Learning in the Credit Card Market

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- Learning through experience facilitates optimization
  - We may not be born rational, but learning makes us so

- Large literatures measure learning dynamics in the lab and in the field
  - Data limitations mean there are relatively few papers measuring learning in the field with micro-level (household) data

Today's paper:

- We measure learning dynamics in the credit card market
- We use a panel dataset which has three years of credit card records for 128,000 consumers, for a total of four million observations
- We study late payment fees, over limit fees, and cash advance fees

- Fees average \$16/month for new accounts (*and* trigger interest rate $\Delta's$)

- Controlling for person fixed effects, fee payments fall by 75% during first four years of account life

- We estimate a learning model with the Method of Simulated Moments

- We find that learning is driven by feedback

- Making a late payment (i.e. paying a fee), cuts the probability of another late payment by 44%

- Learning is powerful, but not monotonic

- Card holders act as if their knowledge depreciates
  - Monthly probability of a fee payment *increases* as previous fee payments recede into the past
  - We estimate that knowledge depreciates between 10-20% per month

- Nonetheless, the net effect of learning is to generate large reductions in fee payments

Intuition

(Thanks to Devin Pope for the suggestion and the slide)

Related work on rationality, learning, and mistakes in consumer credit

- Ausubel (1991): Rents and over-optimistic consumer spending forecasts
- Gross and Souleles (2002): Borrowers increase spending when credit limits raised
- Miravete (2003): Consumers switch telephone calling plans to minimize monthly bill payments
- Shui and Ausubel (2004): Teaser rates and reluctance to switch contracts

- DellaVigna and Malmendier (2004): Equilibrium with present bias and naivete

- Agarwal, Chomsisengphet, Liu, and Souleles (2005): Consumers switch credit card contracts in response to mistakes

- Fishman and Pope (2006): Video renters more likely to return videos on time if recently fined for returning them late

- Agarwal, Driscoll, Gabaix and Laibson (2007): U-shaped pattern of fee payment, APRs by age

Organization of talk:

- Data
- Model and Estimation
- Alternative Explanations
- Conclusion

1 Data

- Representative credit card panel from a large bank (1/2002 – 12/2004)

- We focus analysis on three types of fees:

1. **Late Payment Fees**: \$30-\$35. Penalty pricing (i.e. APR $>$ 24%) may be imposed

2. **Over Limit Fee**: Also \$30-\$35. Penalty pricing may also be imposed

3. **Cash Advance Fee**: Greater of: 3% of the amount advanced, or \$5. No penalty pricing, but 16% APR on cash advances

Descriptive Analysis 1: Fee payment by account tenure

- We estimate:

$$f_{i,t}^{j} = \alpha + \phi_i + \psi_{time} + Spline(Tenure_{i,t}) + Controls_{i,t} + \epsilon_{i,t}.$$

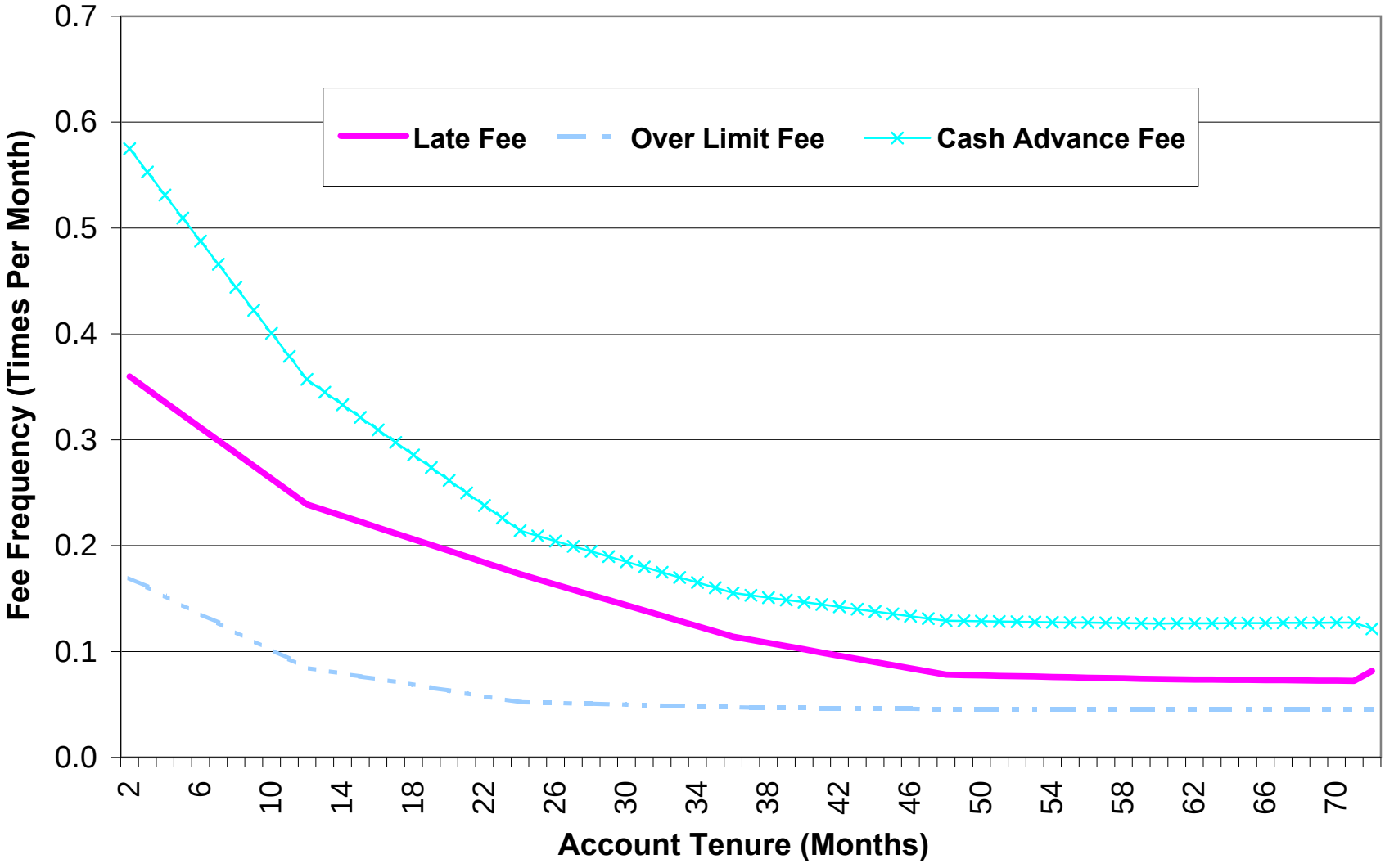
$f_{i,t}^{j}$ is a dummy variable for payment of fee type j by account i at tenure t

Account and time fixed effects: ϕ_i, ψ_{time}

Spline: Takes tenure (time since account opened) as its argument, knot points every 12 months

