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Explaining the fixed cost component of discounting: the importance of students' liquidity constraints

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Abstract

Utilizing experimental data on choices over real monetary rewards made by university students, we provide evidence that two measures of liquidity, income and employment status, significantly explain differences in patterns of discounting. We find an average fixed cost component of discounting in the range of $5 for unemployed students and near $0 for employed students. An increase in annual disposable income of $1000 decreases the fixed cost component of discounting by approximately $0.20 to $0.25. These findings can help resolve the puzzle that some studies in the literature find evidence of present-bias and magnitude effects and some do not.

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1. Introduction

Experimental studies have documented a variety of discounting behaviors inconsistent with the traditional exponential discounting model. Perhaps most notable are the findings of present-biased preferences and of a magnitude effect.[1] Present-bias describes time preferences of individuals who have discount rates that decline over time (Benhabib et al., 2010; Laibson, 1997; Meier and Sprenger, 2010; Takeuchi, 2011; Thaler and Benartzi, 2004). The magnitude effect is that individuals appear to be more patient when experimental reward sizes are larger (Andersen et al., 2013, 2014; Benhabib et al., 2010; Hardisty et al., 2013). Present-biased preferences are often modeled with hyperbolic or quasi-hyperbolic (β, δ) discounting functions, where present-bias is proportional to the reward amount.[2] As such, estimated rates of time preference would not change with larger rewards meaning that the present-biased "β" term cannot explain a magnitude effect. One explanation for the magnitude effect is that individuals discount future outcomes with a fixed cost (Benhabib et al, 2010). The fixed cost discounting model treats the present-bias as a fixed dollar amount; discount rates will decline as the fixed dollar amount becomes smaller relative to the reward size. Thus the appeal of the fixed cost theory of discounting is that it can explain present-biased preferences in addition to the magnitude effect.

However, the experimental evidence is mixed in regards to these "anomalies." For example, Andersen et al. (2013) find little evidence of a magnitude effect and Andersen et al. (2014) find no evidence of quasi-hyperbolic discounting or fixed cost discounting. In contrast, Benhabib et al. (2010) find a statistically significant present-bias in the form of a fixed cost, with an average magnitude of $4 across their subjects. The differences in these results is then somewhat of a puzzle. As Andersen et al. (2014) note, most evidence of present-biased preferences stems from experiments with college-age students.[3] Indeed, Benhabib et al. (2010) utilizes a sample of 27 college-aged students and Takeuchi (2011) analyzes a sample of 56 students whereas Andersen et al. (2014) utilizes a representative sample of 413 adult Danes.

One notable difference between college students and the general adult population is that the typical student may have lower income and less liquidity than a typical working adult. Perhaps this lack of income and liquidity is driving the differences in the results. If so, we may expect to see significantly more present-biased preferences among the subgroup of students that have less liquidity and lower disposable income. There is some previous evidence that liquidity constraints may be an important factor in explaining students' intertemporal choices that appear present-biased; Stahl (2013) uses hypothetical questions where one treatment is anchored to 2 days before Christmas, when the average student may be more liquidity constrained. The present study differs because we have real monetary rewards, we estimate the size of the fixed cost component of discounting for the more liquidity constrained individuals, and we relate liquidity constraints to the concept of a magnitude effect.

Using experimental data on a sample of students who make choices over real monetary rewards, we test this hypothesis that liquidity is related to the extent of present-bias. We find evidence that employed students and students with higher income exhibit a significantly smaller

[1] Frederick et al. (2002) review experimental studies and list hyperbolic (present-biased) discounting and the magnitude effect among several other anomalies.

[2] A consequence of present-biased time preferences is that we can see preference reversals for sets of choices that have identical rewards and intervals between the earlier and later rewards (Thaler, 1981).

