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Time Preferences of Undergraduates:

Does Studying Economics Change the Discount Function?*

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Abstract: This paper models the intertemporal preferences of undergraduates with a quasi-hyperbolic discount function. Using this model, which nests exponential and hyperbolic discounting, undergraduates' discount functions can be decomposed into two components: a measure of present bias and a standard exponential discount factor. Data is analysed on the intertemporal preferences of 174 undergraduates from the Faculty of Social Sciences at the University of Warwick. No significant differences in the level of present bias are identified for first-year students from different degrees. Further, differences in the degree of present bias are only significant at the 10% level for economics students in different years. However, significant differences emerge when the sample is extended to include an unexpected class of future-biased preferences. In the extended sample, economics finalists behave significantly (at the 5% level) more in line with conventional economic theory than first-year economics students. Some weak support is found for the claim that exposure to economic theories can change an individual's discount function.

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1 Introduction

In general, people are impatient. They prefer more now to less later. However, when choosing between pay-offs that vary in both magnitude and schedule, different people may have different preferences. For example, to make an informed choice in Problem 1, an individual must calculate how much the future pay-off (B) is worth to them now by discounting the utility they will receive from B by the fact that they have to wait 5 years before they receive that utility. This calculation depends on the discount function, which may vary person to person.

A.£100,000 immediately or B. £150,000 in 5 years

(PROBLEM 1)

Two aspects of discount functions vary between individuals. Firstly, different discount functions may have different functional forms. Secondly, even for discount functions with the same functional form, individuals may apply a different discount rate. While the determinants of different discount rates are interesting, this paper addresses the more overlooked issue of what determines the functional form of the discount function.

This paper firstly outlines three different discount functions. Secondly, several key papers from the literatures on discounting and learning effects are identified. A justification for connecting these two literatures is also provided. The paper then describes the methods used to collect and process data from undergraduates. The model to be estimated is stated, before outlining some key features of the data. In the penultimate section, the evidence for the hypothesis is examined and different explanations for future bias are considered. The main conclusion of this paper is that the discount functions of economics finalists are significantly different from the discount functions of first-year economics students.

2 Theoretical Background: Three Discount Functions

Discounted Utility Theory assumes agents discount in a simple manner. As in Equation 1, agents apply a constant discount rate exponentially (Samuelson, 1937):

$$U_t\left(c_1, \ldots, c_T\right) = \sum_{k=0}^{T-t} \left[\delta^k u\left(c_{t+k}\right)\right] \qquad \text{where } \delta = \frac{1}{1+\rho} \tag{1}$$

The utility (U), in period t, from receiving a pay-off (c) in k years is calculated using a constant discount factor (δ) which is in turn derived from the discount rate (ρ). This exponential discount function, embraced by the economic orthodoxy, has become a fundamental component of all conventional intertemporal models. It is so dominant because it is the only discount function that avoids time inconsistencies (Frederick et al., 2002). The absolute time interval between pay-offs (5 years in the example below) is all that matters when discounting exponentially (Loewenstein and Prelec, 1992). Thus, in Problem 2, if an exponential discounter prefers A to B, they must prefer C to D.

A.£100,000 immediately	or	B. £150,000 in 5 years
C.£100,000 in 50 years	or	D. £150,000 in 55 years
		(PROBLEM 2)

However, evidence consistently rejects exponential discounting as a model of how individuals actually act (Frederick et al., 2002). In particular, people are inconsistent. The hyperbolic discount function[1] (Equation 2) incorporates psychological insights into how individuals perceive time to provide a more accurate description of human behaviour (Rodriguez and Logue, 1988):

$$U_t\left(c_1,\ldots,c_T\right)=\sum_{k=1}^{T-t}\left[(1+\alpha k)^{\frac{-\gamma}{\alpha}}u\left(c_{t+k}\right)\right] \tag{2}$$

One such psychological insight is present bias, a special case of time inconsistency. A present-biased individual may prefer A to B, while also preferring D to C. That is, they place a higher relative weight on immediate pay-offs than future pay-offs, even with the same absolute time interval. Consequently, present-biased individuals will systematically depart from their long-term plans in later periods.[2] This yields dynamic inconsistency (Thaler, 1981), which is incompatible with Discounted Utility Theory. Economists define rationality relative to the actions of the always-optimising and ever-consistent homo economicus. Thus, because present-biased preferences are inconsistent, they are, in this narrow economic sense, irrational.[3]

Laibson (1997) developed the following quasi-hyperbolic discount function which nests together exponential and hyperbolic discounting in a simple way:

$$U_t\left(c_1,\ldots,c_T\right)=u\left(c_t\right)+\beta\sum_{k=1}^{T-t}\left[\delta^k u\left(c_{t+k}\right)\right] \qquad \text{where } \delta=\frac{1}{1+\rho} \tag{3}$$

In this model, one variable (β) captures the extent to which an individual discounts either exponentially or hyperbolically. When β=1 the individual is not present biased, and the discount function is exponential. Conversely, when $\beta<1$ the individual is present biased, and the discount function is hyperbolic. This feature of the quasi-hyperbolic discount function is leveraged in this paper to analyse whether the intertemporal preferences of undergraduates become more rational in the later years of their degrees.

[1]For the hyperbolic discount function, α indicates how much the function departs from constant discounting. As α tends to 0, this hyperbolic discount function tends to the exponential discount function with discount rate γ (Loewenstein and Prelec, 1992).

[2]After 50 years, if an individual displayed present-biased preferences (preferring A to B and D to C) they would, without any commitment device, now prefer C to D because this effectively becomes a choice between A and B.

[3]The rest of this paper uses this definition of rationality.

3 Literature Review

3.1 Learning and Selection Effects

The experimental literature on cooperation suggests economics students behave more in line with conventional economic theory than non-economics students. Expected Utility Theory, the conventional theory for cooperation games, predicts agents act self-interestedly. In a comparison of 11 similar experiments investigating free-riding, Marwell and Ames (1981) found economics graduate students were more self-interested, contributing significantly less to a public good, than any other group. Further, in a one-off ultimatum game, economics finalists behaved more self-interestedly than non-economics students when asked to share money with another participant (Carter and Irons, 1991). The tendency for certain groups to behave according to conventional economic theory is not isolated to students. In a study on charitable donations, Frank et al. (1993) found the percentage of economics professors who donated no money to charity was 9.3%. The percentage of professors who made no contribution was much lower, between 1.1% and 4.2%, for other disciplines.

Two explanations exist for the behavioural differences observed in these studies. One theory suggests people with certain preferences are drawn to the discipline of economics (Cipriani et al., 2009). A competing theory argues that, throughout an economics degree, as students are exposed to the perfectly rational homo economicus, they adjust their behavior to fit that paradigm (Hellmich, 2019). Carter and Irons (1991) refer to these two theories as the selection and learning effect respectively.[4] However, whether both effects exist, and which dominates, is still debated. Of 12 studies investigating the selection effect, 8 identified evidence for its existence. Of 18 studies investigating the learning effect, 10 identified evidence of its existence (Hellmich, 2019).

3.2 Estimating the Discount Function

Ashraf et al. (2006) categorised individuals as hyperbolic if their preferences displayed present bias (impatience now and patience later). However, this method has two shortcomings. Firstly, as respondents are categorised according to some typical values, some hyperbolic individuals may not have been identified.[5] Secondly and more generally, information is lost by reducing the degree to which an individual's preferences are present biased to a simple binary variable.

A more powerful method of identifying hyperbolic individuals avoids these shortcomings. The titration procedure (Hardisty and Weber, 2009; Barile et al., 2018) uses a series of pairwise comparisons to identify the level of extra compensation required to make an individual indifferent between this higher delayed and compensated outcome and a lower immediate outcome. Identifying and examining these in-

[4] Rubinstein (2006) refers to the learning effect as the indoctrination effect.

