

Econ 219B

Psychology and Economics:
Applications
(Lecture 4)

Stefano DellaVigna

February 11, 2004

Outline

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

5 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

5.1 Consumption-savings Choice

- Laibson (1997) to Laibson, Repetto, and Tobacman (2003)
- Stylized facts:
 - low liquid wealth
 - substantial illiquid wealth (housing+401(k)s)
 - high credit card borrowing
 - consumption drop-off at retirement
- **T.-F.** Structural model, MSM (building on Gourinchas and Parker, 2002) with:
 - borrowing constraints
 - illiquid assets
 - realistic features
- Estimated $\beta = .66$

2.1 Data

Statistic	m_e	se_{m_e}
% borrowing on 'Visa' ? (% <i>Visa</i>)	0.68	0.015
borrowing / mean income (<i>mean Visa</i>)	0.12	0.01
C-Y comovement (<i>CY</i>)	0.23	0.11
retirement C drop (<i>C drop</i>)	0.09	0.07
median 50-59 $\frac{wealth}{income}$	3.88	0.25
weighted mean 50-59 $\frac{wealth}{income}$ (<i>wealth</i>)	2.60	0.13

Benchmark Model	Exponential	Hyperbolic	Data	Std err
Statistic:	$m_s(1, \hat{\delta})$ $\hat{\delta} = .857$	$m_s(\hat{\beta}, \hat{\delta})$ $\hat{\beta} = .661$ $\hat{\delta} = .956$	m_e	se_{m_e}
<i>% Visa</i>	0.62	0.65	0.68	0.015
<i>mean Visa</i>	0.14	0.17	0.12	0.01
<i>CY</i>	0.26	0.35	0.23	0.11
<i>Cdrop</i>	0.16	0.18	0.09	0.07
<i>wealth</i>	0.04	2.51	2.60	0.13
$q(\hat{\theta})$	512	75		

- Soph. or naiveté – does not matter
- **T.** Consumption-savings within growth model (Barro, 1999):
 - complete markets
 - log utility
 - equivalence of exponential and (soph) hyperbolic preferences

5.2 401(k) Savings

- Madrian and Shea (2001); Choi et al. (2002)
- Stylized Facts:
 - Status-quo effects in:
 - * participation,
 - * contribution rate,
 - * portfolio composition
- F. See above
- Need naiveté to get large status quo

TABLE 1. Automatic Enrollment in Three Companies

	Company A	Company B	Company C
Industry	Office Equipment	Health Services	Food Products
Employment	32,000	30,000	18,000
Date automatic enrollment implemented	January 1, 1997	April 1, 1998	A) January 1, 1998 ^a B) November 1, 1999 ^a
Employees affected by automatic enrollment	Hired on or after January 1, 1997	Hired on or after April 1, 1998	A) Eligible on or after January 1, 1998 ^a B) Eligible before January 1, 1998 and not participating on November 1, 1999 ^a
Length of opt-out period	60 days	30 days	30 days
Default contribution rate	2%	3%	3%
Default investment fund	Stable value	Money market	Stable value
Matching provisions	\$0.67/\$1 up to 6% of pay put into company stock	\$0.50/\$1 up to 6% of pay after 1 year of employment	\$0.50/\$1 up to 6% of pay
Other changes in 401(k) plan over study period	Three new funds in 1999 One fund closed in 1999	1 year length of service requirement eliminated on April 1, 1998	1 year length of service requirement for employees under age 40 eliminated on January 1, 1998

Source: Summary plan descriptions and conversations with company officials.

^a In Company C, the first round of automatic enrollment affected employees eligible on or after January 1, 1998. This includes all employees hired on or after January 1, 1998 as well as any employees hired during 1997 who were under the age of 40 on December 31, 1997. The second round of automatic enrollment in Company C affected all employees not subject to automatic enrollment during the first round: those hired prior to 1997 and employees hired during 1997 who had reached the age of 40 by December 31, 1997.

