, residents of the 5 states with the highest benefits spend 56 percent of the period observed on welfare; in the 5 states with the lowest benefits the participation rate is 37 percent.

The estimate of the fertility function's parameters suggests that the probability of an additional birth is decreasing with age and with the number of children. The estimate also indicates that, relative to those who stay home, the probability of an additional birth is lower for workers and higher for those on welfare. We note, however, that our simple exogenous model of subsequent valid in this more realistic model, and that in practice the two discount parameters are separately identified with reasonable precision.

6.3 Parameter Estimates and Simulations

Table 4 presents estimates of the parameters of the model under the assumption that agents are naive. Estimation of the model with sophisticated agents remains in progress. The estimated present-bias factor $\beta = 0.61$ and the estimated standard discount factor $\delta = 0.92$ together imply a one-year ahead discount rate of 78%. Inferential studies such as Hausman (1979), and Warner and Pleeter (2001) estimate (one-year ahead) discount rates ranging from 0 to 89% depending on the characteristics of the individual and intertemporal trade-offs at stake. Experimental studies have estimated this figure to be approximately 40% in an average population.

Table 4: Parameter Estimates, Naïve Agents

		parameter	point estimate	std. error
utility parameters	time discounts	β	0.61	0.33
		δ	0.92	0.05
	net stigma	ϕ	4046.74	1123.81
	home production	e_0	3953.13	545.79
		e_1	370.55	150.52
		e_2	-148.1	56.09
		η	5101.51	522.17
wage & skill parameters	constant	ln(r) + ha0	8.22	0.15
	yrs. of school	α_1	0.037	0.012
	experience	α_2	0.115	0.016
	experience^2	α_3	-0.0064	0.001
	1st yr. exper.	α_4	0.086	0.041
	exper. decay	α_5	0.191	0.091
continuation values	no. children	ω_1	510.04	479.97
	no. children^2	ω_2	-6143.43	1294.87
	experience	ω_3	29.03	43.36
	experience^2	ω_4	107.39	38.16
	welfare lag	ω_5	-5325.95	4066.26
	work lag	ω_6	1147.05	1256.76
variance/ covariance	std. dev. ε_0	$\sigma_{\varepsilon 0}$	3174.12	901.47
	std. dev. ε_1	$\sigma_{\varepsilon 1}$	0.342	0.099
	std. dev. ε_2	$\sigma_{\varepsilon 2}$	5050.12	909.82
	cov(ε_0,ε_2)	$\sigma_{\varepsilon 0 \varepsilon 2}$	-2550.08	674.2
	std. dev. meas err.	σ_{me}	0.272	0.12

N=4487 log likelihood = -3821.45

5.6 Firm pricing

- **T.** Two-part tariffs chosen by firms to sell investment and leisure goods (DellaVigna and Malmendier, 2004)

- **F.** Pricing of magazines (Oster and Scott-Morton, 2003)

- See later Section on Firm Response

5.7 Payday effects

- Shapiro (2003), Melvin (2003), Huffman and Barenstein (2003)

- Stylized facts:

  – Purchases increase discretely on payday

  – Effect more pronounced for more tempting goods

  – Food intake increases as well on payday

- **F.** Next lecture

2 Lessons from Self-control II

1. Empirical evidence of type 1 (Madrian and Shea, 1999; Choi et al.:, 2001; Huberman and Regev, 2001):

   - **Time Series** (or **Event Study**) evidence
   - At time t, change in regime
   - Simple difference: Look at (After t - Before t)
   - Worries:

   (a) Endogeneity of change

   (b) Other changes occurring at same time

   (c) How many observations? Maybe $n = 1$?

2. Empirical evidence of type 2 (DellaVigna and Malmendier, 2004; Miravete, 2004; Sydnor, 2004; Souleles, 2004):

   - **Contract choice** evidence

   - Need to observe:

     (a) menu of options

     (b) later utilization

   - Use revealed preferences to make inferences from contract choice in (a)

   - Compare to actual utilization in (b)

   - Worries: hard to distinguish unusual preferences (self-control) and wrong beliefs (naiveté, overconfidence)

3. Empirical evidence of type 3 (Ausubel, 2004; Bertrand at al, 2004; John List's work; Duflo and Saez, 2003):

   - **Field experiment** evidence

     (a) Naturalistic setting

     (b) Randomize tratment

   - Observe effect of treatment

   - Plus: Randomization ensures clean identification

   - Minus: Not easy to run

3 Self-Control: Summary

- Present bias/Hyperbolic Discounting

- Reasons for success:

  1. Simple model (one-, then two- parameter deviation). YES!

  2. Powerful intuition (immediate gratification) YES!

  3. Support in the laboratory OK

  4. Support from field data (strong) YES!

- Lead to wholly new subfield (behavioral contract theory/behavioral IO)