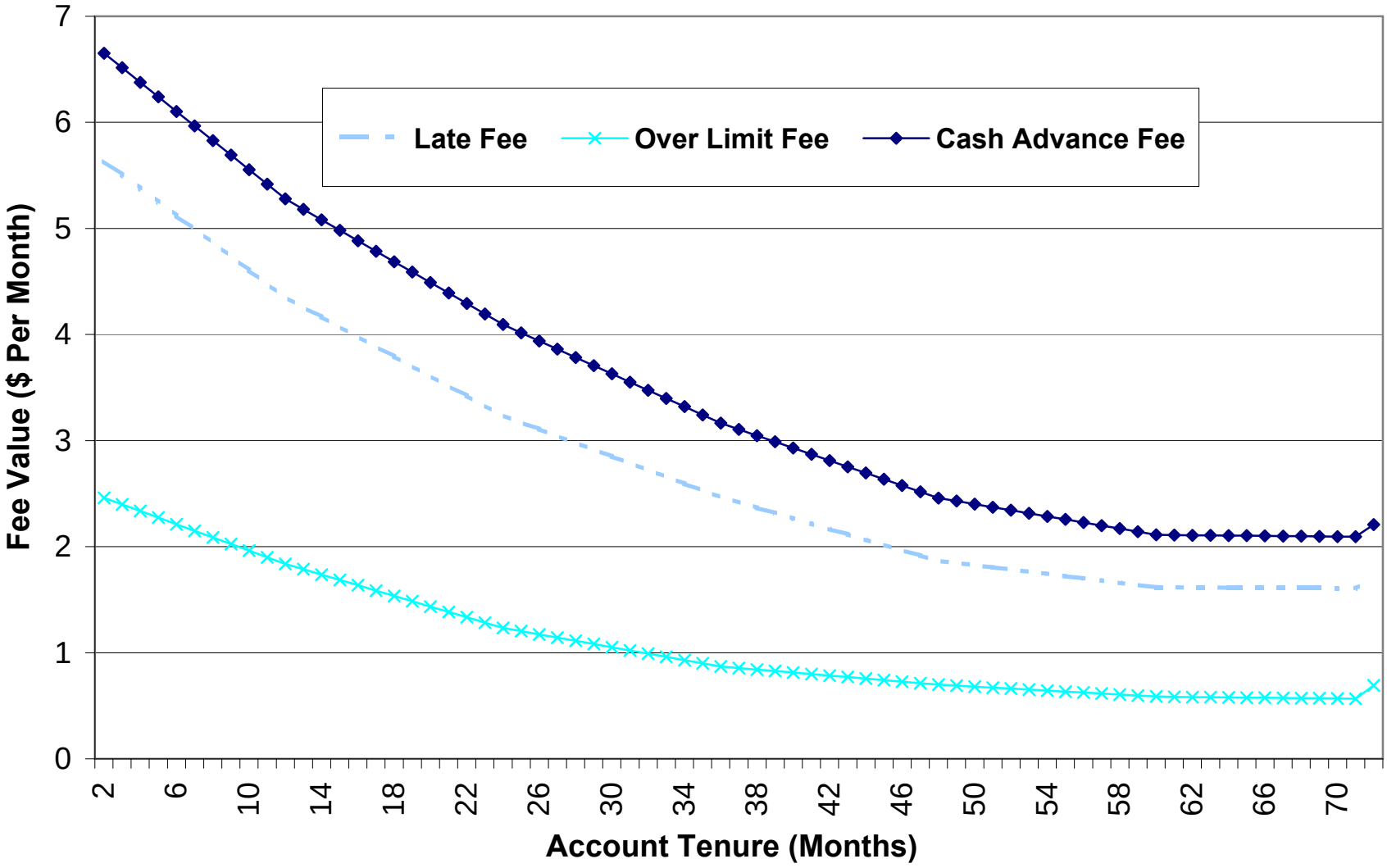
Controls: quantity purchased, bill activity dummy, bill existence dummy, debt/limit

Figure 1: Fee Frequency and Account Tenure



- In the first four years,
  - Frequency of cash advance fee payment drop from 57% to 13%
  - Frequency of late fee payment drops from 36% to 8%
  - Frequency of over limit fee payment drops from 17% to 5%
- Results qualitatively the same if fee value is used rather than fee dummy

Figure 2: Fee Value and Account Tenure

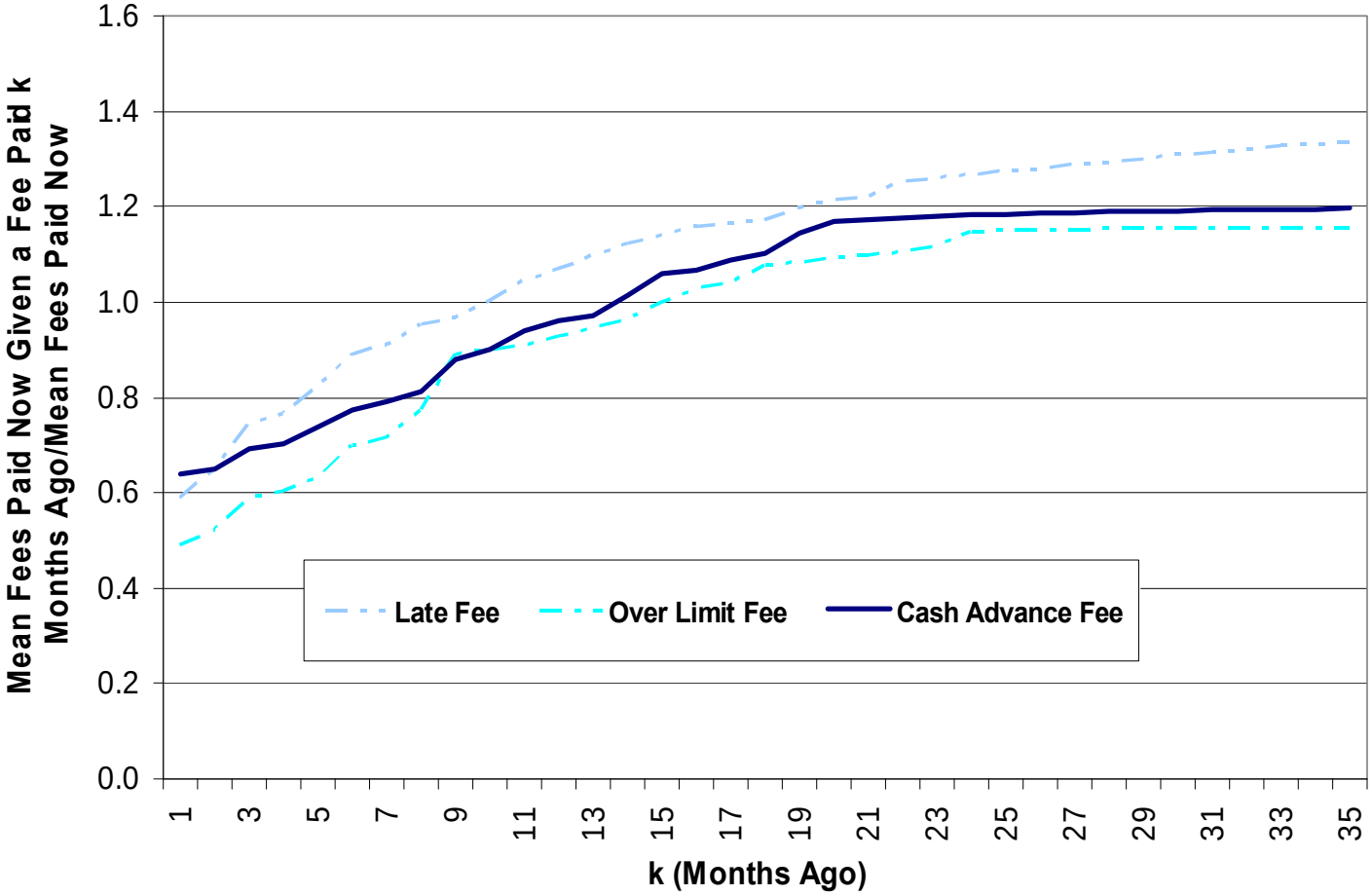


Descriptive Analysis 2: Impact of past fee payment on current fee payment

- We calculate:

$$
\begin{aligned}
L_k &= \frac{E\left[f_t | f_{t-k} = 1\right]}{E\left[f_t\right]} \\
&= \frac{\text{Probability of paying a fee given the agent paid a fee } k \text{ periods ago}}{\text{Probability of paying a fee}}
\end{aligned}
$$

Figure 3: Impact of Fees Paid k Months Ago on Fees Paid Now



Notes: This figure plots $L_k=E(f_t|f_{t-k}=1)/E(f_t)$, the ratio of the conditional mean of fees f_t paid now given a fee was paid k months ago to the mean of fees paid now. If this value is 1, having paid a fee k months ago has no effect on current fee payment; if it is less than one, having paid a fee k months ago reduces current fee payment; if it is greater than one, it increases fee payment.