**TABLE 2. The Distribution of 401(k) Contribution Rates by Tenure for Employees
Hired Before and After Automatic Enrollment**

Tenure (months)	Hired Before Automatic Enrollment				Hired After Automatic Enrollment			
	Non- Participant	< Default	Default	> Default	Non- Participant	< Default	Default	> Default
Company A								
6-11	--	--	--	--	8.4%	1.3%	63.4%	26.9%
12-17	--	--	--	--	8.5	1.4	61.0	29.1
18-23	--	--	--	--	8.8	1.4	56.5	33.4
24-29	46.9%	1.7%	12.0%	39.4%	9.0	1.7	53.3	36.1
30-35	40.8	1.4	10.9	46.9	8.4	1.6	50.3	39.7
36-41	40.2	1.7	12.7	45.5	6.8	1.3	48.5	43.4
42-47	35.3	0.9	10.7	53.2	8.3	1.6	45.8	44.3
48-53	31.5	1.9	13.4	53.3	--	--	--	--
Company B								
3-5	68.9%	3.0%	3.6%	24.5%	13.5%	1.2%	71.8%	13.6%
6-11	64.0	3.0	4.4	28.6	13.7	1.3	66.2	18.9
12-17	64.2	2.7	3.4	29.8	12.7	1.6	54.9	30.8
18-23	53.4	3.4	4.5	38.8	12.0	1.5	47.5	39.0
24-26	47.3	3.9	5.3	43.6	12.1	1.4	41.4	45.0

Authors' calculations. The sample in the first four columns is employees hired before automatic enrollment. The sample in the second four columns is employees hired after automatic enrollment.

**TABLE 3. The Distribution of 401(k) Fund Allocations by Tenure for Employees
Hired Before and After Automatic Enrollment**

Tenure (months)	Hired Before Automatic Enrollment				Hired After Automatic Enrollment			
	Non- Participant	Zero Balances	100% Default Fund	Other Allocation	Non- Participant	Zero Balances	100% Default Fund	Other Allocation
Company A								
6-11	--	--	--	--	8.4%	4.6%	58.7%	28.4%
12-17	--	--	--	--	8.5	4.4	57.2	30.0
18-23	--	--	--	--	8.8	2.3	54.7	34.3
24-29	46.9%	2.3%	8.9%	42.0%	9.0	2.1	52.7	36.3
30-35	40.8	1.9	6.2	51.1	8.4	1.4	49.8	40.4
36-41	40.2	1.5	8.8	49.4	6.8	1.3	49.1	42.8
42-47	35.3	0.8	6.7	57.2	8.3	1.2	47.2	43.2
48-53	31.5	0.9	8.8	58.8	--	--	--	--
Company B								
3-5	68.9%	--	0.7%	30.4%	13.6%	--	76.7%	9.7%
6-11	64.0	--	0.9	35.1	13.5	--	71.2	15.3
12-17	64.2	--	2.9	32.9	13.7	--	64.0	22.3
18-23	53.4	--	2.2	44.4	12.0	--	50.0	38.0
24-26	47.3	--	2.3	50.4	12.1	--	43.6	44.3

Authors' calculations. The sample in the first four columns is employees hired before automatic enrollment. The sample in the last four columns is employees hired after automatic enrollment.

5.3 Addiction

- Gruber and Koszegi (2001) and Gruber and Mullainathan (2002)
- Stylized facts:
 - Diffusion of addictions (drugs, alcohol, tobacco, obesity)
 - repeated efforts of quitters
 - Antabuse
 - rational addiction?
- **(F.)-T.** Data on response of consumption to present and future taxes (Gruber and Koszegi, 2001): cannot separate present bias vs. rational addiction
- **F.** Data on happiness (Gruber and Mullainathan, 2002): smokers happier in states one year after smoking taxes are raised

