Benjamin Holland
Thesis Block 6
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The Variable Effects of Exposure and Experience on Future Exponential Growth Bias

A study examining how personal housing financing decisions may subconsciously drive individual exponential growth bias

Abstract:

Exponential growth bias (EGB) is a largely unnoticed bias that plagues the financial decision making of most individuals in the United States. It is characterized as the tendency to linearize exponential compound saving and interest rates, and it shows itself through poor decision making around wrong estimates and/or no understanding of how money grows through time. Based on the theory that education and valid experience might tame EGB, a model was built to measure variable drivers of individual EGB related to exposure. Based on previous theory that more extreme situations demand more incentive for participation, it was hypothesized that the government dictated interest rates at times of individual's first home purchases could subconsciously influence EGB, for two main reasons. First, a more expensive payment plan carries greater incentive to fully understand, and second, a first home purchase is a fundamentally monumental financial decision with potential to positively or negatively shape bias. A variable for interest rate at the time of a first home purchase was created a combined with more lifetime-housing-exposure variables theorized to influence EGB, to model overall effects of individual housing exposure on EGB. The results showed that government set interest rates hold no statistically significant influence on an individual's current EGB, however, the marginal coefficients showed the correlations consistent with the theory. The model statistically significantly determined that the variables for number of homes purchased in a lifetime and price paid for a first home are inversely correlated with current EGB. In addition, income and education levels were statistically proven to be inversely correlated with current EGB.

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1. Introduction:

An individual must make personal financial decisions throughout one's lifetime while constantly faced with various opportunities to save or borrow, each directly effecting the degree of personal well-being in the future. Unfortunately, the effect of exponential growth bias (EGB) frequently plagues the financial decision making of households throughout the United States, often causing them to make choices they are not fully capable of understanding. EGB is formally defined as an individual's instinctive tendency to instinctively linearize exponential equations. The bias consists of false rationales among saving and debt domain decisions, as individuals misinterpret the growth of money through time and ignore interest rates completely. The effect is an unintentional, yet wrongful linearizing of an exponential equation and and the consequences are often impactful. Consumers effected by EGB end up grossly underestimating the lender-favorable impacts of interest rates and time structured within debt repayment schedules, while at the same time misunderstanding the value of interest rates and time in the savings domain with personal savings investments. For these reasons individuals with EGB live with negative financial consequences, too often taking on excess debt and failing to adequately save. In 2011, McKenzie and Liersch where the first to highlight these consequential results of EGB, directly correlating the effects of EGB with an observable underestimation of compound-savings growth rates and annual interest rates (with credit cards) over time.

As is the plague of many biases, frequently an individual with EGB will be unaware it exists, unintentionally and repeatedly making the same mistakes (Levy and Tasoff, 2015). For example, individuals are continuing to use methods of high-cost borrowing, showing an inability to care and/or comprehend how loan amortization schedules work. Stango and Zinman show how, blind by EGB, 20% of adults chose pawn shops and payday loans over banks when they needed money (Stango and Zinman, 2015). These individuals demonstrate a bias to avoid loan payments due to tendencies to linearize and underestimate the time it will take to be debt free. While interest on a bank loan is usually significantly less than the interest a pawn shop charges when the owner makes a deal for 60% of selling price potential, some individuals avoid a payment schedule and take the high-cost borrowing option over the lower-cost option for, convenience sake. In addition to their convenience, high-rate loans are sometimes the only available option for individuals looking to borrow money. Those who repeatedly fail to get loans from local banks due to poor credit history or past criminality, are often forced to go to pawn shops and get payday loans, accepting the harshest loan repayment plans out of desperation. For these reasons, underlying EGB can sometimes be influenced by convenience, but also be driven by lack of options in those most susceptible individuals. The result is a created environment for the bias to perpetuate among those most susceptible, with those who are least capable of paying sometimes making the greatest payments.

Interestingly, scientific research on the prominence of EGB is widely available among academia, yet specific proposals to tame or combat EGB are less common. This research aims to explore in depth whether there is any possibility that uncontrollable factors may be subconsciously driving EGB in individuals. It aims to determine whether housing market experience coupled with uncontrollable factors such as government set interest rates impact EGB later in life. Specifically, the research aims to uncover the possibility that exposure characteristics such as one's first purchase of a home at a given (relatively high, or relatively low) interest rate has a lasting effect on EGB, building on my theory of exposure, and testing how familiarity with housing purchases, refinancing, and payment plans influences future EGB.