- Having paid a fee last month reduces probability of paying a fee this month by:
  - 40 percent for cash advance fees and late fees
  - 50 percent for over limit fees
- By the time one year has passed, the effects of past fee payment on current fee payment has almost disappeared

2 Model and Estimation

- F_t : stock of *F*eedback

- $f_t \in \{0, 1\}$ current feedback

- Then:

$$F_t = \delta^t F_0 + \psi t + \sum_{s=1}^{t} \delta^{t-s} f_s$$

- $1 - \delta$: depreciation

- ψt : consumer learning through passage of time

- Assume probability of paying a fee at $t+1, P_{t+1,}$ is:

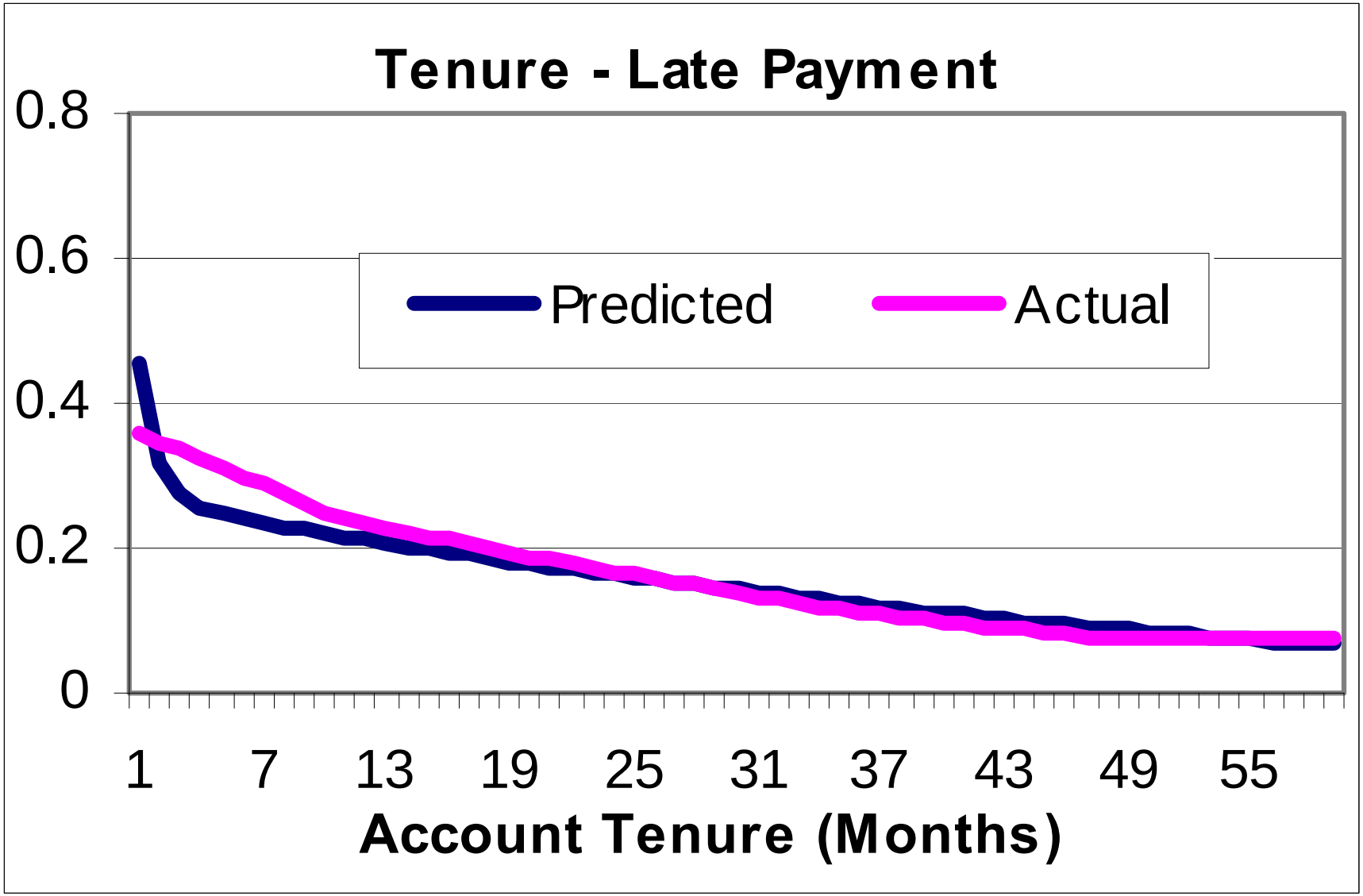
$$P_{t+1} = ae^{-\beta F_t/a} + b.$$

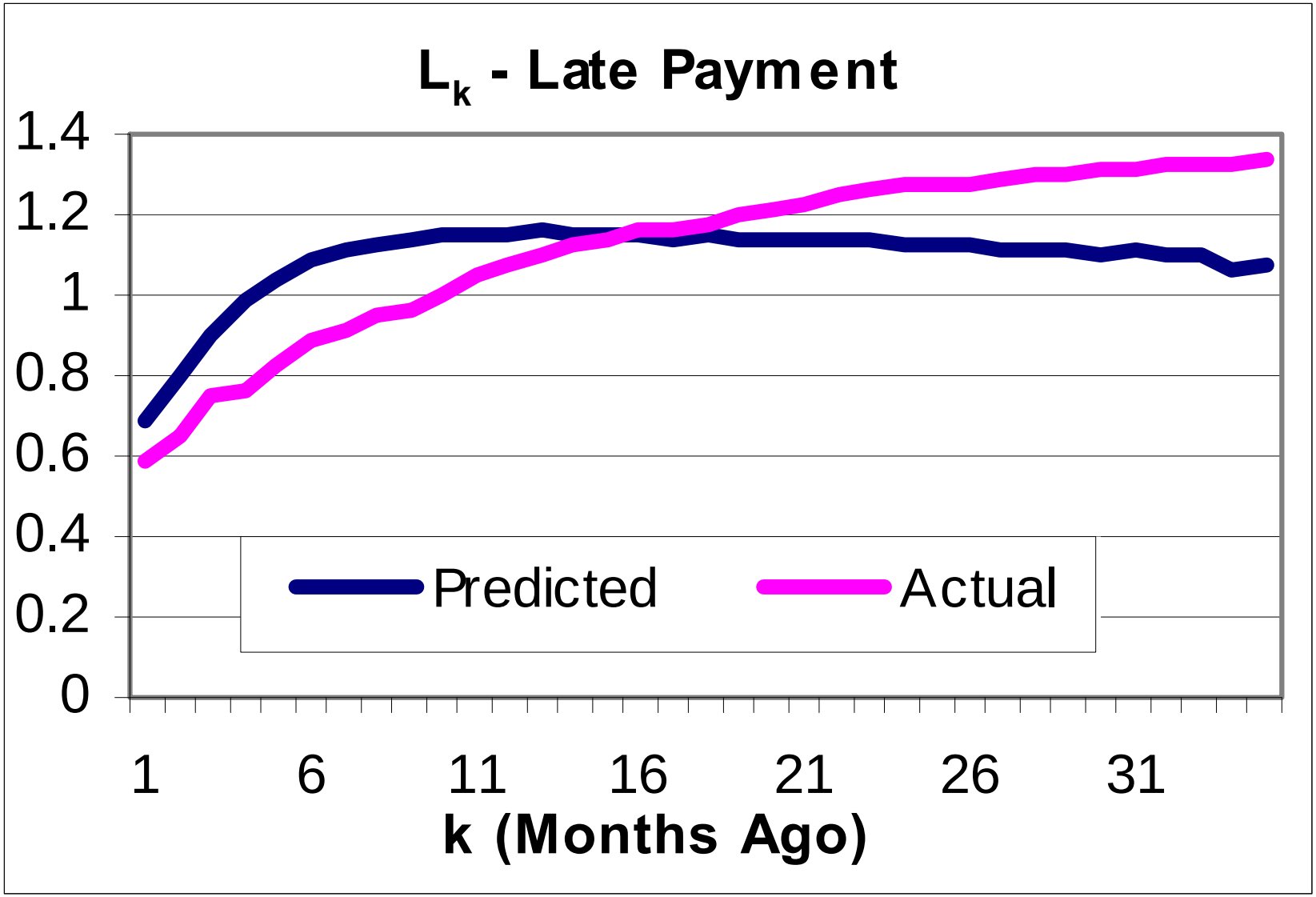
- Key parameters:
  - β : short-term learning
  - b : long-run propensity of fee payment for a consumer who never forgets, if $F_0 = 0$
    - In the estimation, we allow for two different values of b, b^H and b^L
    - $a + b$: initial propensity of fee payments if $F_0 = 0$
  - F_0 : initial stock of feedback