- Next: Reference Dependence

- Status:

    1. Simple model (four new features). YES?

    2. Powerful intuition (reference points) YES!

    3. Support in the laboratory YES!

    4. Support from field data (strong) OK, more needed

4 Reference Dependence: Intro

- Evidence for reference dependence from experiments

- Prospect Theory (1979) utility function:

  1. Narrow Framing
  2. Loss Aversion
  3. Concavity over gains
  4. Convexity over losses
  5. Probability weighting function non-linear

- Most field applications use only (1)+(2), or possible (1)+(2)+(3)+(4)

- Loss Aversion — kink at reference point

- Reference point?

- Open question – depends on context

- Koszegi-Rabin (2004): rational expectations equilibrium

- Narrow framing?

- Consider only problem at hand (labor supply, stock picking, house sale)

- Neglect other relevant decisions

5 Labor Supply: A Framework

- Camerer et al. (1997), Farber (2004, 2005), Fehr and Goette (2002, 2005), Oettinger (2001)

- Daily labor supply by cabbies, bike messengers, and stadium vendors

- Framework (notation as in Farber, 2005, with $\nu = 1$):

  - effort h (no. of hours)

  - hourly wage w

  - Returns of effort: $Y = w * h$

  - Linear utility $U(Y) = Y$

  - Cost of effort $c(h) = \theta h^2/2$ convex within a day

- Standard model: Agents maximize

$$U(Y) - c(h) = wh - \frac{\theta h^2}{2}$$

- Model with reference dependence:

- Threshold T of earnings agent wantes to achieve

- Loss aversion for outcomes below threshold:

$$U = \begin{cases} wh - T & \text{if } \; wh \geq T \\ \alpha (wh - T) & \text{if } \; wh < T \end{cases}$$

  with $\alpha > 1$ loss aversion coefficient

- Referent-dependent agent maximizes

$$\begin{array}{rl} wh - T - \frac{\theta h^2}{2} & \text{if } \; h \geq T/w \\ \alpha (wh - T) - \frac{\theta h^2}{2} & \text{if } \; h < T/w \end{array}$$

- Derivative with respect to h:

$$\begin{array}{rl} w - \theta h & \text{if } \; h \geq T/w \\ \alpha w - \theta h & \text{if } \; h < T/w \end{array}$$

- Three cases.

  1. Case 1 ($\alpha w - \theta T/w < 0$).

     - Optimum at $h^* = \alpha w/\theta < T/w$

2. Case 2 ($\alpha w - \theta T/w > 0 > w - \theta T/w$).

   - Optimum at $h^* = T/w$

3. Case 3 ($w - \theta T/w > 0$).

   – Optimum at $h^* = w/\theta > T/w$

- **Standard theory ($\alpha = 1$).**

- Interior maximum: $h^* = w/\theta$ (Cases 1 or 3)

- Labor supply

- Combine with labor demand: $h^* = a - bw$, with $a > 0, b > 0$.

- Optimum:

$$L^S = w^*/\theta = a - bw^* = L^D$$

or

$$w^* = \frac{a}{b + 1/\theta}$$

and

$$h^* = \frac{a}{b\theta + 1}$$

- Comparative statics with respect to a (labor demand shock): $a \uparrow$ –> $h^* \uparrow$ and $w^* \uparrow$

- On low-demand days (low w) work less hard

- Save effort for high-demand days

- **Model with reference dependence ($\alpha > 1$)**:
  - Case 1 or 3 still exist
  - BUT: Case 2. Kink at $h^* = T/w$ for $\alpha > 1$
- Labor supply
- Combine with labor demand: $h^* = a - bw$, with $a > 0, b > 0$.
- Consider Case 2

- Optimum:

$$L^S = T/w^* = a - bw^* = L^D$$

and

$$w^* = \frac{a + \sqrt{a^2 + 4Tb}}{2b}$$

- Comparative statics with respect to a (labor demand shock):
  - $a \uparrow -> h^* \uparrow$ and $w^* \uparrow$ (Cases 1 or 3)
  - $a \uparrow -> h^* \downarrow$ and $w^* \uparrow$ (Case 2)

- Case 2: On low-demand days (low w) need to work harder to achieve reference point T -> Work harder

- Opposite prediction to standard theory

- (Neglected negligible wealth effects)

6 Labor Supply: Estimation

Klaus and Matthew debate Camerer(1997) and Farber (2005)

Camerer, Babcock, Loewenstein & Thaler:

Labor Supply of NYC Cab Drivers: One Day At a Time

QJE May 1997

Claus Bjørn Jørgensen

Introduction

- Classic theory:
  Compensated wage elasticity unambiguously (weakly) positive

- Claim:
  The wage elasticity for NYC cab drivers is negative

- Daily income targeting

Data

- **TRIP** (1994)
  - 192 trip sheets
  - 70 sheets, 13 drivers after screening
  - Fleet drivers
  - Intra-day data
- **TLC1** (1990)
  - 1044 sheets, 484 drivers after screening
  - Fleet drivers, lease-drivers, owner-drivers
- **TLC2** (1988)
  - 712 sheets and drivers after screening
  - Fleet drivers, owner-drivers
- **Phone survey** of fleet managers

Hourly Wage Variability

(TRIP-sample)

Within-Day

- First-order autocorrelation 0.493
- Second-order autocorrelation 0.578
- First and second half of day 0.40

Across Days

- Wages ‘significantly different’
- Uncorrelated

 Ideal data for studying responses to transitory wage changes

Wage Elasticities – simple correlation

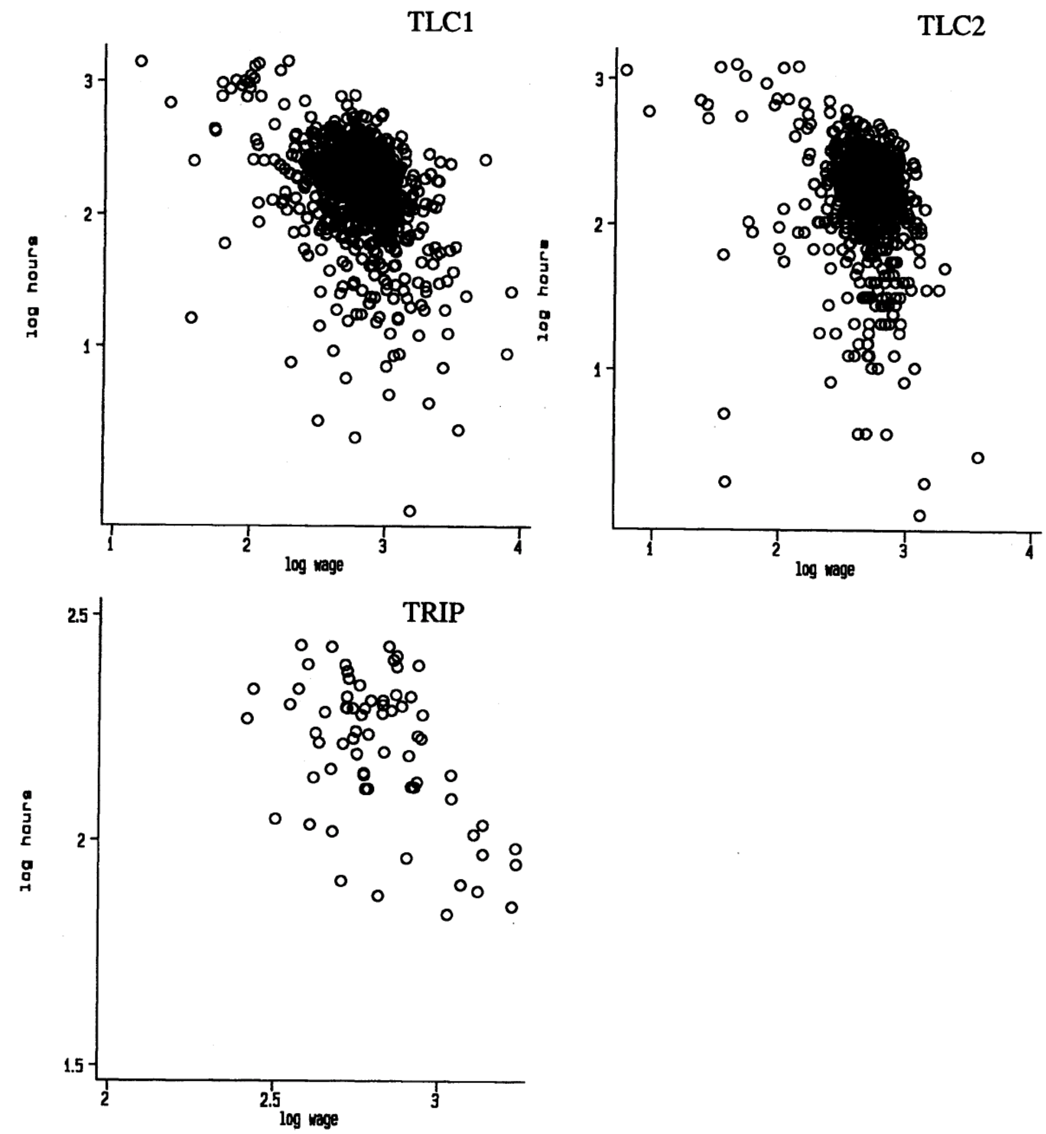

FIGURE I
Hours-Wage Relationships

- Correlation coefficients -.50, -.39 and -.30 respectively

Measurement Error

- If noise in measured hours:

  $$\underbrace{\text{hours} \uparrow \;\Rightarrow\; \text{hourly wage} \downarrow}$$

  $$\Downarrow$$

  spurious neg. elasticity

- Use quartiles of other drivers' earnings the same day as instruments for own hourly wage