We arrive at our first broad hypothesis when considering the effect is that the "What you see, is all there is" heuristic plays significant effect on EGB causing individuals (making a first monumental debt decision) to undervalue increased interest rates later in life should the initial interest rate provided be low (Kahneman, 2011). This satisfies the implication that, the more damaging and immediate an effect is on an individual, the more careful precautions one will take to understand the situation at hand. It is predicted that higher interest rates attached to the initial purchase of a home will incentivize individuals to be more cognizant of their debt payments and be more inclined to properly value interest rates and payments. The indication that indirect exposure to high interest rate provides subconscious experience leads us to believe that interest rates alone can be correlated with the bias. The goal is to build on this notion, examining important variables involved in in lifetime housing decision that in theory could also have unintentional experiential effects on EGB.

A model was built around this theory controlling for previous education, income, and financial literacy. This was important to make sure that responses to future EGB where not exclusively the result of higher education and financial literary levels. Data collection focused on a set of 16 consumer lifetime housing choices, numerically coding individual decisions and regressing against current EGB. Similar methods to by Foltice and Langer were used to include parameter theta into the debt and savings equations to measure bias. Finally, an ordinary least squares regression was run to observe the variable correlations of previous housing exposure to the current measured bias.

The contents of this research paper will begin with a Literature Review outlining research inspirations. Next, the methodology and model will be explained in detail, describing my procedures and initial model. Lastly, a detailed conclusion will provide an in depth discussion of the finding and address further valuable avenues of EBG research.

2. Literature Review:

In *Increasing Saving Behavior through Age-Progressed Renderings of the Future Self?* the authors take a detailed look into how exponential growth bias applies directly to savings for retirement (Hershfield and Goldstein, 2011). Reported at the time, average "time in retirement" (years) was steadily growing meaning there was more urgency for people to properly plan to be in a longer retirement. The problem was people were running out of money and falling short. Using data from the 2004 Survey of Consumer Finances, they find that 43% of families fall short of reaching the target replacement rates by 10% or more. Through a detailed three step experiment the authors were able to confidently conclude that "a new kind of intervention in which people can be encouraged to make more future-oriented choices by having them inter-act with age-progressed renderings of their own likenesses," was effective in reducing exponential growth bias. This study relates to my research in that both are tests in the realm of experience effects on EGB. My study aims to investigate subconscious effects of previous exposure on subconscious bias. Hirschfield and Goldstein highlight the direct correlation between poor savings decisions and a perpetrated bias showing that the tendency to linearizing the growth of money through time is linked to EGB. This finding intrigued further investigation as to what specific exposure factors are capable of influencing EGB. Additionally, Hershfield and Goldstein find that t introduced experience can correlate with EGB suggesting that introduced information can influence the bias without the ones awareness. This finding helped build my theory that government introduced interest rates could represent a similar exposure. Finally, Hershfield and Goldstein find that people can be influenced away from EGB in the retirement savings realm (Hersfield and Goldstein, 2011). Individuals can be influenced away from the most common biases such as "lures to pre-commit to decisions" or, tendency to "elaborate the value of future rewards" by interacting with their projected future selves. This paper was an encouraging find because it takes McKenzie and Liersch implications for retirement's savings and develops the narrative in a new direction. not intently focusing on the effects of fundamental roots of the exponential finance formulas and memorization exposure, but rather demonstrating the concept of introduced experience and its simplicity combined with effective results.

In *Misunderstanding Savings Growth: Implications for Retirement Savings* McKenzie and Liersch take a very similar look into introducing experience to reduce exponential growth bias in individuals in the frame of having employers have discussions with employees about exponential growth before they make critical decisions about how much to save (McKenzie and Liersch, 2011). Much like Hershfield and Goldstein, McKenzie and Liersch take a careful and mathematical surveying approach to evaluating bias. They find that by presenting employees with an estimated account balance for their future 401(k) savings account, employees were more inclined to seriously plan to save money. They also presented employees with illustrative representations of how money grows exponentially in time and found that this had the same effect. The general conclusion was that these findings implicate that savings EGB can be limited in response to "(1) increase awareness of the cost of waiting to save, (2) willingness to start saving early, and (3) anticipated monthly deposits." Interestingly this paper shows how real worker populations compared similarly to undergraduate populations when tested and provided with a "savings intervention." This provides interesting comparison to my findings seeing as my model is able to closely identify the effect of my age parameter.

In *Misperception of Exponential Growth: Are People Aware of their Bias?* the authors suggest that nuances of intervention are often well perceived by individuals and have high potentials to be successful (Cordes, Foltice, Langer, 2015). They link the success of information interventions to the concept that people fear ambiguity and are usually willing to have an outside perspective informing them. (I am hoping to compare this finding—that people are generally wanting knowledge—to my study and determine if there is a correlation between lower interest rates at time of debt purchase and an individual's knowledge—directly proportional to EGB.