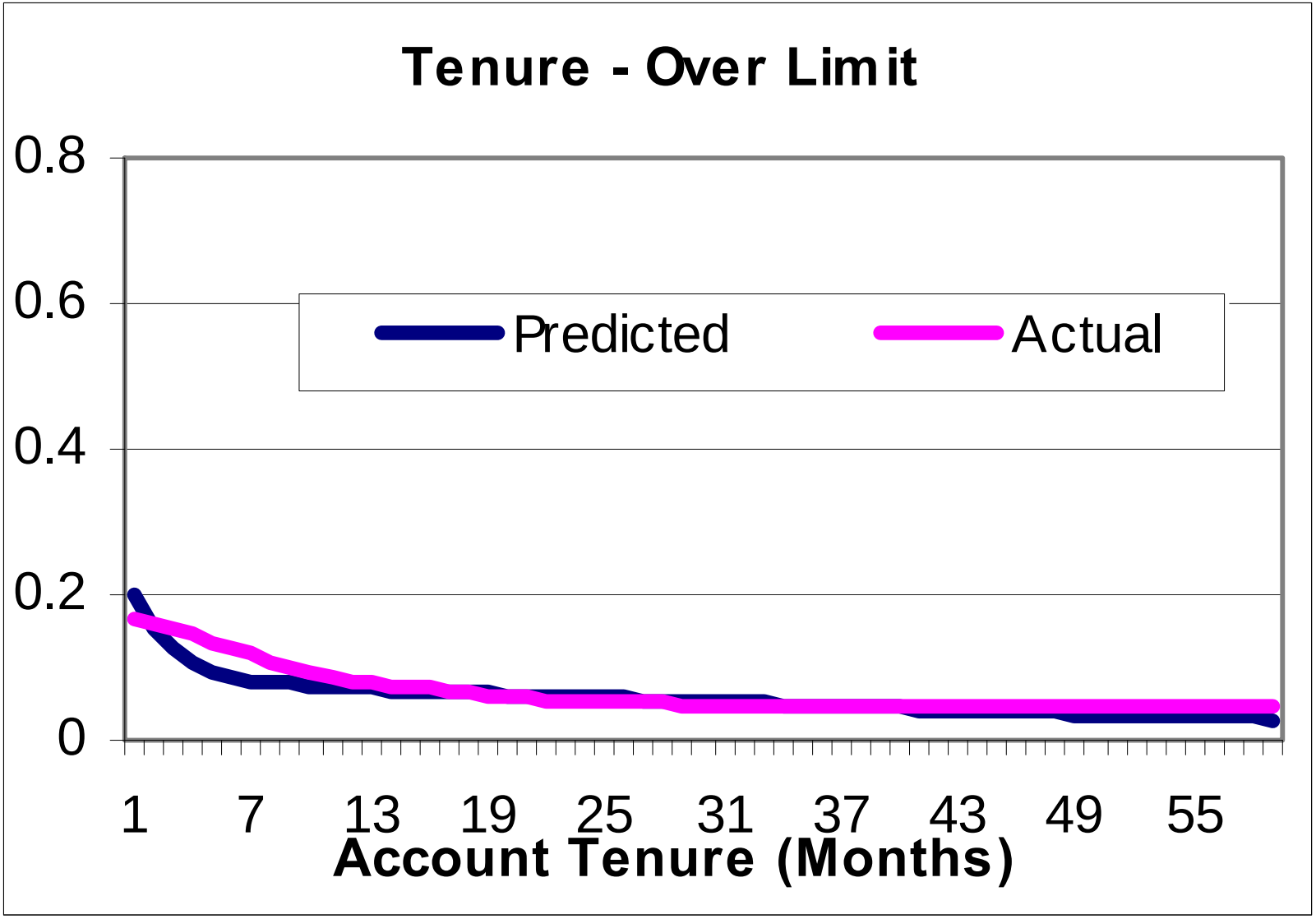
- We estimate the model for all three fee types using Method of Simulated Moments
  - standard errors in parentheses
- Depreciation $1 - \delta$: 20% for late fee, 8% for over limit fee, 10% for cash advance fee
- β : Estimates imply feedback has a large impact on current fee payment
- Probability of paying a fee at tenure 0 is about 35 percent for the late fee, 10 percent for the over limit fee, and 66 percent for the cash advance fee
- Long-run propensities to pay fees about 2 to 3 percent for all fee types

Model Estimation Results

	Late	Over Limit	Cash Advance
δ	0.8007 (0.0016)	0.9187 (0.0020)	0.9060 (0.0002)
β	0.8547 (0.0041)	0.9506 (0.0067)	0.2157 (0.0007)
$\phi = \frac{\psi\beta}{a}$	0.0435 (0.0003)	0.0452 (0.0005)	0.0282 (0.0007)
a	0.9040 (0.0026)	0.5438 (0.0045)	0.8410 (0.0009)
b^L	0.0000 (0.0016)	0.0003 (0.0024)	0.0213 (0.0001)
b^H	0.0298 (0.0002)	0.0198 (0.0001)	0.0195 (0.0001)
$\overline{F_0}$	1.0227 (0.0068)	0.9746 (0.0064)	1.0317 (0.0068)


Tenure - Late Payment
0.8
0.6
0.4
0.2
0
Predicted
Actual
1
7
13
19
25
31
37
43
49
55
Account Tenure (Months)