Results, main regression

TABLE III
IV LOG HOURS WORKED EQUATIONS

Sample	TRIP		TLC1		TLC2
Log hourly wage	−.319	.005	−1.313	−.926	−.975
	(.298)	(.273)	(.236)	(.259)	(.478)
High temperature	−.000	−.001	.002	.002	−.022
	(.002)	(.002)	(.002)	(.002)	(.007)
Shift during week	−.054	−.041	−.016	.028	—
	(.023)	(.035)	(.042)	(.044)	
Rain	−.007	−.001	—	—	−.130
	(.042)	(.041)			(.070)
Night shift dummy	.059	−.036	−.088	−.242	−.202
	(.057)	(.053)	(.040)	(.064)	(.057)
Day shift dummy	—	—	−.030	.068	—
			(.038)	(.048)	
Fixed effects	No	Yes	No	Yes	No
Sample size	70	65	1044	794	712
Number of drivers	13	8	484	234	712

- Sign. negative wage elasticity in most samples
- Around -1 in TLC-samples as predicted by Income Targeting
- Higher in TRIP: Only fleet drivers

Regression by Driver Experience

TABLE IV
IV LOG HOURS WORKED EQUATIONS BY DRIVER EXPERIENCE LEVEL

Sample	TRIP		TLC1		TLC2	
Experience level	Low	High	Low	High	Low	High
Log hourly wage	−.841	.613	−.559	−1.243	−1.308	2.220
	(.290)	(.357)	(.406)	(.333)	(.738)	(1.942)
Fixed effects	Yes	Yes	Yes	Yes	No	No
Sample size	26	39	319	458	320	375
P-value for difference in wage elasticity	.030		.666		.058	

- Experienced drivers:
  - > 4 years in TLC
  - > median in TRIP
- Wage elasticity significantly larger for experienced drivers in TRIP and TLC2
- Insignificantly smaller in TLC1
- Drivers would increase their earnings by 8 pct. if they drove the same no. of hours every day; 16 pct. if elast. = 1
- Learning/natural selection

Regression by Payment Structure

TABLE V
IV Log Hours Worked Equations by Payment Structure TLC1 Data

Type of cab	Fleet	Lease	Owned
Log hourly wage	−.197	−.978	−.867
	(.252)	(.365)	(.487)
Fixed effects	Yes	Yes	Yes
Sample size	150	339	305

- Insignificantly different from zero for fleet drivers
  - They can not increase hours above 12
  - They pay fees daily ⇒ less likely to stop before (figure II)
  - (but the same applies for TRIP…)

- Most appealing explanation:
  (Partial) **Daily Income Targeting**
  - Commitment device for hyperbolic discounters
  - Workers are loss averse around income target
    - Narrow bracketing

- Partly supported by interviews with fleet managers
  - 6 say income targeting
  - 5 say fixed hours
  - 1 supports neoclassical prediction

Reference-Dependent Preferences and Labor Supply:
The Case of New York City Taxi Drivers

Henry S. Farber
Princeton University
Working Paper #497

◇ The Theoretical Model:

□ Fixed Wage:

A straightforward parametric model of labor supply that incorporates a reference point is based on a utility function of income and hours worked of the form

$$U(Y,h) = \alpha(Y-T) - \frac{\theta}{1+\nu}h^{1+\nu} \qquad Y < T \tag{2.1}$$

$$U(Y,h) = (Y-T) - \frac{\theta}{1+\nu}h^{1+\nu} \qquad Y > T \tag{2.2}$$

where

- h = hours,
- Y = income = Wh,
- T = reference income,
- α = parameter determining sharpness of "kink" in utility function ($\alpha > 1$),
- θ = parameter determining disutility of work, and
- ν = elasticity parameter (wage elasticity of labor supply = $1/\nu$).