[3] However, use of college students as participants does not guarantee the finding of present-bias. See, for example, Andreoni and Sprenger (2012).

fixed cost component of present-bias. Therefore, our contribution is to provide one explanation for the seemingly conflicting results regarding non-constant discounting behavior; researchers may be more likely to find evidence of a fixed cost component to discounting when the sample includes more individuals with liquidity constraints. This fixed cost component can then explain observed present-biased preferences and observed magnitude effects.

The present study utilizes the data from Meyer (2015) but contributes to the literature in a different way. Meyer (2015) is primarily concerned with comparing time preferences from different experimental environments. Specifically, Meyer (2015) documents a substantial magnitude effect and finds that estimated time preferences do not significantly differ between two different elicitation mechanisms.[4] In contrast, the present study focuses on liquidity constraints as one potential explanation for a fixed cost of discounting, which can in turn cause researchers to infer magnitude effects and present-biased time preferences.

2. Experimental Data[5]

We utilize data from 76 student participants stemming from 11 experimental sessions. The sessions were run at two universities between spring 2009 and spring 2012. Two elicitation mechanisms were used for the experiment; one was a variant of a Second Price Sealed Bid Auction (hereafter 2PSB) (Vickrey, 1961) and one was a variant of a Becker-DeGroot-Marschak (hereafter BDM) (Becker et al., 1964) mechanism. Our 2PSB mechanism is a matching task because individuals equate the present value of two rewards from two different time periods and our BDM mechanism is a choice task because individuals make a series of choices between a reference reward and later rewards. In each session, the experimenter described all rules of the mechanism (BDM or 2PSB) and the rules for determining experimental payments. The experimenter then guided the subjects through several hypothetical rounds to ensure understanding of the mechanisms. Within each session, subjects then completed multiple binding experimental rounds.[6]

Across the experimental sessions, reference dollar amounts varied from \$10 to \$500. Each respondent completed some rounds with no front-end delay (a reference time period of "now") and some rounds with a 1 month front-end delay. The length of the interval between payment options varied from 1 to 6 months, depending on the session and round. Note that variation in both reference dollar amount and front-end delay is required to identify a fixed-cost component of discounting whereas only variation in front-end delay is required to identify quasi-hyperbolic (β, δ) discounting.

All subjects received at least a \$10 participation fee. Following all rounds, the experimenter conducted a random draw to determine which binding round would be used to determine experimental payments and a random draw to determine which participant would receive payment from the selected binding round. Thus, one subject from each session was paid according to the results of a binding round and the others received a participation fee. This approach has been utilized in previous research to facilitate larger experimental rewards under fixed budgets (Harrison et al., 2002; Meier and Sprenger, 2015).

[4] Meyer (2015) considers exponential and quasi-hyperbolic time preferences, but does not address the issue of a fixed cost component of discounting.

[5] We describe only the essential details of the experiment here in the interest of brevity. Complete details of the experiment including sample experimental scripts are provided in Meyer (2015).

[6] By binding, we mean that these rounds would potentially determine experimental payments.

As mentioned, we are most concerned with the impacts of liquidity constraints on discounting behavior. Ideally we would observe information about participants' access to credit markets to measure liquidity. However, this information is not available to us so we instead select two measures that are related to income as proxies of liquidity constraints: employment status and discretionary income as measured by post-experiment questions. Regardless of whether or not participants have access to credit markets through a consumer credit card, for example, there is reason to believe that the amount of currency on hand or in a checking account would be important indicators of liquidity for certain student purchases. For example, payments between students would probably take the form of cash or check and not credit card. Moreover, previous literature on consumption over the life-cycle, beginning with Flavin (1985), has commonly proxied liquidity constraints with unemployment. We code employment status dichotomously as employed (full-time, part-time, or self-employed) or unemployed (not currently working). We attempt to isolate discretionary income with "Including any money that you earn, any money that is gifted to you (from parents, relatives, etc), and any other source of income NOT including any money that is used for tuition or educational fees, what is your best estimate of your personal income for this year?" The income question was intentionally phrased this way to capture all potential income of this dependent population, both gifted from relatives and earned through labor. Sample mean employment is 50% and sample mean income is approximately $5.2 thousand.