[5] Consider an individual who is indifferent between £100,000 immediately and £170,000 in 5 years, and is indifferent between £100,000 in 50 years and £150,000 in 55 years. This individual still has hyperbolic preferences as they need more compensation to delay a present outcome than a future outcome. However, with the values used in Problem 2, they would not be identified as present biased.

difference points provides insight into the functional form of each individual's discount function. Using the quasi-hyperbolic discount function outlined previously, Ida (2014) decomposed indifference points into two variables: a measure of present bias (β) and a standard exponential discount factor (δ). Thus, this method produces a numerical variable quantifying the degree to which respondents are present-biased and thus the degree to which they discount exponentially or hyperbolically. Using this method allows a more in-depth analysis of the variation in discount functions than a simple binary variable.

Ashraf et al. (2006) also identified a third class of preferences. If the respondent was "patient now, impatient later," they were categorised as future biased. In the quasi-hyperbolic framework, future bias is associated with a $\beta > 1$. While hyperbolic preferences and present bias are well established in the literature, future-biased preferences are unexplained by any model of discounting and are largely overlooked by the literature. Loewenstein (1987) briefly referenced the potential for 'reverse time inconsistencies' where individuals may keep delaying consumption to maintain the anticipation of a future pay-off. More recently, Takeuchi (2011) identified future bias in a laboratory experiment with financial pay-offs. However, only Ashraf et al. have explored what determines whether somebody has future-biased preferences. They used probit models to analyse three explanations for these preferences. Firstly, they believed noise in the survey responses could largely explain future bias. Secondly, they investigated whether a misunderstanding of the questions was relevant. If this explanation was valid, they expected to find a relation between education and the probability of having future-biased preferences. However, no such relation was found, so Ashraf et al. rejected this explanation. Finally, they found some limited evidence indicating that future cash-flow may cause future bias. In particular, females who had access to cash at the time of their survey, but expected this to deteriorate in the future, were more future biased.

3.3 Uniting the Two Fields

This paper seeks to investigate these explanations further by uniting the two literatures and investigating whether the learning effect applies to discount functions. However, some justification is needed for making this connection as, at one level, discount functions and cooperation games are very different. Whereas the latter involves behaving strategically while interacting with other self-interested agents, the former is entirely individual. Economics students may be more self-interested, which, in cooperation games, just happens to align with conventional economic theory. When rational behaviour (following conventional economic theory) diverges from self-interest, as in the case of discount functions, the reasons for expecting economics students to behave more rationally are less obvious.

However, the extension of the learning effect to discounting is plausible. As with the cooperation studies outlined above, conventional economic theory predicts a certain behaviour (exponential discounting) that is not empirically observed. Further, as students are exposed to the rational and consistent behaviour of homo economicus (exponential discounting) they may adjust their behaviour to fit that paradigm. Including students from other degrees is still necessary even if there is no selection effect for discount functions. Learning effects for economics students can be compared to any maturation effects experienced by students on other degrees. The next section lays out how these effects are investigated.

4 Methodology

Data was collected on the intertemporal preferences of 174 undergraduates from the Faculty of Social Sciences at the University of Warwick. This section provides an explanation of how an individual discount function was derived from each survey response. Finally, it outlines the strategy used to test the following hypothesis:

Hypothesis 1: Economics finalists discount more conventionally than first-year economics students.

4.1 Questionnaire

Using Qualtrics, an online survey was prepared and distributed to undergraduates studying: Economics; Economics, Politics and International Studies (EPAIS); and Philosophy, Politics and Economics (PPE). While all respondents studied at least some economics, students on the pure Economics degree completed twice as many economics core modules in the first two years of their degree. Although they may have provided a better control, it was not possible to obtain permissions to distribute the survey to students from degrees with no economics. 267 respondents started the survey but, after incomplete responses were removed, only 174 responses were analysed. The questionnaire was split into two parts. Part 1 identified respondents' intertemporal preferences. Part 2 identified some relevant characteristics of respondents, such as their degree and their year of study. Data was also collected on the time each respondent took to answer the questionnaire and the order in which they received the questions in Part 1.[6]

4.2 Indifference Points

To estimate an individual's quasi-hyperbolic discount function (Equation 3), data is needed on two points of indifference. Firstly, to find the long-run discount rate (δ), which is independent of present bias, an indifference point between two future outcomes is required. Secondly, an indifference point is required between an immediate outcome and a future outcome. This can be compared with δ to calculate how much present bias (β) causes a deviation from the long-run discount rate.[7]

[6] The order of these questions was randomised using Qualtrics' Randomizer function to mitigate any systematic bias that may emerge from encountering and answering the first question.

[7] A full derivation is provided in Appendix A.

Part 1 obtained these indifference points using the titration procedure (Hardisty and Weber, 2009; Barile et al., 2018). Respondents were asked to identify their preference in ten pairwise comparisons of hypothetical financial pay-offs. This question is reported in the following table, for question 1, k=0, and for question 2, k=50:

A.£100,000 in k years	or	A'. £90,000 in k+5 years
B.£100,000 in k years	or	B'. £100,000 in k+5 years
C.£100,000 in k years	or	C'. £110,000 in k+5 years
D.£100,000 in k years	or	D'. £120,000 in k+5 years
E.£100,000 in k years	or	E'. £130,000 in k+5 years
F.£100,000 in k years	or	F'. £140,000 in k+5 years
G.£100,000 in k years	or	G'. £150,000 in k+5 years
H.£100,000 in k years	or	H'. £160,000 in k+5 years
I.£100,000 in k years	or	I'. £170,000 in k+5 years
J.£100,000 in k years	or	J'. £180,000 in k+5 years

As a single indifference point (rather than an interval) was required for each individual, if an individual preferred D to D' and E' to E, their indifference point was assumed to be the midpoint of the D'-E' interval. That is, this individual achieved the same utility from, or was indifferent between, receiving £100,000 immediately and receiving £125,000 in 5 years.[8]

4.3 Model

Using OLS, a model for β is estimated:

$$\beta_i = \alpha + \sum_{j=1}^{6} \phi_j \left(year^{*}degree\right)_{ji} + \sum_{\lambda=1}^{2} \gamma_\lambda gender_{\lambda i} + \sum_{z=1}^{6} \gamma_z income_{zi} + \gamma_3 \delta_i + \gamma_4 \ln(duration)_i + \gamma_5 order_i + \varepsilon_i \quad (4)$$

The model uses robust standard errors to counteract heteroscedasticity. Several of the variables collected in Part 2 of the questionnaire are included in the model as controls. The key independent variable is *Final_Year*Economics*, one instance of the interaction between *year*degree*. Including the interaction term allows a unique learning effect to be identified for each degree. The next section outlines some summary statistics for the variables investigated.

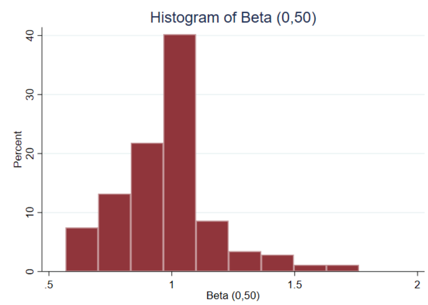
[8] If a respondent prefers a future outcome, consistency requires that they preferred all greater future outcomes. Preferring £130,000 in 5 years over £100,000 immediately cannot be reconciled with preferring £100,000 immediately over £180,000 in 5 years.

5 Data

The long-run discount factor, given by δ, has a mean of 0.954. It is necessary to control for δ, in a regression for β, because long-term impatience is intuitively related to short-term impatience. In addition, other papers have included both β and δ in their analysis (Ida, 2014).