Table 2: Relation Between Cigarette Taxes and Unhappiness

	Very Happy	Pretty Happy	Not Happy	Very Happy	Somewhat Happy	Unhappy
	US Data			Canadian Data		
Tax	-0.027 (.033)	-0.005 (.034)	0.032 (.020)	0.000 (.029)	0.013 (.023)	0.000 (.011)
Predicted Smoking	-0.069 (.038)	-0.014 (.040)	0.075 (.026)	0.198 (.051)	0.194 (.055)	0.096 (.040)
Predicted Smoking*Tax	0.047 (.078)	0.109 (.070)	-0.156 (.045)	0.072 (.062)	-0.058 (.052)	-0.048 (.020)
Married	0.176 (.009)	-0.079 (.011)	-0.095 (.008)	0.118 (.005)	-0.098 (.004)	-0.020 (.004)
Separated/Divorced	0.022 (.009)	-0.020 (.012)	-0.005 (.009)	-0.029 (.008)	-0.025 (.009)	0.023 (.004)
Widowed	0.036 (.012)	0.005 (.015)	-0.041 (.010)	-0.010 (.009)	-0.034 (.009)	0.023 (.004)
High School Dropout	0.053 (.049)	0.011 (.042)	0.029 (.028)	0.135 (.013)	0.144 (.018)	0.022 (.005)
High School Graduate	0.052 (.047)	0.032 (.043)	0.007 (.028)	0.191 (.014)	0.123 (.019)	0.012 (.004)
Some College	0.055 (.049)	0.037 (.047)	0.000 (.029)	0.210 (.021)	0.124 (.014)	0.015 (.005)
College Graduate	0.064 (.046)	0.023 (.046)	0.003 (.030)	0.220 (.027)	0.135 (.017)	0.017 (.003)
Father High School Dropout	0.002 (.004)	0.007 (.005)	-0.008 (.004)			
Mother High School Dropout	-0.007 (.007)	0.007 (.007)	0.001 (.005)			
Father High School Graduate	0.006 (.007)	0.016 (.008)	-0.020 (.005)			
Mother High School Graduate	0.004 (.008)	0.007 (.010)	-0.009 (.006)			
Father Some College	0.009 (.012)	0.000 (.011)	-0.009 (.007)			
Mother Some College	0.005 (.013)	0.012 (.014)	-0.014 (.007)			
Father College Graduate	0.024 (.010)	-0.001 (.010)	-0.020 (.007)			
Mother College Graduate	0.029 (.014)	-0.009 (.013)	-0.017 (.009)			
Lowest Household Income Quartile	-0.044 (.011)	0.025 (.012)	0.027 (.010)	-0.049 (.023)	0.036 (.015)	0.021 (.009)
2nd Household Income Quartile	-0.023 (.010)	0.045 (.011)	-0.014 (.010)	-0.026 (.011)	0.039 (.008)	0.001 (.004)
3rd Household Income Quartile	0.009 (.012)	0.033 (.011)	-0.033 (.009)	-0.010 (.004)	0.020 (.005)	0.006 (.003)

Table 4: "Effect" of Other Taxes

Panel A: US Data				
	Beer Tax	Gas Tax	Sales Tax	Total Revenues
Cigarette Tax	0.038 (.024)	0.035 (.020)	0.033 (.020)	0.029 (.019)
Other Tax	-0.017 (.008)	-0.001 (.001)	0.003 (.004)	-0.004 (.023)
Predicted Smoking	0.055 (.031)	0.060 (.048)	0.060 (.033)	0.125 (.038)
Predicted Smoking*Cigarette Tax	-0.181 (.055)	-0.162 (.043)	-0.159 (.045)	-0.144 (.043)
Predicted Smoking*OtherTax	0.034 (.014)	0.001 (.003)	0.003 (.006)	-0.037 (.021)
Panel B: Canadian Data				
	Beer Tax	Gas Tax	Sales Tax	Total Revenues
Cigarette Tax	0.003 (.008)	0.008 (.006)	0.004 (.010)	0.002 (.009)
Other Tax	-0.006 (.002)	-0.002 (.001)	-0.004 (.001)	-0.006 (.004)
Predicted Smoking	0.082 (.048)	0.072 (.044)	0.067 (.041)	0.059 (.034)
Predicted Smoking*Cigarette Tax	-0.045 (.020)	-0.047 (.021)	-0.048 (.019)	-0.049 (.020)
Predicted Smoking*OtherTax	0.001 (.002)	0.002 (.001)	0.004 (.001)	0.009 (.007)
Demographic Controls	Yes	Yes	Yes	Yes
State Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes

Notes: The dependent variable in each column is a dummy for unhappiness. "Other Tax" refers to a different tax in each column. It refers to a beer or alcohol tax in column (1), gas tax in column (2), sales tax in column (3) and Total state/province revenues in column (4).