From these four papers, I reach the standpoint where it is clear that EGB has negative consequences on individuals as they make daily savings and investment decisions. To reiterate, people fall short of saving for retirement and underestimate the value of time constantly, repeatedly letting an internal bias disappoint them. So far, I have clearly found several suggestions that savings EGB may be mitigated by introducing experience and exposure. Can these observations be applied to my debt domain as well though? Does debt related EGB provide the same consequences as savings, and if so, could experience help this realm at all?

Although most research on EGB to this date has been related to future applications of savings and the consequences of not realizing how money grows over time, many studies confirm similar consequences of EGB in the debt domain. In *Exponential Growth Bias and Household Finance* a study showed how individuals fail to understand payment plans on a day to day basis (Stango, Zinman 2009). Most of the time, payments are underestimated because individuals fail to consider compounding interest that needs to be paid as an "extra" for the lender agreeing to provide money at the given time (ahead of time). The study shows how people take on loans and debts that they will never be able to pay back realistically, thinking that the deal sounds affordable, but ignoring that interest and payments are bound to become more expensive. This leads us to question if there is any way individual experience or exposure can provide substantial EGB relief in the *debt domain* as many papers suggest is possible in the savings domain.

This led us to investigate deeper what exactly a debt decision means to an individual and come up with a shortlist of important things to consider (all things EGB works so hard for you to forget!). Among the shortlist of considerations, is obviously interest rate. *The Changing Behavior of the Term Structure of Interest Rates*, authors Mankiw and Miron explains how the interesting thing about interest rates is that they keep up with the times and they are constantly fluctuating (Mankiw and Miron, 1996). This sparked the idea that interest rates can essentially be treated as an experience, the benefit of the experience varying as different rates have been introduce throughout American history. Stemming from the ideas of Herschfield, Goldstein, McKenzie, and Leirsch, it seems logical to treat historical interest rates as exposure involuntarily presented to the buyer of the loan. Should interest rates be high, and thus more obvious an imposing on consumers lifestyles, the individuals experience could potentially increase based on exposure, encouraging more thoughtful decisions in the future due to pressure to understand high interest loans.

On a slight aside, research exists regarding how interest rate exposure in the corporate world applies to executives (among the most financially literate) as they use interest rates to leverage hedge funds. Although I need to examine this realm further, this finding initially tells us that individuals in Finance use and leverage interest rates as experience *consciously*. This is encouraging to me because it suggests that the average person may catch on to the experience interest rates can provide in debt decisions. This finding came from *Hedging or Market Timing? Selecting the Interest Rate Exposure of Corporate Debt* (Faulkender, 2005).

Now, having an idea to go forward with that regards debt domain experience from government interest rates, I may focus on how my experiment can provide results that are analyzable and interesting.

The following paragraph explains how I arrived at my initial starting point for scaling EGB and developing a system that can help quantitatively address my hypothesized connections between interest rates, experience, and EGB.

In *Equations We Trust,* Foltice examines to a precise degree how exponential growth bias affects college students at a German University in both savings and debt domains (Foltice, 2011). The authors show that calculators do indeed add assistance in reducing EGB when provided, regardless of original capability without a calculator. This leads them to investigate and conclude that the memorization of standard formulas is somewhat helpful in reducing EGB and should be suggested, however the implications are that this learning method is not a one size fits all. What's most interesting and relevant about this paper is not particularly the ending conclusions, but rather the methodologies and sub-findings along the way:

First, the paper provides a bias equation that can precisely evaluate and scale EGB among test participants on a scale of 0-1. The bias equation is new and revised to allow the application across both savings and debt domains and to have the parameter represent not exclusively the perception of interest or exclusively the perception of time. Using this to measure EGB in my tests will provide the most statistically accurate and analyzable data for my model. Second, I find the mathematical and systematic approach to measuring EGB to be very thoughtful and thorough and consider structuring debt questions in the same light. I agree with their structure because it measures the difference of the student's response and the correct answer, provides a relative score, and effectively scales the individual based on EGB.

In *Exponential growth bias and financial literacy,* the authors find that, "since financial literacy is linked to household decision-making, my results indicate that examining the relationship between exponential growth bias and household finance without adequate controls for financial literacy may generate biased results" (Almenberg and Gerdes, 2012). This method of controlling for financial literacy is what has to be done with my model for the same reasons. Because financial literacy is positively correlated with credit score; credit score, negatively correlated with interest rate; and interest rate, hypothesized as negatively correlated with EGB, the model would both positively and negatively correlate financial literacy to EGB. However, if I control for financial literacy, then I can relate interest rates to EGB without a problem.