The degree of present bias, measured by β, has a mean of 0.975. Further, the modal and median β is 1, associated with exponential discounting. Thus, the mean respondent (who has the mean β and δ) achieves the same utility from £100,000 immediately and £144,013 in 5 years; and achieves the same utility from £100,000 in 50 years and £125,954 in 55 years. While measures of central tendency fit theoretical predictions on the nature of β, the distribution does not (Figure 1). A quarter of the respondents were future biased ($\beta > 1$).[9]

Figure 1



Data was also collected on each respondent's year of study, degree, gender, parental household income, time spent completing the survey, and which of the two randomised questions they received first. These variables are all included in the final model. Full summary statistics are provided in Appendix D. The rest of this section points out several key features of the data and justifies the inclusion of each control in the regression.

Firstly, each year group makes up roughly a third of the dataset (Appendix C.4). Thus, there is enough data to assess the learning effect. Secondly, economics students make up 73.1% of respondents (Appendix C.5). Consequently, the subcategories for non-economics students are very small, and conclusions about the selection effect should be treated with caution. Thirdly, it is important to control for gender because previous research has identified women as more patient than men Dittrich and Leipold (2014). The sample is balanced in terms of gender (Appendix C.6). Fourthly, as this paper deals with financial pay-offs, it is necessary to control for income. An individual's current wealth, and how they expect this will change, may affect their preference for more money. However, data on student incomes is noisy. Students may receive money from their student loan, their family, and any part-time work, scholarships, or savings. Consequently, respondents were asked about the annual income of the household in which they grew up. Over 43.1% of students reported a parental household income of £75,000 or above (Appendix C.7). Including more granular categories would provide a better understanding of the financial situation of the respondents. Fifthly, controlling for the time taken to complete the questionnaire gives some measure of the quality of responses. As the pay-offs included in this paper were only hypothetical, respondents may have rushed to complete it as quickly as possible, putting little thought into their responses. To reduce the impact of outliers, the natural log of duration was calculated. The distribution of this new variable is provided in Appendix C.8. Finally, including a variable indicating the question respondents received first intends to confirm that the order in which these questions were asked had no impact.

[9] Ashraf et al. (2006) identified a similar proportion of future-biased respondents.

6 Results

Throughout, the results are reported relative to the default individual. This default individual is a female, first-year economics student whose parents earned over £75,000. Several different specifications of the model are discussed. The primary specification is estimated by OLS with β as the dependent variable. This is estimated over three different sample sizes. Firstly, future-biased preferences are excluded, this is referred to as Restriction 1. Secondly, the entire sample is included. Thirdly, present-biased preferences are excluded, this is referred to as Restriction 2. These restrictions allows an investigation of whether any learning effect is driven by the increased likelihood of discounting exponentially or by the reduced likelihood of having future-biased preferences. Other variations to the primary model are also discussed. Several probit models are estimated, with a binary dependent variable for each class of preferences. A different derivation of β is also considered.[10] Finally, several robustness checks are briefly mentioned. The rest of this section details these results after briefly outlining adapted versions of Hypothesis 1.

When considering only the theoretically justified discount functions (exponential and hyperbolic), β is bounded between 1 and 0. Consequently, a higher β is associated with more rational behaviour. Restricting the domain to exclude any future-biased preferences leaves the hypothesis unchanged. Thus, it is still expected that finalists are more likely to discount exponentially than first-year students:

Hypothesis 1: Economics finalists discount in a more conventional way than first-year economics students.

Hypothesis 1.1: In a regression on β, with first-year students as default, the coefficient on *Final_Year* (whether a student is in their final year) will be significantly positive.

However, extending the sample to include future-biased preferences necessitates a different interpretation of β. In a regression on β, a negative coefficient on *Final_Year* may be interpreted as evidence for Hypothesis 1 because it indicates finalists are less likely to be future-biased. Alternatively, it may be interpreted as evidence against Hypothesis 1 because it indicates finalists are more likely to discount hyperbolically than exponentially. Thus, an updated hypothesis, based on a more relaxed definition of conventional discounting, is required. Under the relaxed definition, conventional discounting refers to discounting explained by either the exponential or hyperbolic model. That is, any preferences that are not future-biased are considered rational. Thus, in the unrestricted sample, it is expected that finalists are more likely to discount in a way explained by any economic theory than first-year students:

Hypothesis 1.2: In a regression on β, with first-year students as default, the coefficient on *Final_Year* (whether a student is in their final year) will be significantly negative.

[10] Previously β and δ had been calculated using the following intervals: Immediately vs. 5 years and 50 years vs. 55 years. In this case, a new β and δ are calculated for each individual using the following intervals: Immediately vs. 5 years and 10 years vs. 15 years.

6.1 Learning Effects

Figure 2: Selected regression results[11]

Model	(1)	(2)	(3)
Dependent Variable	β _50	β _50	β _50
Estimation method	OLS	OLS	OLS
Sample	$\beta \leq 1$		$\beta \geq 1$
First_Year#EPAIS	-0.135***	-0.0488	0.0588
	(0.0360)	*(0.0969)*	*(0.141)*
First_Year#PPE	0.0189	0.0657	0.0752
	(0.0400)	*(0.0514)*	*(0.0651)*
Second_Year#Economics	-0.0393	-0.0573	-0.0441
	(0.0344)	*(0.0363)*	*(0.0420)*
Second_Year#EPAIS	0.0613	0.0181	-0.0697
	(0.0389)	*(0.0597)*	*(0.0754)*
Second_Year#PPE	-0.0551	-0.100	-0.0973
	(0.0366)	*(0.0673)*	*(0.0993)*
Third_Year#Economics	-0.0553*	-0.0832**	-0.0610
	(0.0312)	*(0.0334)*	*(0.0410)*
Third_Year#EPAIS	0.0433	-0.0100	-0.0507
	(0.0401)	*(0.0744)*	*(0.0676)*
Third_Year#PPE	-0.113***	-0.168***	-0.159**
	(0.0369)	*(0.0386)*	*(0.0655)*
Constant	2.865***	4.956***	3.795***
	(0.333)	*(0.434)*	*(0.552)*
Observations	129	174	100
R-squared	0.331	0.548	0.477

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

A significant learning effect is identified in some models. However, as outlined above it is difficult to isolate what drives this learning effect. In a regression with Restriction 1 (Model 1), a learning effect is only identified at the 10% significance level. Further, the coefficient on β is negative, indicating, if anything, finalists are more present biased than first-years. When the sample is extended to include all respondents (Model 2), more evidence of a learning effect is identified. The coefficient on *Final_Year* is -0.083 and significant at the 5% confidence interval. However, again, interpreting this is difficult. To identify whether this significance is driven by finalists discounting more hyperbolically or being less future-biased, a third regression with Restriction 2 is estimated (Model 3). In this regression, no learning effect is identified. Thus, in opposition to Hypothesis 1.1, there is further weak evidence that the significant learning effect is driven by finalists being more present biased and thus discounting more hyperbolically.

In a regression re-estimated as a probit model with the binary dependent variable *hyperbolic* (whether a respondent discounts hyperbolically), no learning effect is identified with Restriction 1 (Model 4), even at the 10% level. However, evidence against Hypothesis 1.1 is identified in a probit model with an unrestricted sample (Model 5). In particular, there are significant differences between both first- and second-year students, and first- and final-year students, but only at the 10% interval. This again indicates finalists are more likely to discount hyperbolically. Estimating a new probit model (Model 6) with the dependent variable *exponential* (whether a respondent discounts exponentially) provides no evidence of learning effects. In fact, this entire model is insignificant. Estimating a fourth probit model (Model 7) with the dependent variable *future-biased* (whether a respondent has future-biased preferences) provides support for Hypothesis

[11] All regression results are presented in Appendix E.

1.2 at the 10% interval, indicating finalists are less future-biased than first-year students.

As a robustness check, data was also collected on how individuals responded to a common delay of 10 years. With this adjustment, there is no evidence of a learning effect with Restriction 1 (Model 8) or Restriction 2 (Model 10). This indicates finalists are no different from first-year students in their tendency either to discount exponentially or to have future-biased preferences. However, a learning effect is identified when the sample is extended to include future-biased preferences (Model 9). This learning effect, significant at the 10% level for Second_Year and at the 5% level for *Final_Year*, is similar to the learning effect identified in the unrestricted sample using the original β (Model 2). As the results identified using a 50-year common delay are largely the same as the results from using a 10-year common delay, they appear to be robust to the length of the delay.