- **T.** Optimal taxes for present-biased addiction (O'Donoghue and Rabin, 2003; Gruber and Koszegi, 2003)
- **F.** Data on increase in obesity over time (Cutler, Glaeser, and Shapiro, 2003). Decrease in fixed cost of preparing food + self-control

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 $\uparrow \implies$ search effort \downarrow
 - Impatience $\uparrow \implies$ reservation wage \longleftrightarrow
 - Impatience $\uparrow \implies$ exit rate from unemployment \downarrow
- Impatience captures variation in β
- Sophisticated or naive – does not matter
- Paserman (2003): structural model estimated by max. likelihood: $\beta = .40$ (low-wage workers), $\beta = .89$ (high-wage workers)

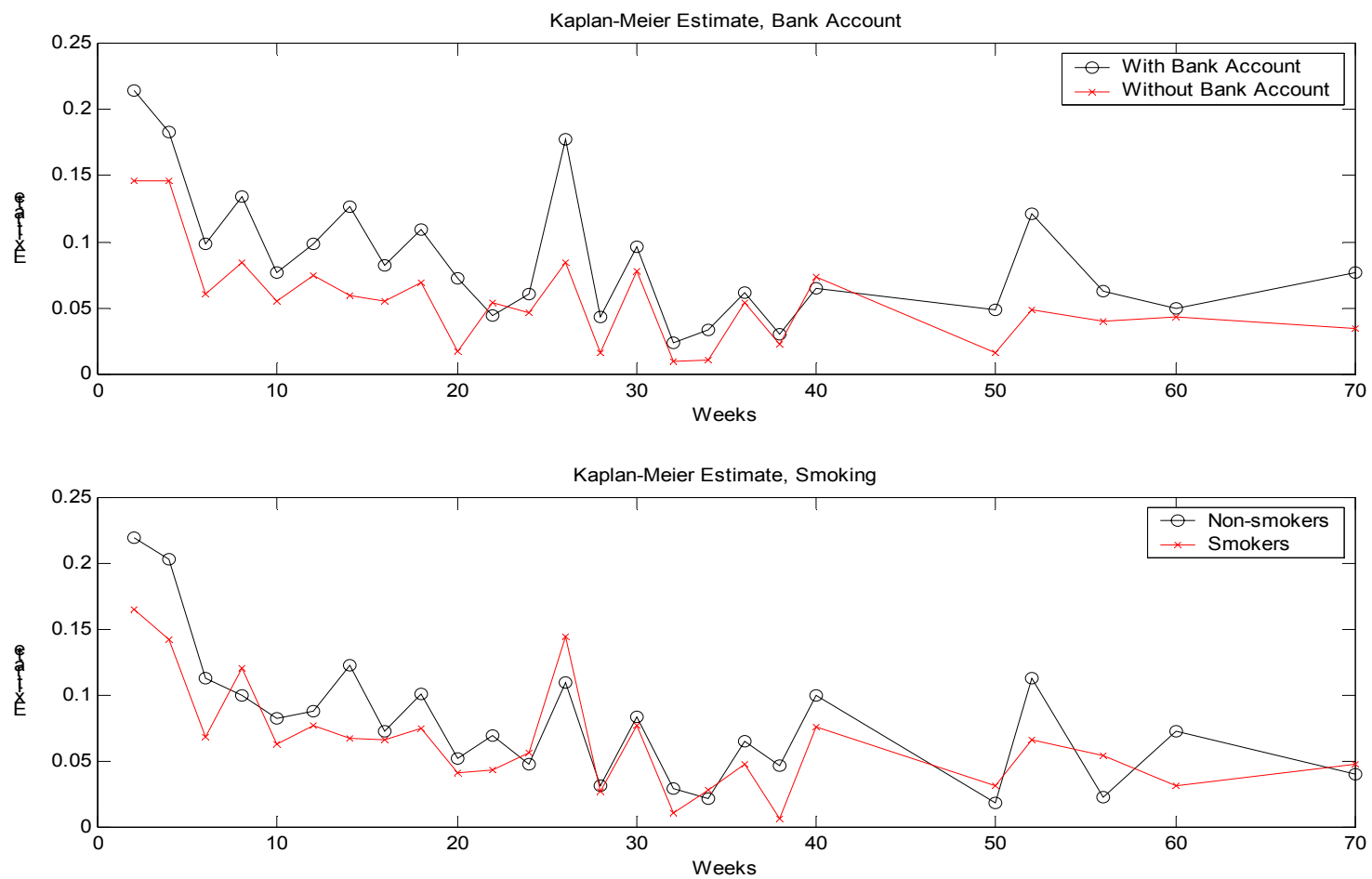


FIGURE 2: Exit Rates in the PSID

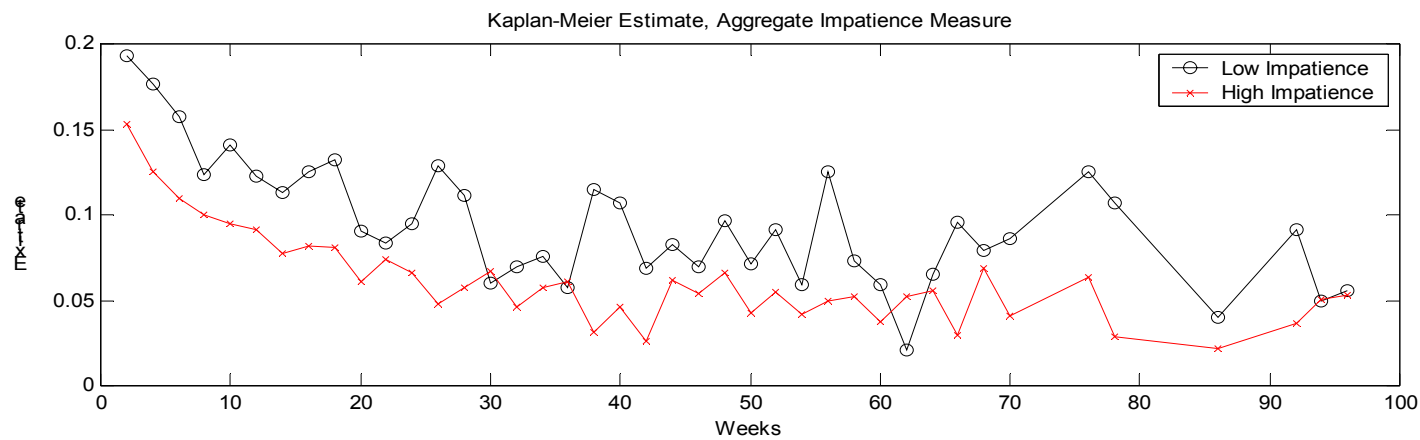
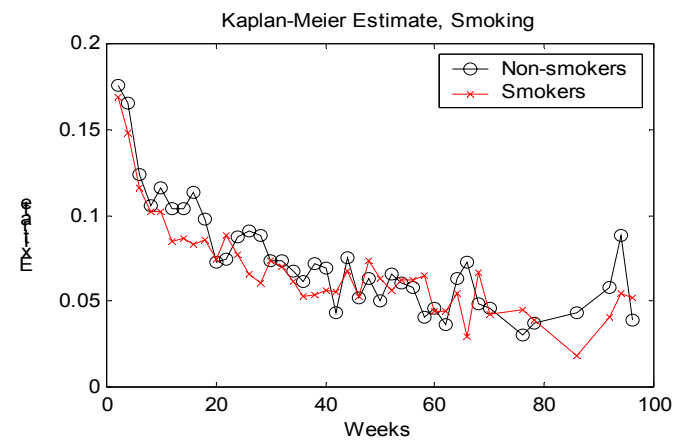
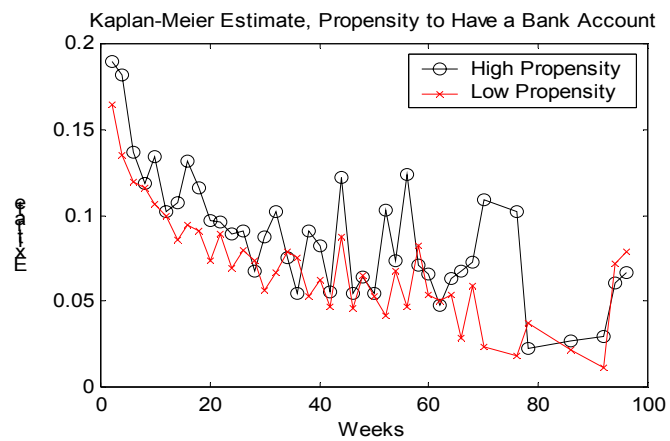


Figure 3: Exit Rates in the NLSY

Table 4: Benchmark Models [†]

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

[†]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	e_0	3953.13	545.79
	production	e_1	370.55	150.52
		e_2	-148.1	56.09
		η	5101.51	522.17
wage & skill parameters	constant	$\ln(r) + \ln a_0$	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
	1 st 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($\varepsilon_0, \varepsilon_2$)	$\sigma_{\varepsilon 0 \varepsilon 2}$	-2550.08	674.2
	std. dev.	σ_{me}	0.272	0.12
	meas err.			
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 Payday effects

- Devin

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 (2003): rational expectations equilibrium
- Narrow framing?
- Consider only problem at hand (labor supply, stock picking, house sale)
- Neglect other relevant decisions

6 Labor Supply: Cab Drivers

- Rob L.