Wage	Hours	Elasticity
$W < W^*$	$h = (\frac{\alpha W}{\theta})^{1/\nu}$	$\frac{1}{\nu}$
$W^* < W < W^{**}$	$h = \frac{T}{W}$	-1
$W > W^{**}$	$h = (\frac{W}{\theta})^{1/\nu}$	$\frac{1}{\nu}$

where

$$W^* = (\frac{\theta}{\alpha})^{(\frac{1}{1+\nu})} T^{(\frac{\nu}{1+\nu})} \tag{2.3}$$

and

$$W^{**} = \theta^{(\frac{1}{1+\nu})} T^{(\frac{\nu}{1+\nu})}. \tag{2.4}$$

$\gamma W_0(t)$ where $W_0'(t) \leq 0$ and γ is a positive constant. On this basis income after h hours of work is $Y(h) = \int_0^h W(t)dt$. reference-dependent utility in this case is

$$U(Y(h), h) = \alpha(Y(h) - T) - \frac{\theta}{1+\nu} h^{1+\nu} \qquad Y < T \tag{2.5}$$

$$U(Y(h), h) = (Y(h) - T) - \frac{\theta}{1+\nu} h^{1+\nu} \qquad Y > T \tag{2.6}$$

□ Variable, non-increasing wage:

In order to derive the labor supply function in this case note that the hours required to earn the target (h_T) solves

$$T = \gamma \int_0^{h_T} W_0(t)dt \tag{2.7}$$

Define two functions of hours as

$$h^* = (\frac{\alpha\gamma W_0(h)}{\theta})^{1/\nu} \tag{2.8}$$

$$h^{**} = (\frac{\gamma W_0(h)}{\theta})^{1/\nu} \tag{2.9}$$

The labor supply function in this case is defined by

Region	Hours	Elasticity
$h^* < h_T$	$h^* = (\frac{\alpha\gamma W_0(h)}{\theta})^{1/\nu}$	$\frac{1}{\nu}$
$h^{**} < h_T < h^*$	h_T	-1
$h^{**} > h_T$	$h^{**} = (\frac{\gamma W_0(h)}{\theta})^{1/\nu}$	$\frac{1}{\nu}$

◇ **The Empirical Model:**

Specify the net utility of stopping at time *t* for driver *i* on shift *j*. The shift ends if *net utility >0*.

$$S_{ijt} = X_{ijt}\beta + \delta I[Y_{ijt} \geq T_{ij}] + \epsilon_{ijt}, \tag{3.1}$$

where

- T_{ij} represent the reference income level for driver i on shift j,
- Y_{ijt} represent the income level for driver i on shift j at trip t,
- X_{ijt} is a vector of variables that determine the difference between current utility and the continuation value,
- β is a parameter vector to be estimated,
- ϵ_{ijt} is a random component with a standard normal distribution.
- $I[Y_{ijt} \geq T_{ij}]$ is an indicator function that equals one if income exceeds the reference income equals zero otherwise, and
- δ is a positive parameter that represents the increment to the latent variable when income exceeds the reference income.

◇ Since reference income level is not known, it is estimated in the following way:

$$T_{ij} = \theta_i + \mu_{ij}, \tag{3.5}$$

where θ_i is an individual mean reference income level and μ_{ij} is a random component, distributed normally with mean 0 and variance σ^2, representing daily deviations from θ_i in the reference income level.

◇ Now, estimating this model requires deriving the Likelihood function for unconditional probability of stopping, given that the reference income level is unknown.

□ First note the probability of stopping after trip *t*, conditional on reference income:

$$P_{ij}^t|T_{ij} = (P_{ijt}^s|T_{ij}) \cdot \prod_{k=1}^{t-1}(1 - P_{ijk}^s|T_{ij}), \tag{3.6}$$

□ Now note the unconditional probability of stopping after trip *t*, given that reference income can fall in any of the income intervals from the first trip to the last:

$$\begin{aligned} P_{ij}^t &= P_{ij}^t|(T_{ij} \leq Y_{ij1}) \cdot Pr(T_{ij} \leq Y_{ij1}) \\ &+ \sum_{h=2}^{t}(P_{ij}^t|(Y_{ij(h-1)} < T_{ij} < Y_{ijh}) \cdot Pr(Y_{ij(k-1)} \leq T_{ij} < Y_{ijk})) \\ &+ P_{ij}^t|(T_{ij} > Y_{ijt}) \cdot Pr(T_{ij} > Y_{ijt}). \end{aligned} \tag{3.7}$$

This is the key equation. Each component of this unconditional probability can be converted to a Probit specification and aggregated across all drivers and shifts to form the Likelihood function, from which maximum likelihood estimates of the parameters are derived.