3. Econometric Model and Results

As previously mentioned, a fixed cost theory of discounting predicts that we will find both a present-bias and a magnitude effect in observed time preferences. Before turning to the more complicated specification that directly models this fixed cost, we first investigate the traditional exponential discounting model, which is well known for its simplicity. In the traditional exponential discounting model, the discounting function applied to time *t* is given by

$$D(t) = \delta^t = \frac{1}{(1+\rho)^t} \tag{1}$$

where δ is the constant exponential discount factor and ρ is the constant exponential discount rate. A present-bias implies that individuals will be relatively more patient for choices that are anchored to a future date compared to choices that are anchored to the present. That is, the discount rate should be lower for choices with a front-end delay compared to that from choices with no front-end delay if there is a present-bias. A magnitude effect implies that individuals will be relatively more patient for choices that involve larger rewards compared to choices that involve smaller rewards; the discount rate should be lower for larger reference dollar amounts. Thus, by comparing the estimated rates from two groups of individuals across these two dimensions, we can begin to establish whether or not one of the groups is more likely to apply a fixed cost to its discounting. The main hypothesis of this paper is that liquidity plays an important role in explaining a fixed cost component of discounting so we group individuals according to our two measures of liquidity—employment status and income level.

We specify an intertemporal utility function that is time separable and stationary over time. We also assume that the instantaneous utility function is linear for this analysis.[7] An individual is

[7] As noted in the literature (for example, Andersen et al., 2008; Andreoni and Sprenger, 2012; Laury et al., 2012) the assumption of linear utility will result in overestimates of discount rates if the utility function is truly concave.

indifferent between the reference time period monetary reward, c_t, and the delayed monetary reward, c_{t+k}, when

$$D(t)c_t = D(t+k)c_{t+k}. \tag{2}$$

The left side of equation 2 is the discounted utility of the reference payment option (U_{ref}) and the right side of equation 2 is the discounted utility of the delayed payment option ($U_{delayed}$). Denote the latent index of the utility differences with

$$\Delta U = U_{ref} - U_{delayed}. \tag{3}$$

We follow Hey and Orme (1994) and Andersen et al. (2012, 2013) in specifying a Fechner behavioral error. The Fechner error specification replaces (3) with

$$\Delta U' = \frac{U_{ref} - U_{delayed}}{\omega} \tag{4}$$

where ω is the behavioral noise parameter. We then specify the likelihood function in the same manner as described in Meyer (2015).[8] Denote the choices of an individual from the BDM mechanism as y_i, where $y_i = 0$ for a choice of a reference payment option, $y_i = 1$ for a choice of a delayed payment option, and $y_i = -1$ for an indifferent observation. Also, we indicate the observations from the 2PSB mechanism with $2PSB_i$. The log-likelihood function over the *n* observations is then

$$LL = \sum_{i=1}^{n} I(y_i = 0)\ln\Phi(\Delta U_i') + I(y_i = 1)\ln(1 - \Phi(\Delta U_i')) + I(y_i = -1)(\tfrac{1}{2}\ln\Phi(\Delta U_i') + \tfrac{1}{2}\ln\left(1 - \Phi(\Delta U_i')\right) + I(2PSB_i)\left(\ln\phi\left(\frac{\Delta U_i}{\mu}\right) - \ln(\mu)\right), \tag{5}$$

where *I*(.) is the indicator function, $\Phi(.)$ is the cumulative normal distribution, $\phi(.)$ is the normal density function, and μ is a behavioral error term from the 2PSB data.