As mentioned above, financial literacy will need to be controlled for in order to correlate interest rates with EGB. Thankfully, meta-analysis provides a great starting point in current discussions on what is important in measuring literacy. In *Measuring Financial Literacy,* Huston, composes a study analyzing past, proposed methods of measuring financial literacy (S.J. Huston, 2010). Her data provides helpful findings of shortfalls in most of the models. For example, she finds that "(72%) of financial literacy studies in her sample did not include an absolute, clear definition of financial literacy. She highlights obstacles of measuring financially literacy but also points out important factors to keep in mind when developing a methodology. Her concrete approaches towards taking this measurement provided a basis for us to begin building my model.

3. Methods

This study comprised a random test of 192 participants, all 18+ years old with equal proportions male and female. Participants were drawn from a scattered variety of U.S. cities to randomize the impact of lifestyle and upbringing differences from region to region. The average participant was 44 years old.

A four-part extensive survey was developed to value each variable in our model. Questions where carefully crafted to value the dependent variable (EGB) and all independent lifetime-housing exposure variables—including the control variables: financial literacy, previous education, level of income.

The study begins with 20 true/false questions for to participants to answer. This section contains only questions that are carefully are constructed to quantify individual financial literacy, questions that have been used in many other academic papers on financial literacy (HSRI Financial Literary Test, 2007). Participants are then graded on correctness out of 20 and valued accordingly on a scale of 0 to 1. The individual(s) with the highest score (most financially literate*)* would be attributed a score of 1.00, whereas individual(s) with the lowest score (most financially *illiterate)* would be attributed a score of 0.00.

Participants then moved to the next section of the survey where they were asked to answer 18 questions without a calculator. This section of the survey featured formulaic questions designed and used by Foltice and Langer in previous studies to value and scale the dependent variable, individual EGB (Foltice, Langer,2001). Ten questions regarded personal debt financing, and eight questions regarded traditional savings practices—four prospective, and four retrospective. The structure of these debt questions and savings questions along with the calculations used in to transform EGB into a measurable value of theta have been shown below:

DEBT (long term) - - 10 different long term debt questions: You borrow $__ for __ years, paying a yearly fixed interest rate of __%, agreeing to pay off the entire loan plus interest by making __ equal monthly payments. Assume all payments have been made on time and no additional payments have been made. After making payments on this loan for __ years (__ payments), what is the remaining balance of the initial loan? Please provide your best estimate.

SAVINGS (prospective) 4 different prospective savings questions: how much an initial investment of $10,000 grows over x-years earning a constant y% annual interest rate.

SAVINGS (retrospective) 4 different retrospective savings questions: what one-time investment is needed to reach a savings goal of $100,000 after x-years while earning a constant annual interest rate of y%.

a. To measure our focus variable EGB I valued bias on each response individually in Section B, part B. I fit the bias measure $fi,t(\theta)$ to the growth saving formula to calculate θ.

i. $fi,t(\theta)$ = (1 + i)(1− θ)^t
ii. FV = PV * $fi,t(\theta)$
iii. θ = (fi,t^−1)(FV/PV) = (1 / ((1 + i)^t))*(FV/PV) – (1)

b. Question EGB1 asks how much do you need to invest today to have 100,000 in 30 years, i=2%, annually. The exact correct answer is an initial investment today of $55,207.10. If the participant answered 60,000, showing slight bias by underestimating compound savings growth through time, they would be assigned a θ value of .079.

i. θ = (1/1.02^30)(100,000/60,000) – (1) = .079

c. My measurement for θ is adjusted so that the perfectly unbiased participant is assigned a value of θ (1). Coincidently, this allows for values to help quickly differentiate normal from reverse bias. Any participant with a calculated θ that is negative, shows tendency to overvalue the compound growth of money through time. A participant who answered 50,000, would show reverse EGB in that they ended up overestimating the compound savings growth of money through time (2).

i. (1) θ =(1/1.02^30)(100,000/55,207.10) – (1) = 0
ii. (2) θ =(1/1.02^30)(100,000/50,000) – (1) = - .104 (negative/reverse bias)

d. The exact same approach was used to calculate θ when participants were next asked how much 10,000 grow to in 30 years, compounded annually at 3%. The only difference here is that participants provided us with FV estimate and we solved for PV. The exact correct answer is that a lump sum $10,000 today will be worth $24272.62 in 30 years. If the participant answered $20,000, showing observable bias by underestimating compound savings growth through time, they would be assigned a θ value of
i. θ = (1/1.03^30)(20,000/10,000) – (1) = .176

e. Once a θ value had been calculated for participant responses to each EGB question, the bias measure was averaged for every individual. This provided me with a way to assess each person's overall EGB averaged over a question series. This calibrated, 0-centered scale of θ values was then used as my dependent variable calculation throughout the model.

In this EGB testing section of the study I explicated explained how calculators external aids of any sort were strictly prohibited. However, stated several times in the directions for this section, was how participants are *strongly encouraged* to use pen and paper to organize multiple-step work and thought process.