◇ **Empirical estimation of the components of equation 3.7 (Probit specification):**

□ Probability of reference income falling in each interval:

$$Pr(T_{ij} \leq Y_{ij1}) = \Phi[(Y_{ij1} - \theta_i)/\sigma]. \tag{3.8}$$

$$\begin{aligned} Pr(Y_{ij(k-1)} < T_{ij} \leq Y_{ijk}) &= Pr(T_{ij} \leq Y_{ijk}) - Pr(T_{ij} \leq Y_{ij(k-1)}) \\ &= \Phi[(Y_{ijk} - \theta_i)/\sigma] - \Phi[(Y_{ij(k-1)} - \theta_i)/\sigma]. \end{aligned} \tag{3.9}$$

$$P^T_{ij(t+1)} = Pr(T_{ij} > Y_{ijt}) = 1 - \Phi[(Y_{ijt} - \theta_i)/\sigma]. \tag{3.10}$$

□ Probability of stopping, conditional on 3.8, 3.9, and 3.10, respectively:

$$P^t_{ij}|(T_{ij} \leq Y_{ij1}) = \Phi[X_{ijt}\beta + \delta] \cdot \prod_{k=1}^{t-1}(1 - \Phi[X_{ijk}\beta + \delta]). \tag{3.11}$$

$$P^t_{ij}|(Y_{ij(h-1)} < T_{ij} \leq Y_{ijh}) = \Phi[X_{ijt}\beta+\delta]\cdot\prod_{k=1}^{h-1}(1-\Phi[X_{ijk}\beta])\cdot\prod_{k=h}^{t-1}(1-\Phi[X_{ijk}\beta+\delta]). \tag{3.12}$$

$$P^t_{ij}|(T_{ij} > Y_{ijt}) = \Phi[X_{ijt}\beta] \cdot \prod_{k=1}^{t-1}(1 - \Phi[X_{ijk}\beta]). \tag{3.13}$$

◇ Now, simply correlating this unconditional probability with *observed* stopping behavior, denoted by the following change in notation:

$$C_{ij} = P^s_{ij}. \tag{3.14}$$

then aggregating over all drivers *n* and shifts *m*, generates the likelihood function:

$$L = \prod_{i=1}^{n} \prod_{j=1}^{m_i} C_{ij}, \tag{3.15}$$

◇ **The alternative model: not reference dependent.**

- Probability of stopping after trip *t* :

$$P^s_{ijt} = Pr(S_{ijt} > 0) = \Phi[X_{ijt}\beta,] \tag{3.17}$$

- And the cumulative probability that the shift ends after trip *t* :

$$C_{ij} = \Phi[X_{ijt}\beta] \cdot \prod_{k=1}^{t-1} (1 - \Phi[X_{ijk}\beta]). \tag{3.18}$$

◇ **Estimation of the reference dependent model:**

- the following parameters are estimated from the likelihood function (equation 3.15):

- the coefficient vector (β) of the X vector in the stopping probability function (equation 3.1),
- the parameter (δ) indexing increment to the probability of stopping after the reference level of income is reached,
- the vector of individual mean reference income levels (θ), and
- the variance (σ^2) of the random component (μ) in the reference income function (equation 3.5).

- indicators for eight categories of hours worked at trip end,
- six indicators for the day of week,
- indicators for eighteen clock hours at trip end,
- a day-shift indicator,
- an interaction of day-shift with clock hour 3-4PM meant to capture the likelihood that a day-shift driver must turn the car over to a night-shift driver at that time of day,
- four variables measuring weather including daily snowfall, hourly rainfall, high heat (maximum temperature $>=$ 80 degrees), and cold (minimum temperature $<$ 30 degrees), and
- an indicator for location outsize of Manhattan.

Table 1: Maximum Likelihood Estimates of Reference-Dependent Stopping Model

Variable	$\hat{\beta}$	Driver	$\hat{\theta}$
Hour $\leq$ 2	-1.046	1	217.71
	(0.173)		(24.57)
Hour 3-5	-0.671	2	105.51
	(0.135)		(16.37)
Hour 6	-0.424	3	166.27
	(0.136)		(10.93)
Hour 7	-0.175	4	173.41
	(0.117)		(19.37)
Hour 9	-0.097	5	157.12
	(0.169)		(9.29)
Hour 10	0.536	6	253.58
	(0.179)		(30.66)
Hour 11	0.485	7	191.49
	(0.218)		(20.29)
Hour $\geq$ 12	0.952	8	205.47
	(0.242)		(12.91)
Min Temp $<$ 30	0.034	9	162.00
	(0.092)		(18.86)
Max Temp $\geq$ 80	-0.269	10	191.42
	(0.130)		(19.48)
Hourly Rain	0.036	11	324.46
	(0.139)		(96.63)
Daily Snow	0.243	12	290.58
	(0.192)		(20.78)
Non-Manhattan	0.405	13	182.66
	(0.142)		(13.72)
Day Shift	-0.446	14	278.48
	(0.151)		(14.54)
End of Day Shift	1.21	15	127.43
	(0.241)		(12.04)
Constant	-1.11		
	(0.185)		
$\hat{\delta}$	5.63	$\hat{\sigma}^2$	2779.58
	(3.63)		(375.8)

Note: The sample includes 12187 trips in 538 shifts for 15 drivers. The model also includes 6 indicators for day of the week, and 18 indicators for hour of the day The hours from 5AM to 10AM have a common fixed effect. Standard errors are reported in parentheses. The maximized log-likelihood value is -1612.6.