L_k - Late Payment
1.4
1.2
1
0.8
0.6
0.4
0.2
0
1
6
11
16
21
26
31
k (Months Ago)
Predicted
Actual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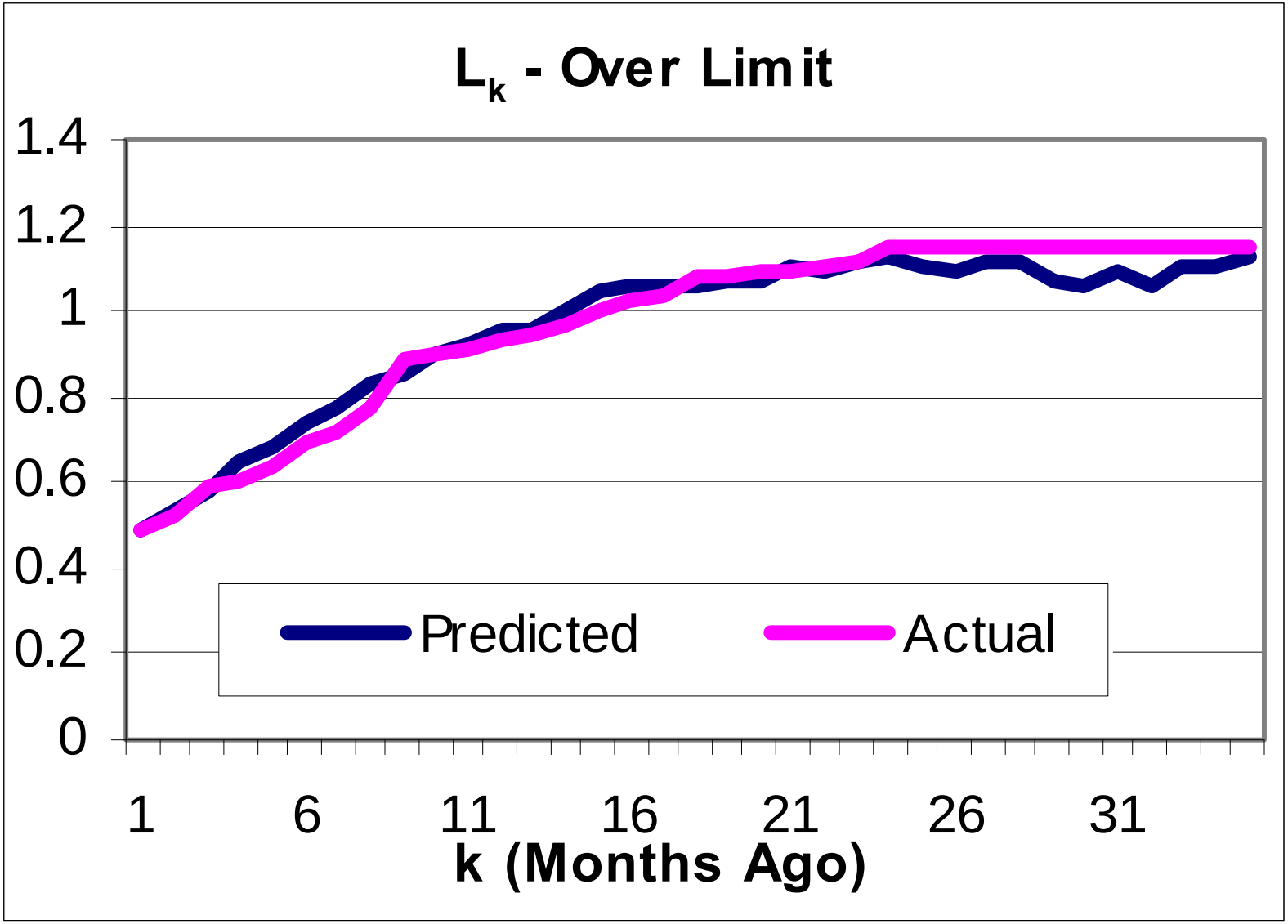
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1.2
1
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0.6
0.4
0.2
0
1
6
11
16
21
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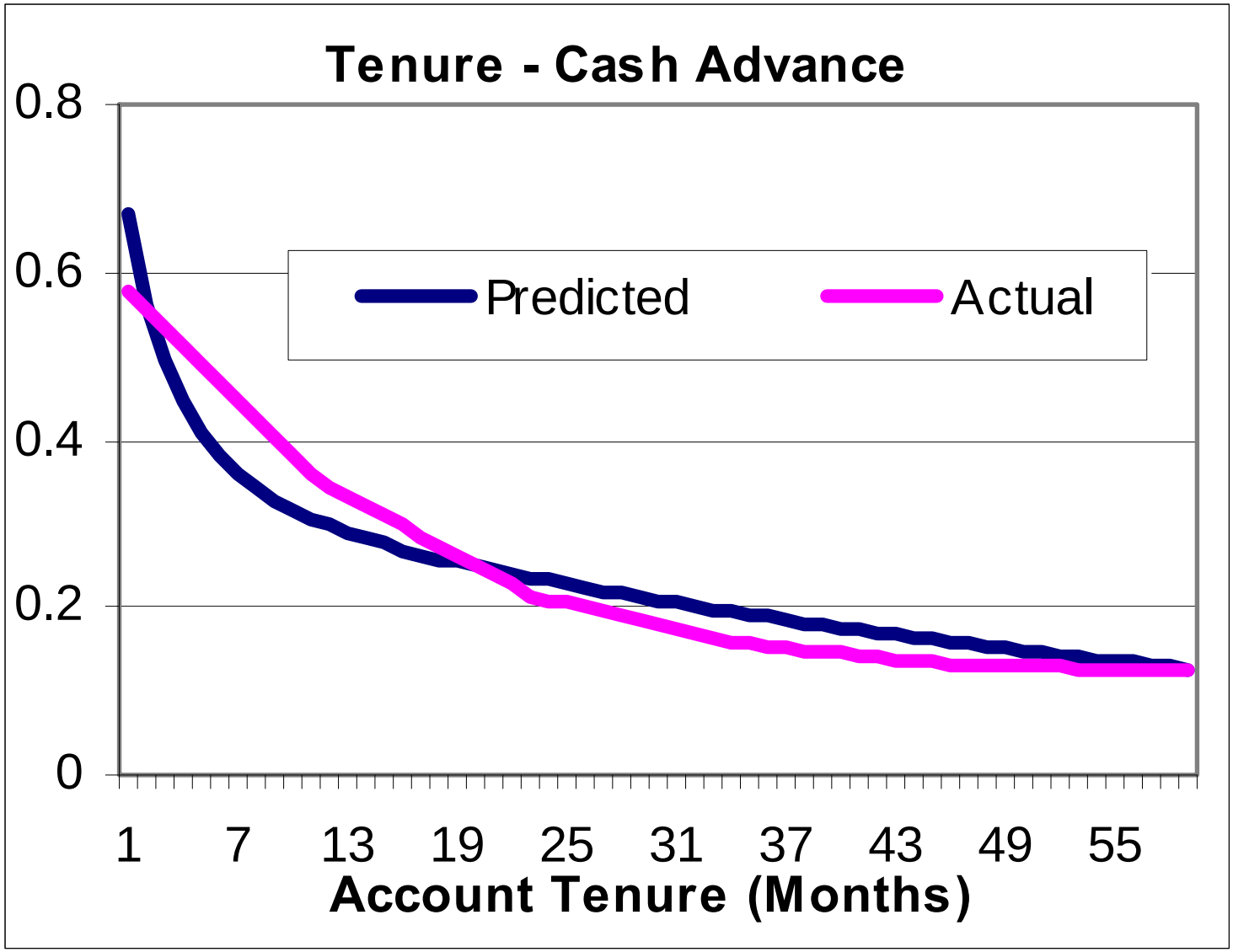
k (Months Ago)
Predicted
Actual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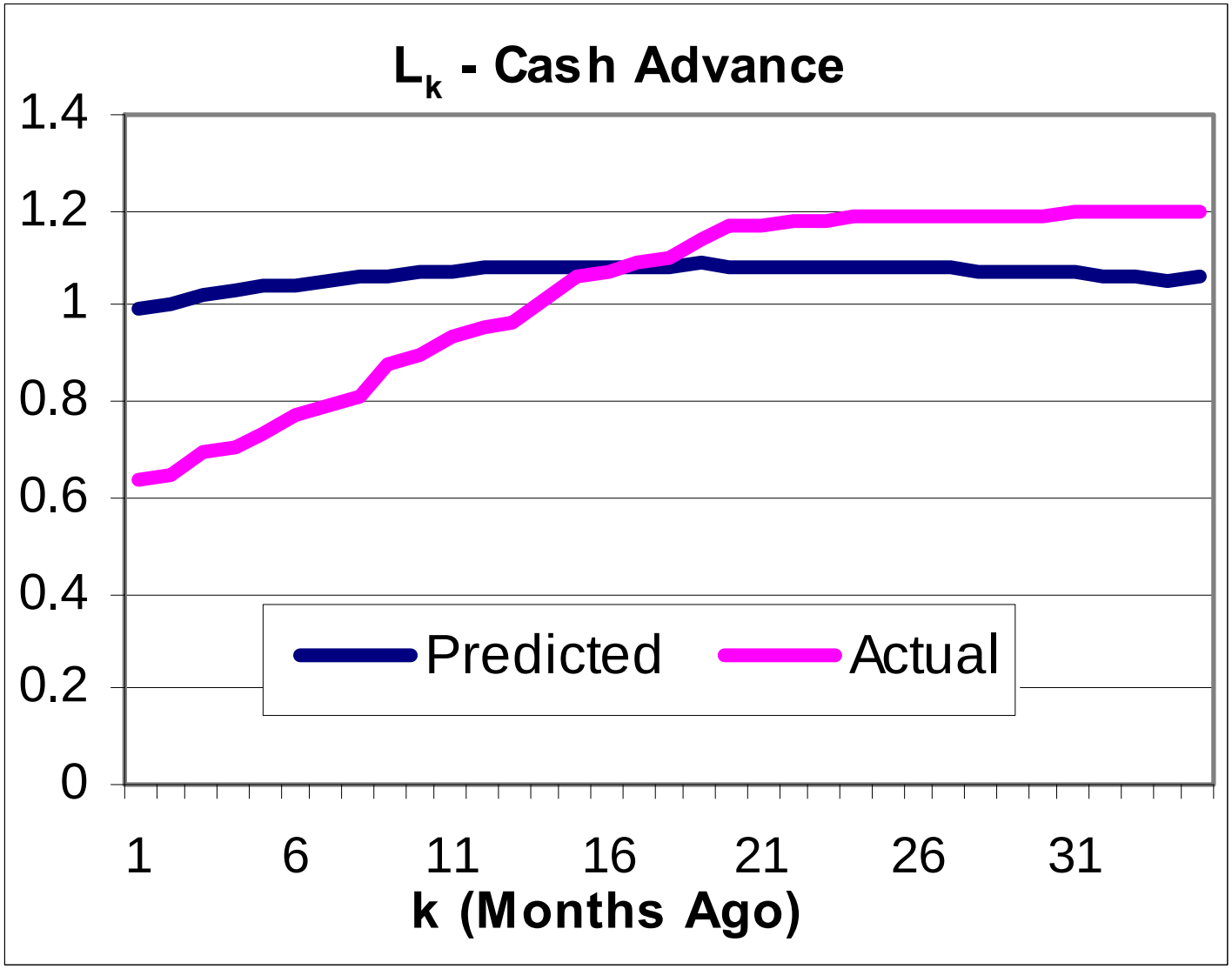
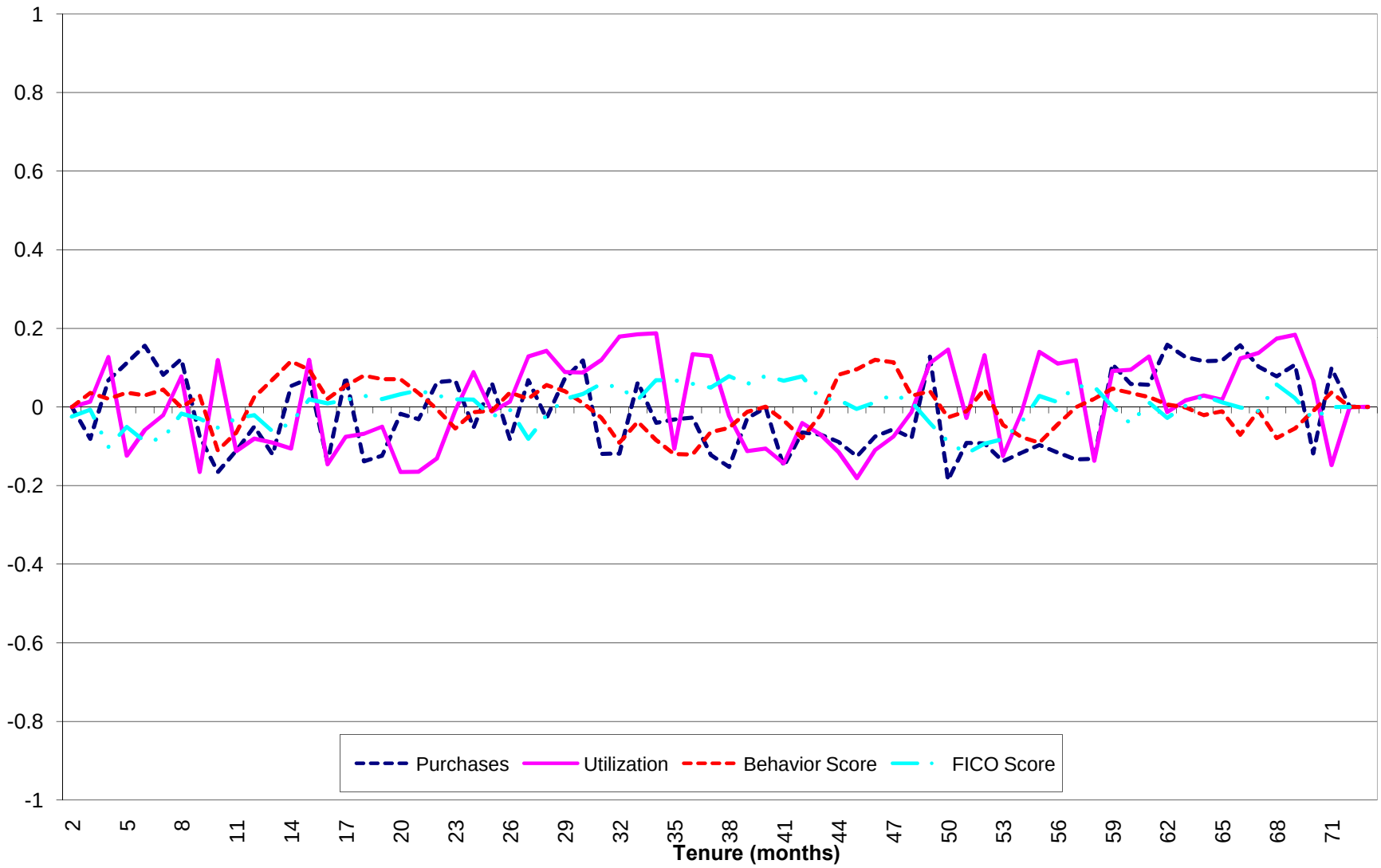
Account Tenure (Months)