Table 1 presents maximum likelihood results for the exponential discount rate using various subsamples of the data. We first group the individuals according to their employment status (column 1 is employed and column 2 is unemployed) and then according to their income level (column 3 is income at or below the median of \$3500 and column 4 is income above the median). Overall, the point estimate of the discount rate is lower for employed individuals than for unemployed individuals and the point estimates are remarkably similar between high income and low income individuals. We then divide the choices into 1) those involving a front-end delay versus those that do not and 2) those involving a large magnitude reference reward (\$100 or \$500) versus those involving a small magnitude reference reward (\$10 or \$50). In terms of front-end delay, the estimated rate is substantially smaller for unemployed individuals and for low income individuals when there is a front-end delay compared to no front-end delay. This is consistent with a present-

However, here we are interested not in the absolute magnitude of the discount rate but in differences in the pattern of discounting based on liquidity.

[8] The MLE is programmed in Stata and clusters standard errors at the subject level. Harrison and Rutstrom (2008) provide helpful pedagogical notes for estimating MLE models of utility functions within Stata.

bias. On the other hand, the estimated rates do not differ much depending on the front-end delay for employed individuals or for high income individuals.

Table 1: Exponential Discounting: Maximum Likelihood Estimates

	(1) Employed	(2) Unemployed	(3) High Income	(4) Low Income
All Choices	0.479***	1.037***	0.788***	0.789***
	(0.140)	(0.277)	(0.189)	(0.240)
Front End Delay				
Yes	0.433***	0.879***	0.799***	0.608***
	(0.142)	(0.235)	(0.221)	(0.194)
No	0.604***	2.24***	0.521***	1.989***
	(0.194)	(0.615)	(0.196)	(0.508)
Reward Size				
Small	2.482***	65.947	3.124*	46.086
	(0.877)	(81.669)	(1.836)	(61.177)
Large	0.445***	1.000***	0.772***	0.745***
	(0.137)	(0.269)	(0.195)	(0.233)

Estimates correspond to the annual discount rate, $\rho = (\frac{1}{\delta})^{12} - 1$, where δ is the monthly discount factor. Standard errors in parentheses are estimated via the delta method and are clustered at the subject level. *** p<0.01, ** p<0.05, * p<0.1.
Estimates of the behavioral error terms are omitted from the table but available upon request.

Moving on to reward size, we do find smaller estimated rates for large reward sizes relative to the smaller reward sizes which is consistent with a magnitude effect. However, the extent of the differences between the rates from large and small rewards clearly depends on employment status and income level. The estimated rate from the small reward sizes is 66 times larger than the rate from the large reward sizes for unemployed individuals whereas the small reward rate is only 5.5 times larger than the large reward rate for employed individuals. Similarly, the estimated rate from the small reward sizes is 62 times larger than the rate from the large reward sizes for low income individuals whereas the small reward rate is only 4 times larger than the large reward rate for high income individuals. Thus, we have some suggestive evidence that both present-bias and the magnitude effect are more pronounced for low income and unemployed individuals.

Next, to formally test for a fixed cost component of discounting, we pool all of the data and adopt the discounting specification introduced in Benhabib et al. (2010) and utilized by Andersen et al. (2014). We use the same log-likelihood function as described by (5) but replace the exponential discounting function (1) with the fixed cost specification from Benhabib et al. (2010),

$$D(t) = \begin{cases} 1 & \text{if } t = 0 \\ \beta[1-(1-\theta)\delta t]^{(1/(1-\theta)} - \left(\frac{b}{c_t}\right) & \text{if } t > 0 \end{cases} \tag{6}$$

where β<1 represents quasi-hyperbolic discounting, θ is a parameter that allows for a variety of discounting functions, *b*>0 represents a fixed cost component to discounting, and c_t is the delayed reward dollar amount. Note that this specification is quite flexible because it nests the traditional exponential model with $\theta = \beta = 1$ and $b=0$ and the quasi-hyperbolic model with $\theta=1$ and $b=0$.