◇ Estimation of the alternative model:

Table 2: Probit Estimates of Stopping Model

Variable	(1)	(2)	(3)	(4)
Hour $\leq$ 2	-0.776	-0.803	-0.635	-0.690
	(0.116)	(0.134)	(0.177)	(0.195)
Hour 3-5	-0.411	-0.407	-0.309	-0.325
	(0.088)	(0.098)	(0.120)	(0.131)
Hour 6	-0.369	-0.388	-0.334	-0.324
	(0.098)	(0.102)	(0.109)	(0.114)
Hour 7	-0.173	-0.164	-0.136	-0.132
	(0.089)	(0.092)	(0.094)	(0.096)
Hour 9	-0.068	-0.037	-0.063	-0.048
	(0.110)	(0.114)	(0.116)	(0.118)
Hour 10	0.308	0.370	0.321	0.349
	(0.125)	(0.132)	(0.136)	(0.146)
Hour 11	0.319	0.426	0.360	0.390
	(0.155)	(0.163)	(0.169)	(0.180)
Hour $\geq$ 12	0.798	0.777	0.684	0.738
	(0.161)	(0.170)	(0.182)	(0.188)
Min Temp < 30	-0.055	0.077	0.086	0.082
	(0.062)	(0.073)	(0.074)	(0.074)
Max Temp $\geq$ 80	-0.109	-0.163	-0.156	-0.151
	(0.073)	(0.082)	(0.082)	(0.082)
Hourly Rain	0.032	0.100	0.103	0.105
	(0.098)	(0.102)	(0.101)	(0.102)
Daily Snow	0.089	0.122	0.112	0.118
	(0.148)	(0.153)	(0.153)	(0.154)
Non-Manhattan	0.553	0.537	0.530	0.533
	(0.086)	(0.088)	(0.088)	(0.088)
Day Shift	0.379	0.049	0.037	0.038
	(0.073)	(0.109)	(0.109)	(0.110)
End of Day Shift	0.595	0.577	0.561	0.572
	(0.181)	(0.201)	(0.201)	(0.205)
Shift Income $\div$ 100	---	---	0.151	---
			(0.104)	
Constant	-0.723	-0.946	-1.219	-0.974
	(0.131)	(0.158)	(0.245)	(0.166)
Driver (14)	No	Yes	Yes	Yes
Day-of-Week (6)	Yes	Yes	Yes	Yes
Hour-of-Day (18)	Yes	Yes	Yes	Yes
Accumulated Income (9)	No	No	No	Yes
Log L	-1673.9	-1619.6	-1618.6	-1614.1

Note: The sample includes 12187 trips in 538 shifts for 15 drivers. The hours from 5AM to 10AM have a common fixed effect. The ten income categories in column 4 are <25, 25-49, 50-74, 75-99, 100-124, 125-149, 150-174, 175-199, 200-224, and $\geq$225. The base category is at midnight Saturday on the night shift in the eighth hour in dry moderate weather. Standard errors are reported in parentheses.

◇ **Conclusion:**

- ☐ Reference dependent model fits the data better (yay)

- ☐ But, are reference levels stable enough for this model to be useful?

- ☐ Need they be stable for the model to be useful? (what if we just used this specification in lieu of FE, even if we don't understand it)

- ☐ How do we explain idiosyncratic changes in the reference level?

- ☐ Are they really idiosyncratic? How could we predict the changes?

Table 4: Labor Supply Function Estimates
OLS Regression of log Hours

Variable	(1)	(2)	(3)	(4)
Constant	4.012	3.882	3.776	3.778
	(0.349)	(0.354)	(0.379)	(0.381)
log(wage)	-0.688	-0.647	-0.636	-0.637
	(0.111)	(0.112)	(0.115)	(0.115)
Night Shift	---	---	0.128	0.134
			(0.062)	(0.062)
Min Temp $<$ 30	---	---	---	0.024
				(0.058)
Max Temp $\geq$ 80	---	---	---	0.055
				(0.064)
Rainfall	---	---	---	-0.054
				(0.071)
Snowfall	---	---	---	-0.093
				(0.035)
Driver Effects	No	Yes	Yes	Yes
Day-of-Week Effects	No	No	Yes	Yes
R-squared	0.063	0.162	0.185	0.198

Note: The sample includes 584 shifts for 21 drivers. The dependent variable is log hours worked (driving time plus time between fares excluding declared breaks and breaks between fares one hour or longer). The mean of the dependent variable is 1.84. Standard errors are in parentheses.

rainfall, drivers do drive fewer hours when it has snowed. The estimated elasticity is again unchanged.