L_k - Cash Advance
1.4
1.2
1
0.8
0.6
0.4
0.2
0
1
6
11
16
21
26
31
k (Months Ago)
Predicted
Actual

3 Alternative Explanations to Learning and Backsliding

- Correlation between financial distress and tenure
  - Do new account holders experience more financial/personal distress?
  - We find FICO and behavior (credit risk) scores unrelated with account tenure
- Correlation between purchases and tenure
  - Do new account holders spend more, generating higher fees?
  - We find purchases are not related to account tenure

Figure 5: Demeaned and Normalized FICO Score, Behavior Score, Purchases, and Utilization Rates



- Non-utilization of the credit card
  - Do card holders who pay a fee stop using the card?
  - Effects are too small–we estimate that someone who has paid a fee every month for the past six months is only 2% less likely to use his or her card next month than someone who had no fee payments

Time-varying financial needs

- Suppose ν_t is a time-varying cost of time, and $\Pr(f_t = 1) = \nu_t$
  - Then, in the regression $f_t = \theta f_{t-1} + controls, \theta = cov(\nu_t, \nu_{t-1}) / var(f_{t-1})$
  - We estimate this regression using time fixed effects and other controls
  - We find $\theta = -0.75, -0.52, -0.28$ for the three kinds of fees
  - These imply that the negative monthly autocorrelation of time cost must be less than $<$ -0.75

- We think this is unlikely, because:
  - Presence of time fixed effects rules out events happening at regular intervals, e.g. summer vacations
  - Financial needs of more than one month's duration ruled out
  - Need would have to be well above average one month, well below the next
    - Rules out episodes of high opportunity cost followed by a return to the status quo
  - Evidence on income processes suggests a positive autocorrelation

4 Conclusion

- Consumers learn how to avoid fees
  - New accounts generate fees of \$16/month plus penalty pricing
  - Through negative feedback — paying fees — consumers learn to avoid triggering such fees in the future. Controlling for person fixed effects, fee payments fall by 75% during the first 4 years of account life
- Consumers' hard-earned knowledge depreciates 10-20% per month
  - As fee-paying lesson recedes into the past, consumers tend to backslide
- On net, learning dominates backsliding