In summary, finalists have a significantly lower β than first-year students. However, with this data it is not possible to isolate what is driving this. The evidence weakly suggests that, relative to first-year students, finalists are less likely to have future-biased preferences but are also more likely to discount hyperbolically. Thus, this evidence supports Hypothesis 1.2 but rejects Hypothesis 1.1. No significant differences were identified between second-year students and finalists. Similar learning effects were identified for PPE students. This indicates that any learning effect emerges from modules taken by both Economics and PPE students, or that it is just a maturation effect. However, only 31 PPE students completed the survey. The sample size of each category, when divided by year and preference class, is so small that these results should be treated with great caution.

6.2 Selection Effects

As outlined previously, there is less intuition behind expecting a selection effect in discount functions than there is for social cooperation games. Further, the selection effect is only significant for EPAIS students under Restriction 1 (Model 1). As this is based on the differences between only four students, this paper can say very little about selection effects.

6.3 Determinants of Future-Biased Preferences

As mentioned previously, Ashraf et al. (2006) suggested three explanations for future-biased preferences. The first explanation predicted that noise in the survey responses was responsible for the existence of future-biased preferences. In this case all variables should be insignificant. However, this explanation is not supported by the data. Firstly, all but one of the models are significant. Secondly, even if the learning effect is not significant, delta, the measure of long-run discounting, is significant. Further, males have a significantly lower β than females, except under Restriction 1. Thus, these responses are not just noise.

The second explanation suggested future-biased responses were driven by a misunderstanding of the questions. Students who were unfamiliar with discounting may not have thought through their answers, yielding unexplained future-biased preferences. While Ashraf et al. identified no relationship between responses and education, such a relationship is identified with this data. Under their interpretation, the supposed learning effect, as outlined above, may just emerge from more finalists understanding the questions. To investigate this further, ln(*duration*) (the natural log of time respondents took to complete the survey) was included in the regressions. Although this is not a perfect measure of understanding, it is the best available proxy for the quality of a response. People who may not have understood the questions may have rushed through the survey leading to some unexplained future-biased preferences. Consequently, if the misunderstanding explanation held, ln(*duration*) would be negatively associated with β. Upon a visual inspection of the correlation between ln(*duration*) and β (Appendix C.9), there is no obvious relationship between the two. Further, ln(*duration*) is insignificant, even at the 10% level, in all regressions. It may be argued that *duration* is insignificant because the misunderstanding effect is already being captured by the inclusion of different years of study. However, even in a regression of only first-year students (Model 15), ln(*duration*) is insignificant. Thus, the misunderstanding explanation also fails.

Ashraf et al.'s final suggestion was that an expected deterioration in financial situation would lead to future-bias. The schedule of pay-offs in this paper was chosen to mitigate any such cash-flow effects which may occur for smaller delays. Although no data was collected on the respondents' expectations of their future financial position, data was collected on parental income. For this explanation to be valid, those in a better financial position (higher parental income) should be more future biased (Appendix B). Income is significant for some categories in some models. Where it is significant, the coefficient is negative. This indicates the default individual, who is in the richest category, has a higher β. This provides some weak support for the cash-flow explanation. This effect is stronger when β is derived from the 10-year delay which fits with the understanding that the cash-flow explanation is more relevant for shorter-term pay-offs.

Ultimately, of Ashraf et al.'s three suggested explanations for future-biased preferences, only the cash-flow explanation is supported by this data. However, they may have missed an important explanation. While Ashraf et al. assumed education would decrease the misunderstanding of the questions, they did not consider that education may change the discount function itself. This paper finds that the learning effect, because it changes the discount function, may be significant in determining whether somebody has future-biased preferences.

7 Concluding Remarks

The results of this paper must be taken with caution. Firstly, even the full sample size is less than 200 observations. Future research should repeat this work with more observations. Secondly, the actual behaviour of respondents may deviate from their responses to hypothetical pay-offs. Offering financial pay-offs may solve this problem. However, the magnitude and schedule of pay-offs in this paper cannot feasibly be used, and scaling them down, even proportionally, would change people's preferences. Thirdly, respondents were incentivised to complete this survey by the chance to win a £10 Amazon Voucher. Respondents with less money are both more likely to opt-in to this survey and more likely to be present biased. Thus, selection bias may lead to an over-estimation of present bias in this sample. Finally, removing the δ variable, which drives much of the variation and is strongly significant throughout, makes the models insignificant. Nonetheless, the contributions this paper makes are unique.

This paper explores the determinants of the discount function with a new level of detail. Some evidence for the learning effect exists. That is, finalists have significantly different discount functions than first-year students. However, more research is required before it can be identified whether this is because finalists are more present biased, or less likely to have irrational future-biased preferences. No selection effect is identified. This paper also extended Ashraf et al.'s investigation of the determinants of future-biased preferences. While some weak support for the cash-flow explanation is identified, the noise and misunderstanding explanations are rejected.

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A Appendix A: Deriving β and δ

The quasi-hyperbolic discount function is:	$U_t(c_1,\ldots,c_T) = u(c_t) + \beta\sum_{k=1}^{T-t}\left[\delta^k u(c_{t+k})\right]$ where $\delta = \frac{1}{1+\rho}$
Assuming utility is linear in consumption:	$U(c_t) = c_t$
The discount function can be simplified to:	$U_t(c_1,\ldots,c_T) = c_t + \beta\sum_{k=1}^{T-t}\left[\delta^k c_{t+k}\right]$ where $\delta = \frac{1}{1+\rho}$
	k refers to the delay in period
	t refers to the period in which utility is being assessed
	In this case utility is always immediately, hence t=0.
By design, an agent receives a pay-off in one period only. They choose whether that period is k or *k+5* (where k=0,10,50) when they choose which of each pair they prefer. As a result, utility can be expressed by one term.	
Utility from an immediate pay-off:	$U_0(c_0) = c_0$
Utility from an immediate pay-off:	$U_0(c_k) = \beta\delta^k c_k$
For k=0 an individual chooses between:	$U_0(c_0) = c_0$
	$U_0(c_5) = \beta\delta^5 c_5$
Indifferent between the pay-offs when:	$U_0(\tilde{c}_0) = U_0(\tilde{c}_5)$
	$\tilde{c}_0 = \beta\delta^5\tilde{c}_5$
	$\beta = \frac{\tilde{c}_0}{\delta^5\tilde{c}_5}$
	$\delta^5 = \frac{\tilde{c}_0}{\beta\tilde{c}_5}$
To solve these equations, another set of simultaneous equations is required. This is derived from a second pairwise comparison (where k=50) where an individual chooses between a pay-off in 50 years and a pay-off in 55 years.	
This yields the following:	$U_0(c_{50}) = \beta\delta^{50}c_{50}$
	$U_0(c_{55}) = \beta\delta^{55}c_{55}$
Indifferent between these pay-offs when:	$U_0(\tilde{c}_{50}) = U_0(\tilde{c}_{55})$
	$\beta\delta^{50}\tilde{c}_{50} = \beta\delta^{55}\tilde{c}_{55}$
Rearranging yields:	$\delta^5 = \frac{\tilde{c}_{50}}{\tilde{c}_{55}}$
Equating two expressions: for δ^5 yields	$\beta = \frac{\tilde{c}_0}{\left(\frac{\tilde{c}_{50}}{\tilde{c}_{55}}\right)\tilde{c}_5}$
Hence the β and δ of each individual can be expressed in terms of their responses.	

B Appendix B: Decisions on Magnitude and Scale of Pay-Offs

In the process of preparing this questionnaire, the pay-offs were carefully chosen to maximise the variation in responses, considering the respondents were undergraduates. Without this variation (if all undergraduates chose the same option) it would not be possible to analyse what causes differences in discount functions because there would be no differences. Several of these variation-maximising decisions are now outlined.