Overview

•Introduction:

- The question and why it is hard: Labor Supply Response to Wages
- Data on workers with fluctuating wages who choose their own hours: New York City Taxi Trip Sheets
- Behavioral stories: reference dependence; narrow framing; self control
- Invitation to participate
- Estimating hours as a function of hourly wage: Camerer
- Estimating the hazard of quitting as a function of time and hours: Farber
- Conclusions: What do we know? Research opportunities?

Big Questions; Scarce Data

Question: How do workers react to short term changes in available wages?

Central Problem: Workers rarely choose their own hours.

Possible Solution: Study taxi drivers because they choose their hours.

Data

Source

- New York City taxi meters summarize total trips and fare; drivers write origin, destination, time, and fare on “trip sheets”.
- Summary Government data (Camerer); detailed company data (Camerer and Farber).

Data problems

- **Limits on driver choices:** partners, 12 hour leases, limits on taxi availability to work extra days, self selected fixed schedules. Camerer: drivers who rent cabs for 12 hour shifts show much less evidence of target driving than drivers who own cabs or lease by the week.
- **Farber data problems:** 1/3 of his drivers quit about 5PM; probably give cars to partners and cannot extend their days. Camerer discards 63.5% of his sample because of discrepancies between meters and trip sheets; Farber has no meter data.
- **No tip data;** no argument that it is consistently X% of fares. So potentially significant noise in wage data.

Behavioral Explanations Why Drivers Control Earnings One Day at a Time

- **Narrow framing:** choosing one day at a time is easy
- **Reference dependence:** failing to reach a target may be more painful than gains beyond the target are fulfilling
- **What are our prior beliefs** considering evidence about intertemporal choice?
- **Self control:** daily targets prevent procrastination; and reduce temptation to spend immediately

Overview

- Introduction:
- **Estimating hours as a function of hourly wage:**
 - Camerer's approach: hours as a function of wages; instruments for wages
 - Camerer finds that as wages go up, labor supply goes down, especially for inexperienced drivers. Leasing arrangements matter.
- Estimating the hazard of quitting as a function of time and hours: Farber's paper
- Conclusions: What do we know? Opportunities for more research?

Estimating hours as a function of wages

- Define: Hourly wage = total earnings / hours worked
- Est. $\log \text{ hours worked} = a + b * \log \text{ hourly wage} + \beta X + e$
- Farber notes: this is equivalent to:
 $\log \text{ hours} = a + b' * \log \text{ total earnings} + \beta X + e$
and if people follow targets closely, there will be little variation in total earnings.

Potential Bias

- Division bias means measurement error in hours will bias estimates of b toward negative values.
- We are trying to estimate $Y=A+BX$ where $X = Z/Y$. If hours worked, Y , over reported, Y goes up and X goes down. If hours underreported, Y down, X up.
- Solution: replace wages with instruments for hourly wages: e.g. the 25%, median, and 75% drivers' earnings that day, % of time on the shift the driver had a passenger
- Farber asserts that this is not a good enough solution.

Results: Estimating Hours as a Function of Wages

- People who earned more per hour worked fewer hours. The directly estimated elasticity was between $-.186$ and $-.618$ (4 of 5 estimates significant, $-.186$ was insignificant).
- **More reliable IV estimates are similar, but more scattered (range: 0.005 to -1.313) and less precise (3 of 5 significant).**
- Inexperienced drivers elasticity is more negative than experienced driver elasticity in 2 of 3 samples (and experienced drivers had positive but statistically insignificant elasticity). Inexperienced drive elasticity is often roughly -1 .

Overview

- Introduction:
- Estimating hours as a function of hourly wage: Camerer's paper
- **Estimating the hazard of quitting as a function of time and hours: Farber's claims:**
 - Consistent(?) with standard economic analysis.
 - Negative elasticity comes from specification problems
 - Could there be more evidence of reference dependence in Farber's results than Farber admits?
- Conclusions: What do we know? Opportunities for more research?