In the third and final stages of study, I ask all my demographic questions and life-time housing exposure question, attempting to broaden my understanding of my participant's lifestyles and quantify key independent variables like: interest rate on first home, number of times refinanced, market price of first home, etc. Fill in the blank answers where used to allow participants to enter the best guess for questions asking interest rate at first home and age at first credit card, while multiple choice questions asked demographic questions determining variable like level of income and education. These questions are thoughtfully placed at the end of my survey because, personal in nature, they have the potential to provoke emotional responses that would convolute the previous two sections should the order be reversed. For example, with the demographic section at the front, there is the possibility that participants may get frustrated/annoyed by the personality of the question and quit-out the survey before answering the most curtail research questions.

Finally, following the study, participants were given the chance to provide feedback if they liked through comments. I encouraged participants to give us any reaction possible at the end of each survey so participants could help me brainstorm tweaks to my methodology that might have been more effective. Also, in this section was a question that sincerely asked each participant if they cheated in *any* way, (i.e., used a calculator or google search during the testing). This question was carefully constructed and phrased to convey the general message: "*It's okay if you (the participant) did use external aid in some manor (you are obviously not in any kind of trouble), but please tell us if you did because it is crucial to my research that the thought process to each individual's data is transparent.*

Lastly, I must note that all participants were provided cash incentives to complete my survey. The incentives were minimal but extremely important in encouraging adequate participation to reach my target sample size. Most importantly, the incentives were exactly universal throughout. Regardless of the time you spent on my survey, or the numbers you entered, if completed, each participant revived *equal* pay for their work in my study. Incentives where kept from being too large, discouraging careless participation just to collect money, but at the same time not too small, to draw enough participation. It was countlessly reiterated that the success of my research requires truthful, thoughtful, and fully considered, completely individual responses. This price point balance was settled on after several trial runs of the survey observing response times and listening to participant feedback. After a trial run exposing four rounds initial batches to ten participants each, I was confident in my questions and variable choices, and went forward with the main batch testing. 8 total batches were sent out one at a time, at the same time (8:00am), for four days in a row. Each day a two batches were sent—one called for 45 participant hits and only targeted those who had previously owned a home, and one called for 4 participant hits and only targeted those who had never purchased homes. This survey for those who had never purchased a home, was identical to the original, just incorporated skip logic so that the questions valuing lifetime-housing exposure variable were not presented in their scenario. This allowed us to use non-home owners as part of a control group, while at the same time managed the ratios of home-owners to non-homers without disrupting the data collection. From these series of batch runs, I collected 196 individual responses, 180 from home-owners, and 16 from non-home owners, but two home-owner responses and two non-home owner responses were removed for incompleteness, which left me with a sample size population for the model of n=192.

4. Results:

After several trial runs of the survey, I was confident to begin collecting data for my model. 192 participant responses where converted from Qualtrics into a Stata panel-data set. Dummy values were used for variables: RefinancedLifetime, ForclosedLifetime, PurchasedNoMortgage, and

TimesRefinanced. These variables are assigned yes or no values of 0 or 1. The variable FinancialLiteracy was graded for accuracy and scaled accordingly, and the parameter theta was used as explained in the methods to code values for individual EGB.

The official (non-trial) 4 rounds of survey batches ran extremely smoothly, with no comments communicating unclear questions, and survey flow logic holding up. The result was only 4 total responses that had to be scrapped for incompleteness.

Once data had been collected and loaded into Stata, Model One was developed incorporating the exposure variables most central and fundamental to my theory—plus all three control variables. Model B was developed by removing the four least statistically significant influencers to EGB from Model A, but still including each control variable. The two regression models for the study are shown below with the dependent and independent variables explicitly outlined.

Model A:

Exponential Growth Bias (θ) =

b0 + ***b1*** *CurrentCreditScore* + ***b2*** *MortgageType* + ***b3*** *NumberHomesPurchased*
+ ***b4*** *TimesRefinancedMortgage* + ***b5*** *RefinancedDuringLifetime*
+ ***b6*** *Age1streditCard* + ***b7*** *PurchasedNoMortgage* + ***b8*** *RelationshipStatus1stHome*
+ ***b9*** *InterestRate1stHome* + ***b10*** *MarketPrice1stHome* + ***b11*** *ForclosedLifetime*
+ ***b12*** *LevelEducation* + ***b13****IncomeLevel* + ***b14*** *FinancialLiteracyScore*

Model B:

b0 + ***b1*** *CurrentCreditScore* + ***b2*** *MortgageType* + ***b3*** *NumberHomesPurchased*
+ ***b4*** *TimesRefinancedLifetime* + ***b5*** *RefinancedDuringLifetime* + ***b6*** *Age1stCreditCard*
+ ***b7*** *InterestRate1stHome* + ***b8*** *FinancialLiteracyScore* + ***b9*** *IncomeLevel*
+ ***b10*** *LevelEudcation*

4.1 Summary Statistics

After organizing data in a Stata cross-section, summary statistics were calculated for each variable in our model, displaying mean and standard deviation of responses. By running summary statistics, I got an initial sense of where errors might be abnormal or where outliers may be lying. Using summary statistics, I could get a quick visual sense of the data entries among each specific independent variable in my model. I combined these summary statistics with a correlation matrix to look for initial harbingers of obvious heteroskedasticity. The resulting table is shown below in table 2.