Firstly, as they move into the labour force, the income of a typical student will increase significantly within the next 5 years. Thus, they have a higher marginal utility for money now than they will in the future. Consequently, students may be more present biased than other people. Selecting pay-offs that ensure students do not all prefer the immediate outcome is necessary to yield sufficient variation in the dependent variable β. As the absolute pay-off increases, more people are prepared to wait, even if the relative pay-off is constant. For example, very few students would be willing to wait 5 years for £13 when they can receive £10 immediately. As a result, the pay-offs were very large.

Secondly, the schedule of pay-offs was also chosen to isolate present bias as best as possible. If the common delay is too large, the possibility of death, and never receiving future pay-offs, may confound the results. If the common delay is too small, present (or near-future) bias may also impact the delayed pay-off. A common delay of 50 years is optimal given this trade-off. In addition, a delay of 5 years (Immediately vs. 5 years; 50 years vs. 55 years) was selected to ensure all respondents would have completed their undergraduate degree by the time they would receive the delayed pay-off. Shorter delays would yield an unfair assessment of the learning effect. For example, after a one-year delay, first year students would have remained on a student budget. However, finalists would have entered the labour market after this one-year delay and would be earning significantly more money. Consequently, final year students, expecting a large improvement in their financial situation, may be more impatient, due to the diminishing marginal utility of money. Put simply, receiving £1 when they have less money is worth more than receiving £1 when they have more.

Further, using these delays limits the impact of cash-flow problems that others have identified as the driver of future-bias preferences. Using shorter delays (Immediately vs. 1 month; 6 months vs. 7 months) Ashraf et al. (2006) found people who expected a deterioration in their financial position were more likely to be future-biased. This deterioration may be based on seasonal changes. For example, a farmer may have recently sold their harvest and have lots of cash now, which they will have to rely on for the rest of the year, meaning they have much less money in 6 months. However, pay-offs in 50 years are sufficiently far into the future to avoids this seasonal variation. While this paper has deliberately selected certain pay-offs and time intervals, future research could investigate how changing these factors may influence the results.