There is strong potential for negative bias in the estimated elasticity because the wage is computed mechanically using the inverse of hours worked. Additionally, since the wage is not constant over the working day, it is not likely that the wage measured this way can be considered parametric to the labor supply decision. Absent a convincing exclusion restriction from the hours function to provide an instrument for the wage, I do not have a solution to this problem.

My finding of a negative elasticity of labor supply using this method is consistent with the findings of Camerer, et al (1997) and Chou (2000). In fact, the magnitude of my estimates is comparable to theirs. The consistency of our findings is important because it implies that any differences in results that I find using other empirical models is due to differences in

Table 8: Hazard of Stopping after Trip: Normalized Probit Estimates

Variable	(1)	(2)	(3)	(4)
Hour $\leq$ 2	-0.142	---	-0.137	-0.042
	(0.014)		(0.017)	(0.012)
Hour 3-5	-0.122	---	-0.108	-0.028
	(0.014)		(0.017)	(0.010)
Hour 6	-0.095	---	-0.084	-0.026
	(0.015)		(0.018)	(0.009)
Hour 7	-0.048	---	-0.041	-0.012
	(0.016)		(0.018)	(0.008)
Hour 9	-0.032	---	-0.034	-0.006
	(0.021)		(0.022)	(0.010)
Hour 10	0.014	---	0.011	0.031
	(0.025)		(0.033)	(0.020)
Hour 11	0.098	---	0.086	0.085
	(0.038)		(0.051)	(0.036)
Hour $\geq$ 12	0.117	---	0.109	0.119
	(0.063)		(0.075)	(0.060)
Income $<$ 25	---	-0.109	-0.121	-0.036
		(0.010)	(0.022)	(0.014)
Income 25-49	---	-0.103	-0.067	0.005
		(0.010)	(0.027)	(0.022)
Income 50-74	---	-0.096	-0.063	-0.002
		(0.010)	(0.021)	(0.014)
Income 75-99	---	-0.088	-0.065	-0.010
		(0.010)	(0.020)	(0.011)
Income 100-124	---	-0.077	-0.053	-0.009
		(0.011)	(0.018)	(0.009)
Income 125-149	---	-0.052	-0.035	-0.007
		(0.011)	(0.017)	(0.008)
Income 175-199	---	0.037	0.014	0.011
		(0.018)	(0.021)	(0.010)
Income 200-224	---	0.017	-0.022	0.006
		(0.020)	(0.025)	(0.013)
Income $\geq$ 225	---	0.087	0.009	0.015
		(0.019)	(0.032)	(0.018)
Driver (21)	No	No	No	Yes
Day-of-Week (7)	No	No	No	Yes
Hour-of-Day (19)	No	No	No	Yes
Location (9)	No	No	No	Yes
p -value Hours = 0	0.000	---	0.000	0.000
p -value Income = 0	---	0.000	0.008	0.281
Log L	-2028.9	-2058.7	-2016.5	-1753.1

Note: The sample includes 13461 trips in 584 shifts for 21 drivers. Probit estimates are normalized to reflect the marginal effect at X^* of X on the probability of stopping. The normalized probit estimate is $\hat{\beta} \cdot \phi(X^* \beta)$, where $\phi(\cdot)$ is the standard normal density. The values of X^* chosen for the fixed effects are equally weighted for each day of the week and driver. The hours from 5AM-10AM have a common fixed effect. The evaluation point is at 8 total hours with income of \$150-174 in a dry hour on a day with moderate temperatures in mid-town Manhattan at 2PM. Robust standard errors accounting for clustering by shift are reported.

- My own notes on Camerer (1997)

- Issues with labor supply estimation in Camerer:

  1. Division bias in regressing hours on log wages

     – IV wage using other workers' wage (Camerer)

     – Hazard regression on hours and total earnings (Farber)

2. Are the authors really capturing demand shock or supply shock?

   – Consider standard model above

   – Increase in C (rain) –> $h^* \downarrow$ and $w^* \uparrow$

   – Negative correlation between h^* and w^*

   – Standard issue with estimating demand and supply function

   – Econometric issue: Shocks to both demand and supply

   – Illustrate: Graddy, Fulton fish market

3. What determines the reference point T?

   – Camerer et al.: *Daily* target of earning

   – Does it depend on form of payment?

   – More generally: Intended good performance over a short-enough time frame that allows for keeping track of progress

     * Cab drivers?

     * Stadium vendors?

     * Education?

     * Charitable contributions?

     * Unemployed people