Table 1

	Mean	Standard Deviation	A	B	C	D	E	F	G	H
A	1.004701	2.473951	1.0000							
B	4.061538	1.243612	-0.0423	1.0000						
C	1.897196	.334624	-0.3516	-0.0745	1.0000					
D	4.333943	2.12555	-0.0921	-0.0288	0.1712	1.0000				
E	3.495868	2.513709	-0.0246	0.1215	0.0697	0.3620	1.0000			
F	1.867769	1.494111	0.0375	0.1450	0.0532	0.2328	0.3855	1.0000		
G	1.59292	.4934783	0.1294	0.1874	0.0194	0.3701	0.6016	0.8152	1.0000	
H	1.933884	.2495174	-0.0107	0.0925	-0.0387	0.0052	0.0495	0.0887	0.0934	1.0000
I	11.55224	3.199077	-0.2572	0.1285	0.0588	0.3941	0.3961	0.5434	0.7056	0.2653
J	1.834711	.3729859	-0.2488	0.1324	-0.0554	-0.0770	-0.0302	-0.1590	0.0055	-0.0329
K	2.141667	1.93289	-0.0141	-0.2627	-0.2153	-0.2441	-0.3190	-0.5283	-0.5468	-0.1279
L	21.15625	3.168341	0.1151	-0.3339	0.0896	0.0659	-0.0162	-0.0644	-0.1024	-0.0821
M	1.256198	.4383478	-0.0909	0.1403	0.2193	0.1100	0.0440	-0.0733	0.0468	-0.1124
N	6.753731	1.82891	-0.0730	0.2283	0.0046	-0.0324	0.0961	0.1835	0.1194	0.0679
O	3.470149	1.549632	0.2066	0.3921	-0.0284	-0.0933	0.1764	0.1177	0.0550	0.1224
P	3.254341	.2899241								

	Mean	Standard Deviation	I	J	K	L	M	N	O	P
I	11.55224	3.199077	1.0000							
J	1.834711	.3729859	0.1385	1.0000						
K	2.141667	1.93289	-0.3734	0.2572	1.0000					
L	21.15625	3.168341	-0.0469	-0.1014	-0.0091	1.0000				
M	1.256198	.4383478	-0.0196	-0.0258	-0.0861	-0.0269	1.0000			
N	6.753731	1.82891	0.1298	-0.1475	-0.0508	-0.1446	-0.0572	1.0000		
O	3.470149	1.549632	-0.0318	0.0235	0.0245	-0.2077	-0.0780	0.2455	1.000	
P	3.254341	.2899241	.2045	.0248	.3411	.1196	-0.2734	0.2373	1.0000	

Note. This summary statistics tables shows inter-variable correlations of the model accompanied with standard deviation values and mean values. The table provides evidence that no two variables are proportional and therefore measuring the same values. The variables A-P Are specified below:

A = AverageEgbScore	*B* = CurrentCreditScore	*C* = MortgageType	*D* = InterestRate1stHome
E = MarketPrice1stHome	*F* = #HomesPurchased	*G = RefinancedLifetime*	*H* = ForeclosedLifetime
I = FinancialLiteracyScore	*J* = PurchasedNoMortgage	*K = TimesRefinancedLifetime*	*L* = Age1stCreditCard
M = RelationshipStatus1stHome	N = LevelEducation	*O* = MarketPrice1stHome	*P*= Income

4.2 Summary Regression Statistics, Ordinary Least Squares Regression

An Ordinary Least Squares regression was chosen as my best linear unbiased estimator because in theory my model holds all the formal requirements for OLS to be BLUE. In choosing OLS, I was confident my model was entirely linear, had a random sampling of population, had variation in sample of explanatory variable but no exact linear relationships between independent variable values, had a conditional mean of u is zero, and produced x-variable variances when *u* was held constant.

After an initial OLS regression run, a variety of model integrity and error test were run to verify the model, and confirm that OLS was actually the best linear unbiased estimator in my case. The regression table is shown below, showing model produced beta values and results of 95% significance testing.