C Appendix C: Graphs

Figure 3: C.1

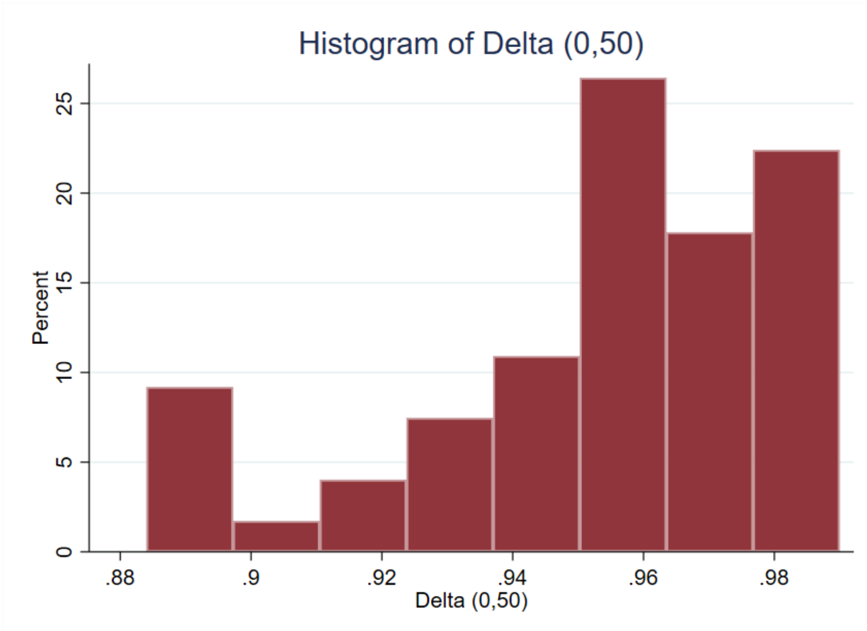


Figure 4: C.2

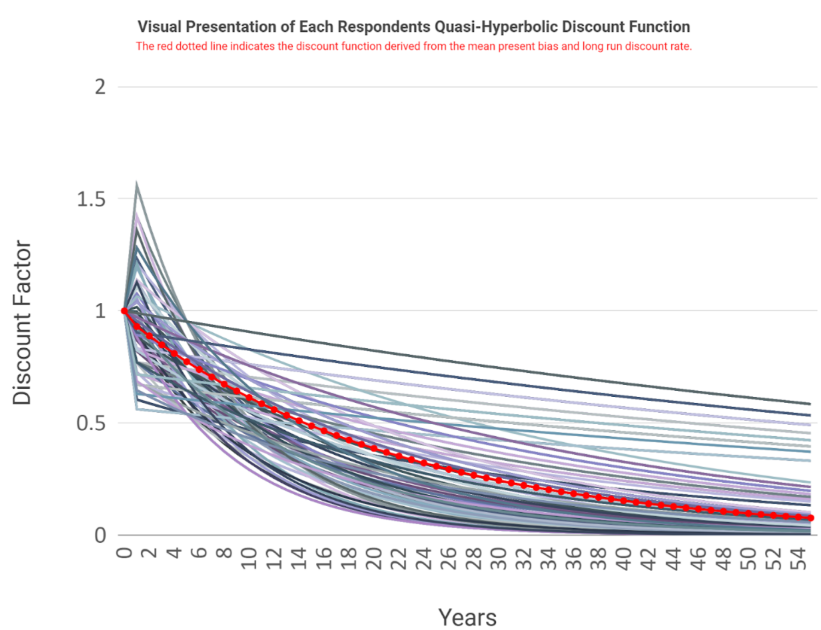


Figure 5: C.3

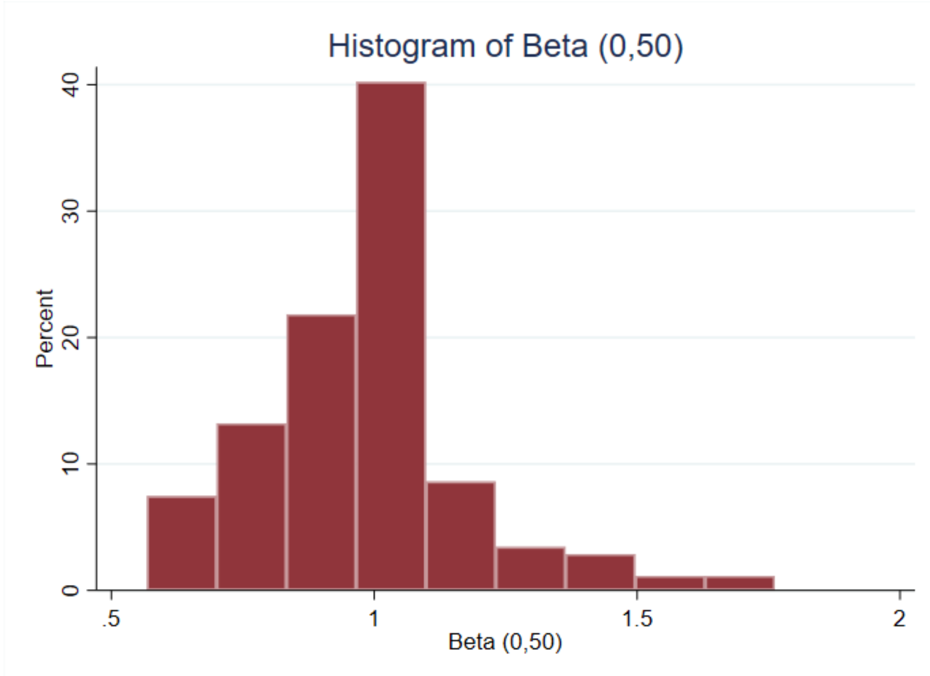


Figure 6: C.4

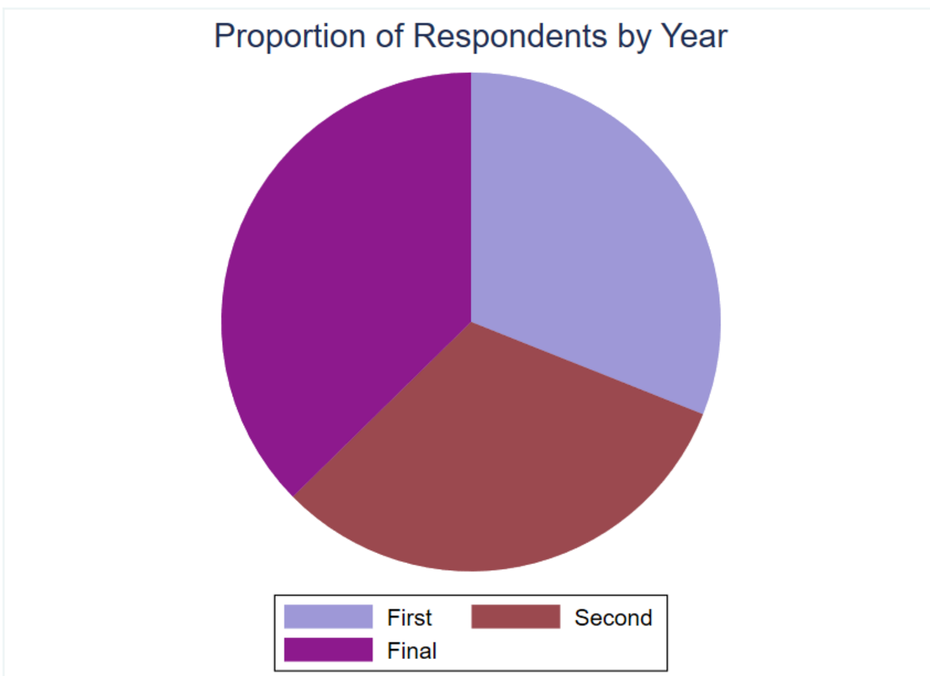


Figure 7: C.5

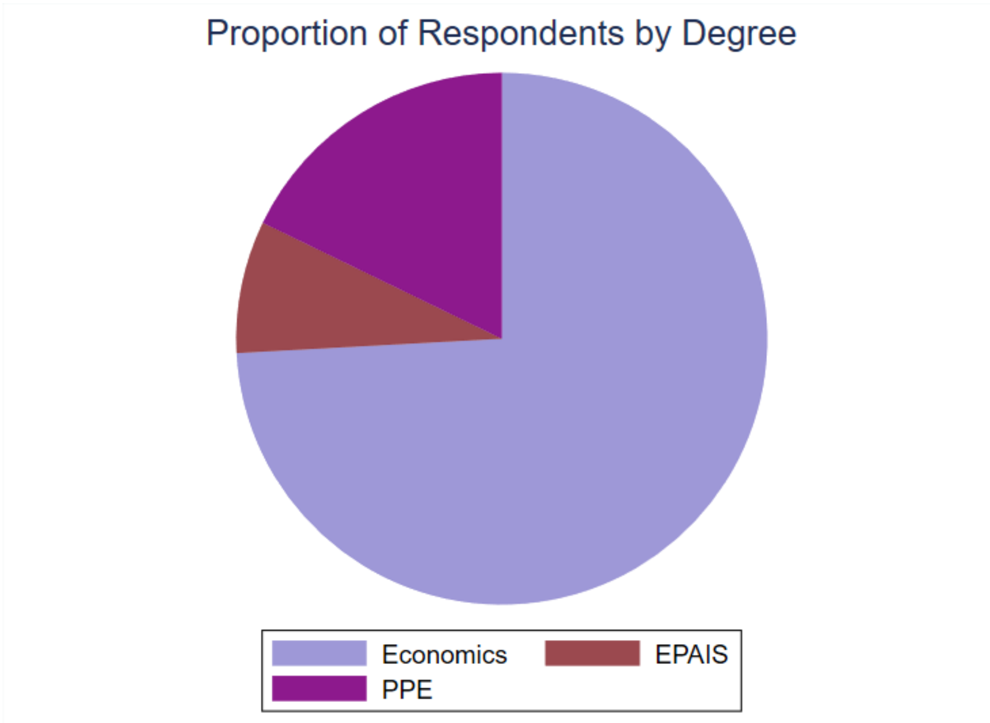


Figure 8: C.6

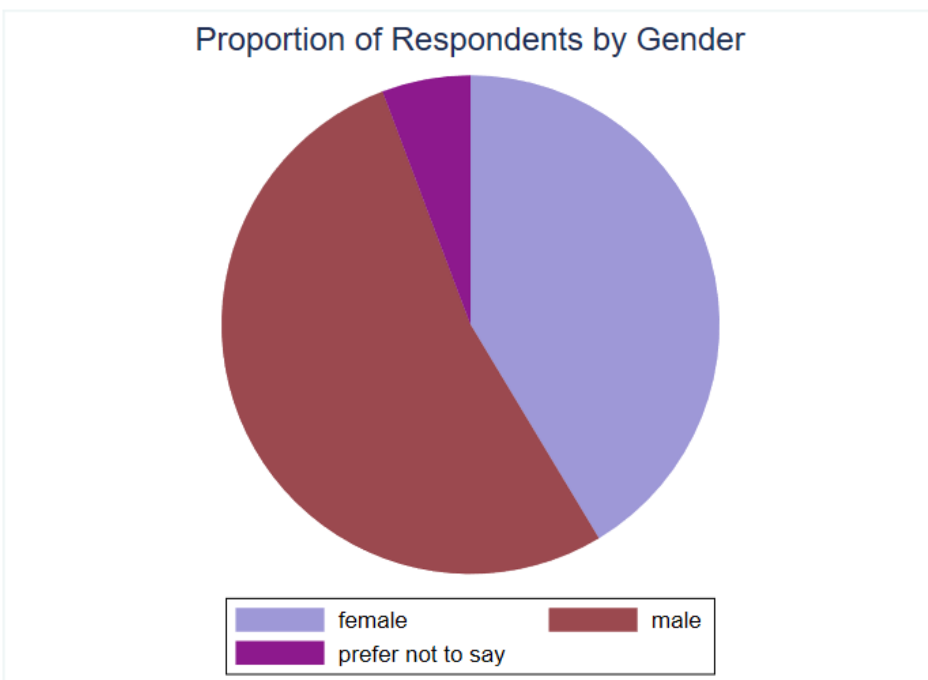


Figure 9: C.7

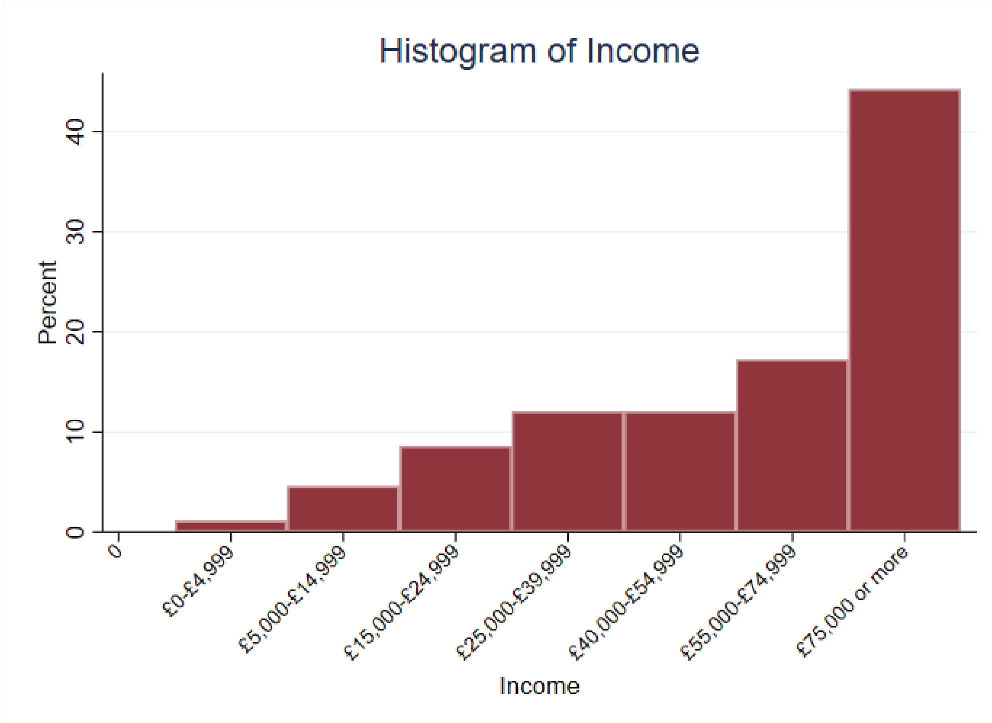


Figure 10: C.8

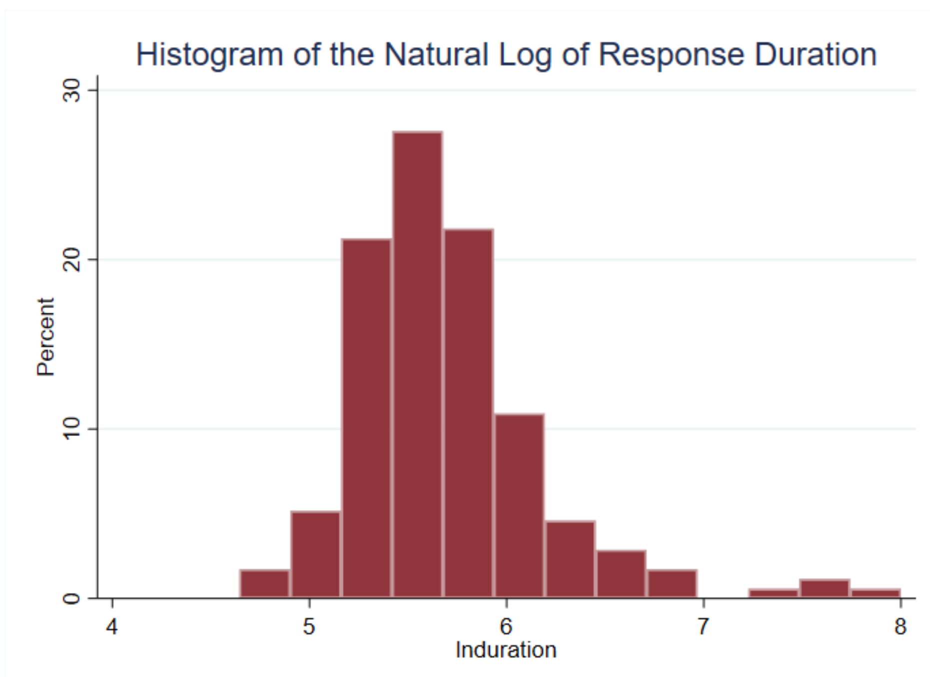
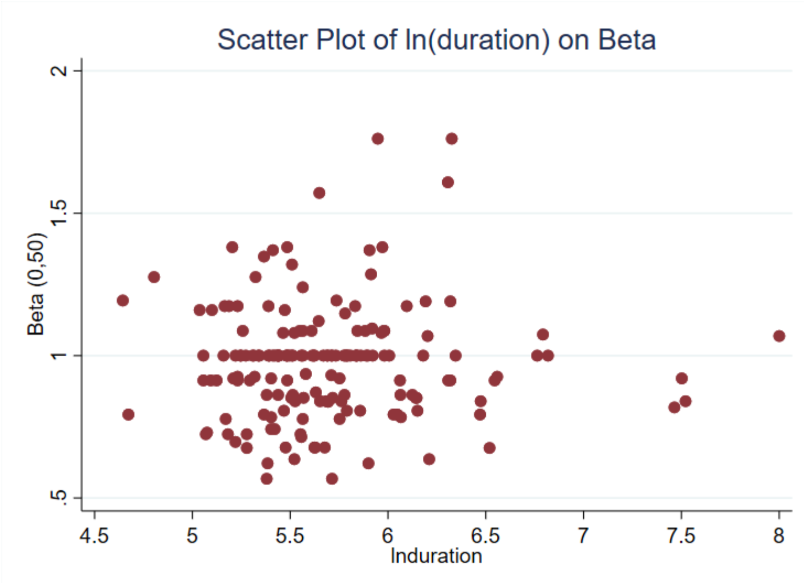


Figure 11: C.9



D Appendix D: Summary Statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max	(6) median
beta_50	174	0.977	0.200	0.568	1.762	1
delta_50	174	0.954	0.0310	0.884	0.990	0.956
beta_10	174	1.007	0.139	0.676	1.476	1
delta_10	174	0.946	0.0293	0.884	0.990	0.956
First_Year	174	0.310	0.464	0	1	0
Second_Year	174	0.316	0.466	0	1	0
Final_Year	174	0.374	0.485	0	1	0
Economics	174	0.741	0.439	0	1	1
EPAIS	174	0.0805	0.273	0	1	0
PPE	174	0.178	0.384	0	1	0
order1	174	1.431	0.497	1	2	1
duration	174	349.9	312.7	104	2,982	275
ln(duration)	174	5.695	0.492	4.644	8.000	5.616
Exponential	174	0.316	0.466	0	1	0
Hyperbolic	174	0.425	0.496	0	1	0
Future-biased	174	0.259	0.439	0	1	0