Table 2 presents maximum likelihood results for several specifications. Column 1 is a baseline specification where we do not allow for any heterogeneity. We show in Meyer (2015) that the behavioral error terms[9] are significantly related to whether or not an individual is employed and the reference dollar amount of the choice. Thus, column 2 and all subsequent columns specify that the error terms are functions of the reference dollar amount and the employment status of the individual. We do not see evidence of quasi-hyperbolic discounting or a fixed cost of discounting in columns 1 and 2, where we do not allow for heterogeneity in the discounting parameters. Furthermore, the estimate of θ is not statistically different from 1, suggesting little support for hyperbolic discounting in general.

One main hypothesis is that liquidity constraints can increase present-bias. This suggests that employment and income should be positively related with the quasi-hyperbolic β parameter if the present-bias is a constant proportion of the reward. Similarly, employment and income should be negatively related with the fixed cost of discounting parameter b if the present-bias is a fixed dollar amount no matter the size of the reward. Columns 3 through 5 allow for this heterogeneity. Column 3 allows only the fixed cost parameter, b, to be a function of employment status and student income. Column 4 allows only the β parameter to be a function of employment status and student income. Column 5 specifies that both the fixed cost parameter, b, and the β parameter are functions of employment status and student income.

Examining Table 2, we see no evidence of quasi-hyperbolic discounting. The β term is not statistically different from 1 in any of the specifications. Nonetheless, column 4 suggests that income and employment serve to negate any quasi-hyperbolic discounting that could be there. Thus, we estimate one more specification that constrains $\beta=1$ (Column 6). In general, there is some weak statistical evidence of a θ parameter that is different from 1 in columns 3-5. However, the estimated magnitude of the difference is small. Furthermore, this statistical significance no longer holds when we constrain the β parameter to be equal to 1 in column 6.

The most important result of all is that we do find a fixed cost component of discounting for a subsample of this student population. Specifically, students with low incomes and who do not work are predicted to have a fixed cost component of discounting. A status of employed is associated with a fixed cost of discounting that is approximately \$4.44 to \$5.51 less than a status of unemployed. Furthermore, each additional one thousand dollars of student income is associated with a \$0.17 to \$0.25 decrease in the fixed cost of discounting.

Next, we use the estimation results and sample data to predict the average fixed cost of discounting for two groups—employed and unemployed students. For employed students, the average predicted fixed cost of discounting ranges from \$0.54 (Column 3) to \$0.66 (Column 5). For unemployed students, the average predicted fixed cost of discounting ranges from \$5.21 (Column 3) to \$4.55 (Column 5). Thus, we conclude that different experimental samples with distinct liquidity constraints could be expected to produce quite different results with regards to a fixed cost of discounting.

[9] We allow for the behavioral errors from the two experimental tasks to differ.