Figure 1: Fee Frequency and Account Tenure by Income

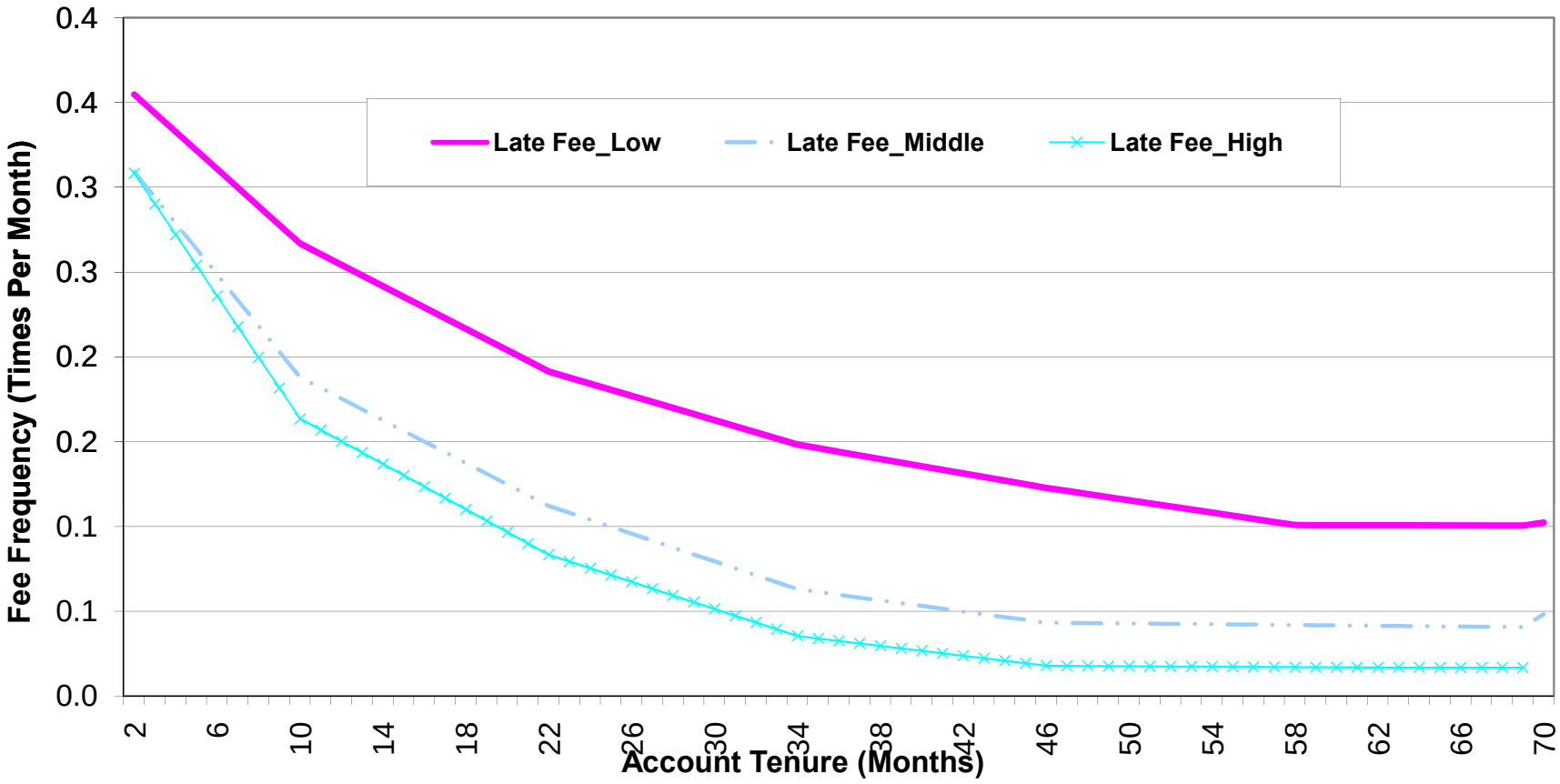


Figure 1: Fee Frequency and Account Tenure by FICO Score

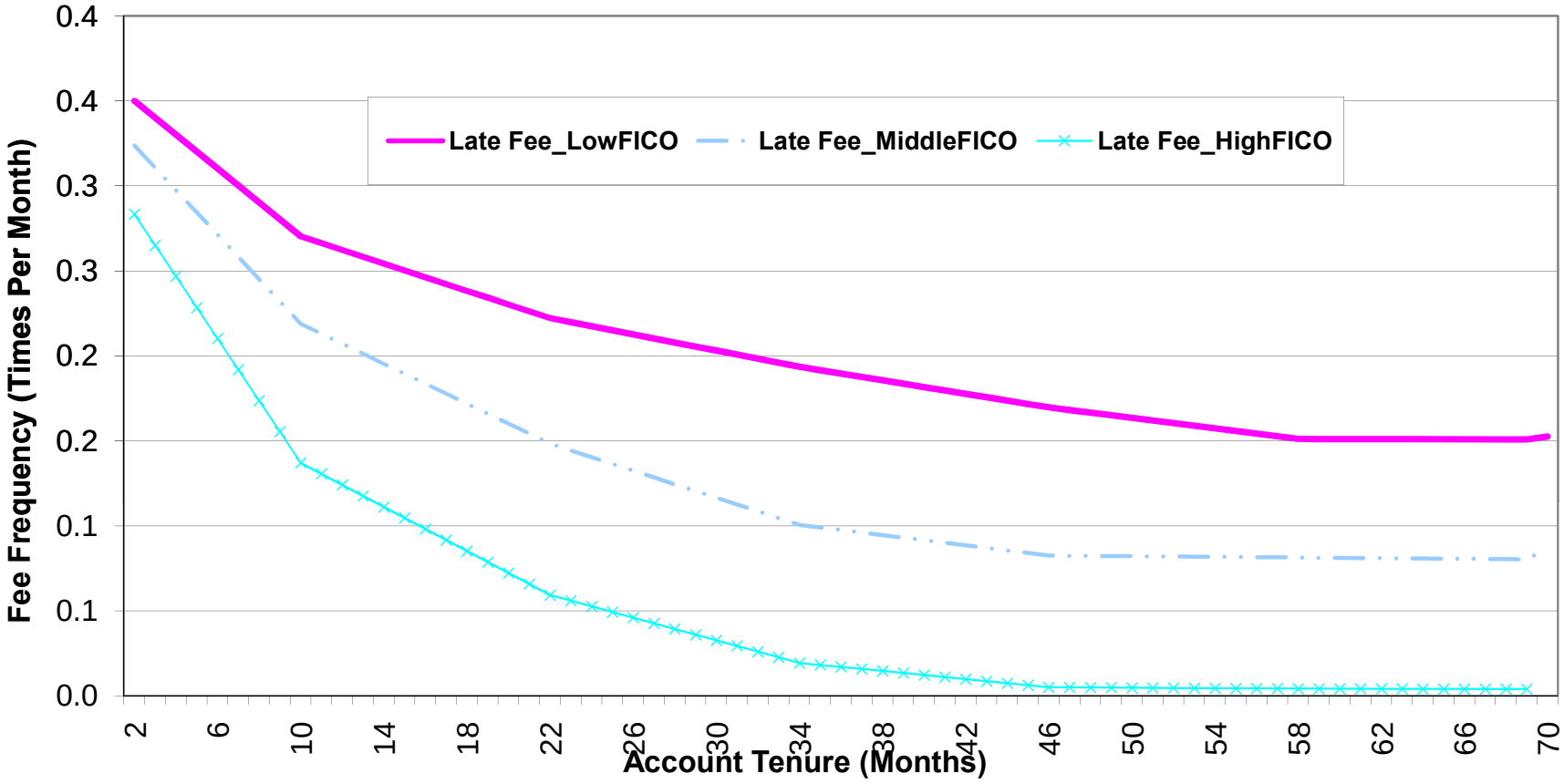