E Appendix E: Regression Results

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Dependent Variable	β_50	β_50	β_50	hyperbolic	hyperbolic	exponential	Future-biased	β_10	β_10	β_10	β_50	β_50	β_50	β_50	β_50
Estimation method	OLS	OLS	OLS	MLE	MLE	MLE	MLE	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Sample	$\beta \leq 1$		$\beta \geq 1$	$\beta \leq 1$				$\beta \leq 1$		$\beta \geq 1$				First-Years	
First_Year#EPAIS	-0.135***	-0.0488	0.0588	2.326***	1.216	-0.974	-0.231	-0.0558	-0.0625	-0.0389	0.0648	-0.0512	-0.0553		
	(0.0360)	(0.0969)	(0.141)	(0.697)	(0.805)	(0.598)	(0.735)	(0.0509)	(0.0658)	(0.0473)	(0.122)	(0.0972)	(0.0944)		
First_Year#PPE	0.0189	0.0657	0.0752	0.172	0.109	-0.136	-0.0219	-0.0434	0.0295	0.0946*	0.123	0.0666	0.0655		
	(0.0400)	(0.0514)	(0.0651)	(0.633)	(0.559)	(0.451)	(0.481)	(0.0350)	(0.0469)	(0.0496)	(0.0829)	(0.0512)	(0.0524)		
Second_Year#Economics	-0.0393	-0.0573	-0.0441	0.637	0.639*	-0.217	-0.373	-0.0249	-0.0548*	-0.0276	-0.00973	-0.0609*	-0.0587		
	(0.0344)	(0.0363)	(0.0420)	(0.412)	(0.372)	(0.322)	(0.352)	(0.0250)	(0.0298)	(0.0292)	(0.0445)	(0.0360)	(0.0365)		
Second_Year#EPAIS	0.0613	0.0181	-0.0697	-0.232	-0.131	0.882	*Insufficient*	0.0347	0.0358	0.0220	0.00618	0.0134	0.00640		
	(0.0389)	(0.0597)	(0.0754)	(0.790)	(0.776)	(0.894)	*observations*	(0.0287)	(0.0507)	(0.0462)	(0.0513)	(0.0573)	(0.0589)		
Second_Year#PPE	-0.0551	-0.100	-0.0973	1.352*	0.801	-0.0883	-0.652	0.000746	-0.0637	-0.0817*	-0.0479	-0.101	-0.106		
	(0.0366)	(0.0673)	(0.0993)	(0.703)	(0.719)	(0.562)	(1.069)	(0.0317)	(0.0451)	(0.0423)	(0.0514)	(0.0676)	(0.0704)		
Third_Year#Economics	-0.0553*	-0.0832**	-0.0610	0.639	0.715*	-0.151	-0.603*	-0.0170	-0.0625**	-0.0426	-0.0668	-0.0850**	-0.0871**		
	(0.0312)	(0.0334)	(0.0410)	(0.407)	(0.375)	(0.310)	(0.358)	(0.0243)	(0.0291)	(0.0257)	(0.0405)	(0.0333)	(0.0339)		
Third_Year#EPAIS	0.0433	-0.0100	-0.0507	*Insufficient*	*Insufficient*	0.947	-0.478	0.0333	0.000440	-0.0381	0.0667	-0.0172	-0.0111		
	(0.0401)	(0.0744)	(0.0676)	*observations*	*observations*	(0.739)	(0.904)	(0.0307)	(0.0456)	(0.0329)	(0.0523)	(0.0745)	(0.0713)		
Third_Year#PPE	-0.113***	-0.168***	-0.159**	1.566**	1.579***	-0.596	-1.207**	-0.0873**	-0.146***	-0.106***	-0.138**	-0.167***	-0.174***		
	(0.0369)	(0.0386)	(0.0655)	(0.692)	(0.613)	(0.508)	(0.544)	(0.0374)	(0.0352)	(0.0392)	(0.0573)	(0.0389)	(0.0382)		
Male	-0.0242	-0.0550**	-0.0609**	0.623*	0.622**	0.141	-0.587**	-0.0169	-0.0488**	-0.0227	-0.0487	-0.0558**	-0.0553**	-0.0327	-0.0567**
	(0.0231)	(0.0222)	(0.0260)	(0.349)	(0.294)	(0.226)	(0.270)	(0.0172)	(0.0192)	(0.0202)	(0.0301)	(0.0220)	(0.0221)	(0.0526)	(0.0227)
Prefer Not to Say	-0.0460	-0.0797*	-0.0422	0.765	0.768	-0.0468	-0.271	-0.0446	-0.0521	-0.0232	-0.0784	-0.0776	-0.0786	-0.168**	-0.0695
	(0.0461)	(0.0480)	(0.0427)	(0.592)	(0.509)	(0.474)	(0.504)	(0.0443)	(0.0443)	(0.0313)	(0.0510)	(0.0474)	(0.0477)	(0.0724)	(0.0479)
£0-£4,999	-0.125***	-0.0857	0.00422	*Insufficient*	1.320	*Insufficient*	0.368	0.0198	-0.0747**	-0.160***	0.00460	-0.0897	-0.0980	0.127*	-0.0807
	(0.0286)	(0.111)	(0.0353)	*observations*	(0.994)	*observations*	(0.941)	(0.0307)	(0.0314)	(0.0337)	(0.0616)	(0.107)	(0.108)	(0.0679)	(0.0998)
£5,000-£14,999	-0.0266	0.0508	0.0580	-0.341	-0.501	-0.329	1.071**	0.0281	0.0714	0.0735	0.0422	0.0495	0.0479	-0.0475	0.0645
	(0.0754)	(0.0574)	(0.0422)	(0.780)	(0.622)	(0.519)	(0.525)	(0.0508)	(0.0612)	(0.0569)	(0.0760)	(0.0583)	(0.0603)	(0.0986)	(0.0572)
£15,000-£24,999	-0.0118	0.0136	0.0413	0.0970	0.226	-0.213	0.0516	0.000716	0.000405	0.0305	0.0145	0.0135	0.0175	0.0882	0.0144
	(0.0366)	(0.0389)	(0.0581)	(0.426)	(0.406)	(0.411)	(0.456)	(0.0297)	(0.0381)	(0.0374)	(0.0706)	(0.0390)	(0.0397)	(0.0858)	(0.0406)
£25,000-£39,999	0.0452	0.0502	0.0387	0.0142	-0.0225	-0.261	0.481	0.0311	0.0362	0.00841	0.0256	0.0485	0.0500	0.0249	0.0651*
	(0.0287)	(0.0324)	(0.0413)	(0.532)	(0.454)	(0.350)	(0.383)	(0.0229)	(0.0263)	(0.0250)	(0.0426)	(0.0321)	(0.0328)	(0.0675)	(0.0344)
£40,000-£54,999	-0.0769**	-0.0697*	-0.0346	0.702*	0.769**	-0.424	-0.397	0.000414	-0.0560**	-0.0870***	-0.0837	-0.0689*	-0.0713*	0.128*	-0.0611*
	(0.0307)	(0.0380)	(0.0652)	(0.426)	(0.372)	(0.346)	(0.513)	(0.0231)	(0.0271)	(0.0298)	(0.0518)	(0.0375)	(0.0375)	(0.0681)	(0.0366)
£55,000-£74,999	0.0224	0.0257	0.00515	-0.356	-0.384	0.0579	0.380	0.0367	0.0113	-0.0413*	-0.0104	0.0254	0.0231	-0.109	0.0359
	(0.0286)	(0.0301)	(0.0352)	(0.366)	(0.330)	(0.297)	(0.399)	(0.0231)	(0.0249)	(0.0222)	(0.0413)	(0.0301)	(0.0295)	(0.0933)	(0.0306)
delta_50	-2.087***	-4.206***	-3.002***	34.76***	39.35***	-2.824	-29.88***					-4.206***	-4.213***	-4.935***	-4.195***
	(0.316)	(0.431)	(0.633)	(8.049)	(6.869)	(3.200)	(4.308)					(0.433)	(0.435)	(0.834)	(0.451)
delta_10								-0.557**	-2.317***	-1.803***					
								(0.241)	(0.335)	(0.344)					
lnduration	0.0130	0.0133	0.0241	0.300	0.221	-0.147	0.178	0.0146	0.00883	0.00170	0.0130		0.0130	0.0669	0.00891
	(0.0211)	(0.0215)	(0.0369)	(0.267)	(0.235)	(0.209)	(0.239)	(0.0187)	(0.0180)	(0.0193)	(0.0282)		(0.0215)	(0.0703)	(0.0204)
order1	0.0151	0.0253	0.0309	-0.247	-0.223	0.221	-0.0642	0.0272	0.0223	-0.00452	0.0303	0.0251		0.0692	0.0290
	(0.0209)	(0.0228)	(0.0299)	(0.267)	(0.237)	(0.208)	(0.245)	(0.0164)	(0.0192)	(0.0188)	(0.0304)	(0.0227)		(0.0530)	(0.0232)
EPAIS														-0.0242	0.0104
														(0.103)	(0.0552)
PPE														0.110**	-0.0163
														(0.0541)	(0.0284)
Second_Year															-0.0690**
															(0.0311)
Final_Year															-0.105***
															(0.0280)
Constant	2.865***	4.956***	3.795***	-35.63***	-39.81***	2.907	27.28***	1.368***	3.188***	2.815***	0.914***	5.034***	5.004***	5.256***	4.972***
	(0.333)	(0.434)	(0.552)	(8.540)	(7.292)	(3.234)	(4.664)	(0.271)	(0.351)	(0.354)	(0.179)	(0.418)	(0.439)	(0.881)	(0.449)
Observations	129	174	100	125	170	172	171	121	174	117	174	174	174	54	174
R-squared	0.331	0.548	0.477					0.169	0.343	0.423	0.151	0.547	0.545	0.635	0.522

Figure 12: Robust Standard Errors in Parantheses ***p<0.01, **p<0.05, *p<0.1