Table 2: Fixed Cost Specification Maximum Likelihood Estimates

Parameter	(1)	(2)	(3)	(4)	(5)	(6)
β (Q-hyperbolic)						
Constant	0.981 (0.0376)	1.059 (0.0910)	1.106 (0.116)	0.951 (0.121)	1.037 (0.131)	β=1 (constrained)
Employed				0.147* (0.0863)	0.0558 (0.0932)	
Income (Th. $)				0.00946*** (0.00313)	0.00573** (0.00250)	
θ	4.069 (2.359)	3.906 (1.963)	4.262* (1.937)	4.362* (1.890)	4.303* (1.913)	2.113 (0.790)
δ	0.0837* (0.0465)	0.159 (0.137)	0.195 (0.195)	0.184 (0.175)	0.191 (0.184)	0.0884*** (0.0222)
b (Fixed Cost)						
Constant	-1.620 (4.163)	0.367 (0.467)	7.137** (3.585)	1.274* (0.717)	5.825** (2.967)	6.572* (3.395)
Employed			-5.509* (2.971)		-4.442* (2.696)	-5.292* (2.857)
Income (Th. $)			-0.253** (0.105)		-0.167** (0.0794)	-0.249** (0.101)
ω (Behavioral Error BDM)						
Constant	35.31*** (5.725)	8.773 (6.035)	4.985 (3.108)	4.596* (2.517)	4.354* (2.242)	5.166* (3.080)
Employed		-9.748* (5.833)	-6.154** (2.903)	-5.645** (2.412)	-5.508*** (2.117)	-6.222** (2.892)
Reference $		0.247*** (0.0580)	0.260*** (0.0549)	0.265*** (0.0577)	0.264*** (0.0543)	0.257*** (0.0556)
μ (Behavioral Error 2PSB)						
Constant	19.08*** (2.846)	5.680** (2.300)	5.940*** (2.107)	4.664** (1.834)	5.495*** (1.731)	5.805*** (2.060)
Employed		-5.276** (2.165)	-5.069*** (1.913)	-3.955** (1.722)	-4.617*** (1.601)	-4.951*** (1.872)
Reference $		0.178*** (0.0233)	0.176*** (0.0229)	0.175*** (0.0231)	0.174*** (0.0225)	0.174*** (0.0223)
LL	-3369.30	-3188.25	-3135.10	-3154.10	-3127.26	-3141.37

Standard errors in parentheses are clustered at the subject level. 76 subjects. 5,180 observations. β and θ are tested against 1. All other parameters are tested against 0.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

4. Conclusion

We present evidence that can potentially explain some of the seemingly conflicting results in the time preference literature. Utilizing the discounting specification developed by Behabib et al. (2010), we find no evidence of quasi-hyperbolic discounting or a fixed cost of discounting when ignoring heterogeneity in liquidity constraints across students. However, we do find evidence of a fixed cost of discounting among unemployed students when appropriately modeling the heterogeneity. Furthermore, this fixed cost of discounting decreases as student disposable income increases. We find an average fixed cost component in the neighborhood of $5 among unemployed students. Differences in the fixed cost of discounting of this scale can be quite important when working with relatively small rewards. For example, Benhabib et al. (2010) find that a fixed cost on the order of $4 on average across subjects results in present-bias and a noticeable magnitude effect.

Students volunteer for experiments because they receive payment for participation. These participants may then walk into the experiment with ideas in mind of what they are going to do with their small experimental participation fee. Then, they are presented with the information that they may not be paid on that day. This may not be much of an issue for a student with sufficiently high income or who is paid regularly for their labor. However, for a student with limited cash liquidity, this could play an important role in driving a fixed cost component of discounting. Only when the offered future reward is large enough to overcome this present-bias will the student accept the later payment.

Where does this leave us? On one hand, we believe the results suggest caution when using student volunteers to infer time preferences, especially when using small rewards. The liquidity constraints faced by the typical college student probably do not match well with those of the general public. On the other hand, individuals in poverty are often liquidity-constrained and the target of policies to improve consumption smoothing.[10] Thus, studying the time preferences of students may be helpful in understanding how similarly constrained individuals would respond to policies.[11] We encourage researchers with access to more representative data to investigate whether or not unemployment plays a similar role in driving a fixed cost of discounting in the wider population.

Finally, we acknowledge two limitations of the present study. First, we interpret the results as the “impact” of liquidity constraints on the fixed cost component of discounting. However, it is also possible that a fixed cost component of discounting causes the observed employment status. To firmly address the direction of causality, we would need an exogenous source of variation in unemployment which is not present for our subject pool. Second, we do not observe savings and borrowing rates available to participants outside of the experiment. One could potentially conduct a more comprehensive analysis of liquidity constraints by censoring responses at relevant interest rates as is done in Coller and Williams (1999) and Harrison et al. (2002) and suggested by Andersen et al. (2014).

[10] For example, payday loan customers are often low-income and significantly liquidity constrained (Lawrence and Elliehausen, 2008).
[11] We thank an anonymous reviewer for making this point.

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