Farber's Data and Probit Model

- Detailed trip data on drivers from one fleet; smaller N; unconfirmed with meter.
- Too small for IV analysis
- Allows a detailed probit model of factors leading people to quit
- $R = b \cdot \text{hours driven} + b \cdot \text{wages so far} + \beta X + e$
- Keep driving as long as $R < 0$ (i.e. now is before the optimal stopping time)
- Notable absence: interactions between low earnings and moderately high hours

Farber's Claims

- When we control for driver fixed effects, income so far on the shift is insignificant (p joint significance 0.281).
- Total hours worked drive the quitting decision.
- Standard model vindicated.
- When he estimates models for 5 drivers for whom he has a great deal of data, 3 of the 5 drivers come up with significant effects of income; two appear to be reference dependent.

Does Farber's Favorite Regression Show Reference Dependence?

Extract from Farber's Table 8:
Normalized Probit Results

Variable	(3)	(4)
Income < 25	-0.121 (0.022)	-0.036 (0.014)
Income 25-49	-0.067 (0.027)	0.005 (0.022)
Income 50-74	-0.063 (0.021)	-0.002 (0.014)
Income 75-99	-0.065 (0.020)	-0.010 (0.011)
Income 100-124	-0.053 (0.018)	-0.009 (0.009)
Income 125-149	-0.035 (0.017)	-0.007 (0.008)
Income 175-199	0.014 (0.021)	0.011 (0.010)
Income 200-224	-0.022 (0.025)	0.006 (0.013)
Income \geq 225	0.009 (0.032)	0.015 (0.018)
Driver (21)	No	Yes
Day-of-Week (7)	No	Yes
Hour-of-Day (19)	No	Yes
Location (9)	No	Yes
p -value Hours = 0	0.000	0.000
p -value Income = 0	0.008	0.281
Log L	-2016.5	-1753.1

Farber's central claim is that when he adds driver fixed effects to the wages and hours regression in column 3 to obtain the regression in column 4 the statistical significance and magnitude of the income variables goes away.

If there were reference dependence, we would expect to see that earnings below the reference point make people less likely to quit and earnings above it make people more likely to quit.

And we see almost exactly this pattern of signs in both Columns 3 and 4! Admittedly the driver fixed effects reduce the magnitude. In column 4, 5 of 6 categories below \$150 have 1-tailed probabilities of 15%.

Overview

- Introduction:
- Estimating hours as a function of hourly wage: Camerer's paper
- Estimating the hazard of quitting as a function of time and hours: Farber's paper
- **Conclusions: What do we know?**
Opportunities for more research?
 - Is Farber talking past Camerer? Beating up on a straw man?
 - Avenues for more research: questions neither author tackled

Is Farber criticizing the real Camerer Paper?

- Farber criticizes Camerer's direct estimate, but Camerer admits the division bias problem and relies on IV estimates.
- Farber uses a much less flexible and less plausible notion of target earnings than Camerer does.
- Both Camerer and Farber find that driver fixed effects in a small trip sheet sample makes reference dependence driving statistically insignificant.

Conclusions

- Learning and heterogeneity of types appear to be important here and may be emerging as important themes in behavioral economics.
- Bottom line(?): Farber raises hard questions about Camerer's econometrics, but they are smaller than he claims and his work does not rule out reference dependence and may even support it. Farber suggests a powerful probit framework that can be modified with interaction terms to analyze better data.

What would econometric models that capture the reference dependence idea look like?

- Interaction of two factors:
 - Marginal benefit of a dollar that is high above the reference point and low (but probably not zero) below it. The difference between high and low is likely to be a factor of 3.
 - MC that rises in time worked.
- The intersection of these two curves will form a 2 dimensional path when we graph optimal quitting time with time on one axis and total earnings on the other. After a certain number of hours worked, cabbies who are getting low MB will quit but cabbies with high MB will keep going. Is an interaction term enough?

Research Opportunities

- Great data is hard to get, but crucial. Trip sheet details like marginal hour earnings, earnings after T hours worked are important, as is having a big N .
- A city without NYC's medallion system would have drivers who make larger and more frequent decisions about how much to work.
- I would love to see a simple table comparing earnings after 6 or 8 hours of drivers who quit after 8 hours and drivers who keep working longer.
- Interact earnings and time at potential quitting times; It is important to allow for losses being more painful than gains, creating a discontinuity.
- The good (?) news: more research is needed. Field trip anyone?