Table 2

	Individual Exponential Growth Bias		
		Model 2	
Variable	Model A	*B*	95% CI
Constant	10.522	6.225	[-2.05, 14.50]
CurrentCreditScore	0.198	-0.243	[-0.88, 0.39]
MortgageType	-0.956*	-2.226*	[-4.65, 0.20]
NumberHomesPurchased	0.614	0.399	[-0.38, 1.18]
TimesRefinancedMortgage	0.521*	-0.281	[-0.73, 0.16]
FinancialLiteracyScore	-0.133	-0.142	[-0.36, 0.07]
RefinancedDuringLifetime	-0.876	-0.862	[-2.16, 0.44]
AgeFIrstCreditCard	-0.075	0.055	[-0.06, 0.17]
IncomeLevel	-0.203	-0.137	[-0.53, 0.26]
LevelEudcation	0.310*	0.334	[0.07, 0.59]
InterestRateFirstHome	0.354	0.399	[0.77, 0.34]
PurchasesWithoutMortgage	1.294		
RelationshipStatusFirstHome	-0.259		
MarketPriceFirstHome	.0860		
ForclosedLifetime	-.124		
F	1.66	1.98	
Prob>F	0.0905	0.0498	
R^2	0.2396	0.2513	
Change in F	-	.32	
Change in R^2	-	.0117*	

*Note. N = 192. CI = Confidence Interval. *p < .05. This regression table shows the variable correlations of lifetime housing decisions with an individual's current EGB. Additional information provided includes 95%confidence intervals for Model 2, as well as an model F-test probability, model F value, and model R-squared value. The change in F value and R-squared value indicate the improvement from model 1 to model 2.*
The choice of fixed mortgages over ARM mortgages lowers individual's EGB; the choice of frequent re-financing over non-frequent refinancing lowers individual EGB; and the choice to pursue more education over less education lowers individual EGB.

- *The R-squared value increased significantly which is uncommon when variables are removed from the model. However, as is the case here, a noticeable increase in R-squared seen when variables are removed, is an indication that in theory, these variables do not fit the model. In this case removing PurchasedNoMortgage, RelationshipStatus1stHome, MarketPriceFirstHome, and ForclosedLifetime, told a better story and theoretically represents a more complete model in fewer variables.*

4.3 Heteroskedasticity of Errors Variance Testing

In an OLS regression, homoskedasticity is assumed. This means that the error variance among the residuals in my model are assumed to be equally and randomly distributed. Because this is an assumption of OLS we must take the time to test for the presence of heteroskedasticity and make the necessary adjustments to our model if we do identify abnormal errors distribution.

Table 3

```
. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of avegbscore

         chi2(1)      =    99.97
         Prob > chi2  =   0.0000
```

Next, a statistical adjustment was made to account for a failed Pagan-Weisberg test. Shown below is the coding that was entered to calculate robust error residuals:

```
.  reg  avegbscore  levedu  curcs  typmorfh  rfh  marprifh  numhompurlif  numtimreflt  forlt  flscore, robust
```

Note: Above is the code to run the Breusch-Pagan, Cook-Weisberg test for heteroskedasticity. This trial test the null-hypothesis that my model holds constant error variance against the alternate hypothesis that heteroskedasticity exists. After an initial run of the Pagan and Weisberg test, I found with high confidence (chi2 = 99.97, Prob > chi2 = 0.0000) that our model rejects the hypothesis of normally distributed variance of error residuals.

Because OLS makes the assumption of homoskedasticity and we just found presence of heteroskedasticity, I must make a fix to continue with the current regression model. The option I chose to implement was to instead run a robust OLS regression. Often least squares regression models are highly sensitive to (not robust against) outliers, and can inflate variation in error. When an OLS model has strong suspicions of heteroskedasticity, then robust residuals are calculated and used so that outlying errors are not considered variance from the normal distribution of error.

Other approaches would be to use a Weighted Least Squares regression or to transform the dependent variable (AverageEgbScore) using a variance stabilizing transformation. The problem is, WLS and dependent variable transformation take on entirely new model assumptions, so using robust calculations of error variance can allow us to move forward with our current OLS model, now adjusted to measure error variance solely on the normal distribution observed, not an error distribution incorporating outliers.

4.4 Non-Normality of Errors Testing

Next, I tested the normality of my errors. An initial Skewness and Kurtosis test for normality was run, returning a low probability that my errors were normally skewed and that there my model was free of kurtosis (prob > chi2 = 0.0000).