Figure 1: Fee Frequency and Account Tenure by Gender

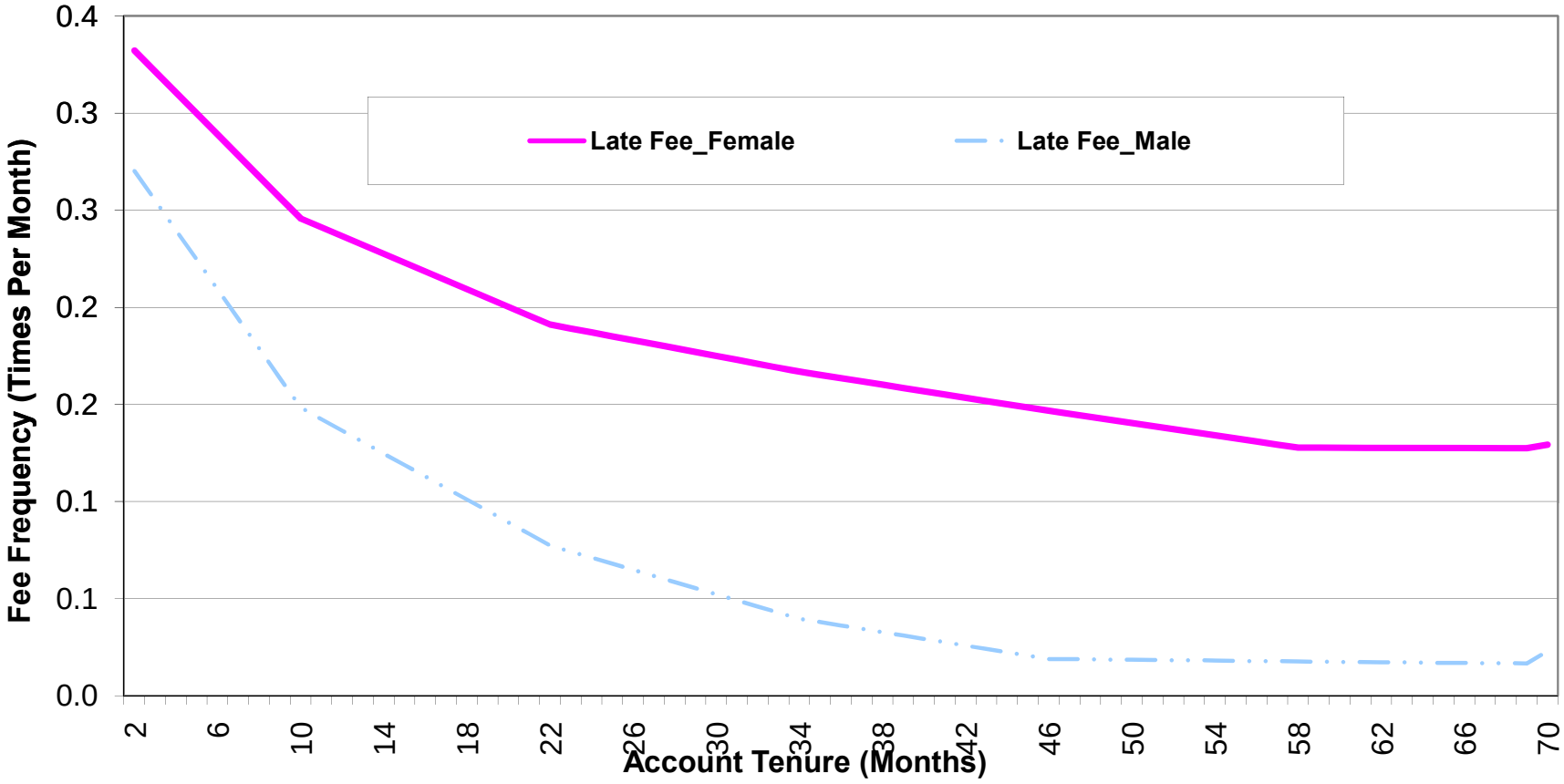
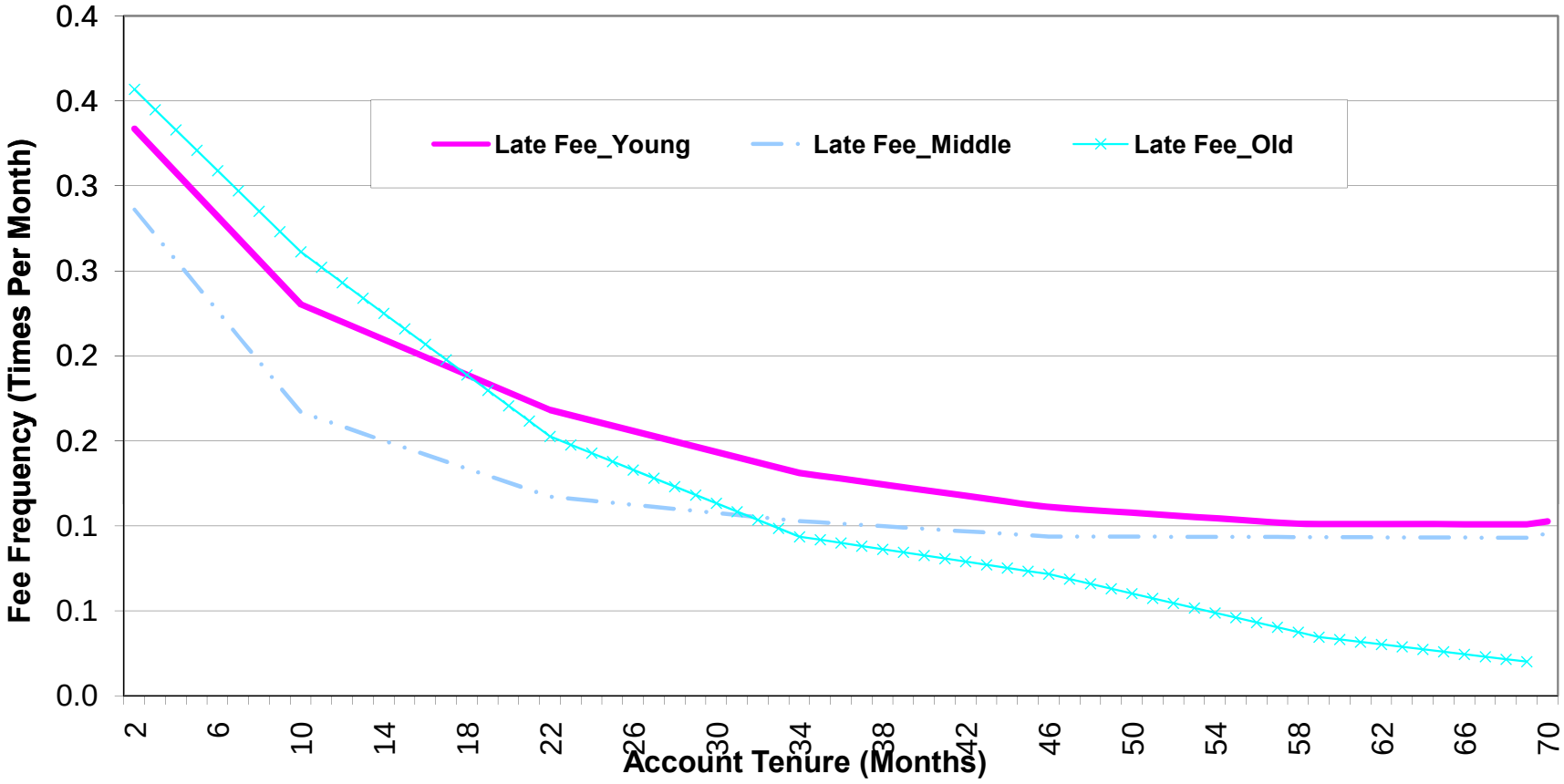


Figure 1: Fee Frequency and Account Tenure by Age



Thank you