Table 4

```
. predict myresiduals, r

. sktest myresiduals
```

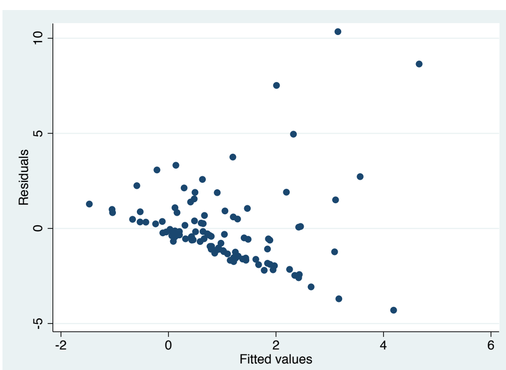
Skewness/Kurtosis tests for Normality

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	joint adj chi2(2)	joint Prob>chi2
myresiduals	194	0.0000	0.0000	46.36	0.0000

Note: In the above table, you will see the Skewness and Kurtosis tests for normality of error residuals. We can see that out of 194 observations, the Pr(normal skewness) and Pr(normal Kurtosis) = 0.000. The joint adj chi2(2) = 46.36 and the joint Prob>chi2 = 0.000 showing clear indication that my model suffers from both Skewness and Kurtosis.

Table 5

```
. rvfplot, yline(0)
```



Note: In the above graph you can see residual values vs fitted values, showing a clear indication of non-normality among errors. Notice the left to right megaphone shape that is a visual harbinger for non-normality of errors.

Unfortunately, there aren't too many simple fixes if skewness and kurtosis are identified in a model. There are a few options though to improving a poor error-normality result. First, you can change the entire model. For example, an independent variable in the model might not actually have a linear relationship with AverageEgbScore, and thus OLS does not truly fit in this case. Fortunately, when individual independent variables where regressed with

AverageEgbScore alone, each did indeed display a linear relationship, meaning changing to a model different than OLS was most likely not a fix to the problem and instead probably counterproductive.

The only other significant option to address non-normal errors and continue with ordinary least squares as the best unbiased linear estimator would be to collect more data. Because the presence of non-normality does not seem to be regression choice or variable transformation error, I am lead to believe that the non-normality could simply be random and indicative of a small sample population.

Lack of data is often the biggest influencer in non-normal error results, and because of this, there sometimes is no scientific fix other than to report and move on. This is my case as other adjustments seem counterproductive to my model. From these non-normality results, I hypothesize that the non-normality is overinflated from large outliers, and that error is randomly and non-normally distributed coincidentally, resulting from an unideal population size of only n=192.

4.5 Multicollinearity Testing

The last significant test I needed to run to check my model integrity, was a test for multicollinearity. Essentially, I was interested in knowing whether or not any of my independent variables where correlated with each other. In other words, I was curious to see if any two variables were essentially measuring the same thing.

Figure 6

```
. cor avegbscore levedu curcs typmorfh rfh marprifh numhompurlif numtimreflt forlt flscore
(obs=194)
```

	avegbs~e	levedu	curcs	typmorfh	rfh	marprifh	numhom~f	numtim~t	forlt	flscore
avegbscore	1.0000									
levedu	0.2262	1.0000								
curcs	-0.0679	0.3454	1.0000							
typmorfh	-0.2661	-0.0710	-0.0451	1.0000						
rfh	-0.0816	-0.0478	-0.0407	0.0822	1.0000					
marprifh	-0.0002	0.2134	0.1175	0.0275	0.3454	1.0000				
numhompurlif	0.0723	0.1120	0.0367	0.0348	0.3235	0.3692	1.0000			
numtimreflt	-0.0768	0.0541	0.1346	0.0375	0.5053	0.5898	0.8113	1.0000		
forlt	0.0619	0.0582	0.1273	-0.0705	0.0827	0.0854	0.0738	0.0939	1.0000	
flscore	-0.1664	0.0029	0.0711	0.0736	0.5191	0.4149	0.5352	0.6932	0.2267	1.0000

Fortunately, I did not find signs of multicollinearity which was a good sign for the model. This finding means that my theory held up and each independent variable had its own independent influence on my dependent variable. I was slightly worried that FinancialLiteracyScore, Income, Level of education, AvEgbScore could essentially be measuring the same factor, but I found that the correlation between these three control variables and AverageEgbScore was actually quite small and far from 1.0000. This meant that no independent variables had to be removed to maintain model integrity.

4.6 Marginal Coefficients Interpretation

The OLS regression table showed that three independent variables: LevelEudcation, MortgageType, and TimesRefinancedMortgage all significant influenced individual's EGB among participants. The coefficients and p values of these variables communicated that, statistically speaking, the choice of fixed a mortgage over a ARM mortgages lowers individual EGB; the choice of frequent re-financing over non-frequent refinancing lowers individual EGB; and the choice to pursue more education over less education lowers individual EGB. All other variables did not show to be significant enough drivers of EGB to mention, but worth noting, however, are their correlations with the bias. Despite insignificant p values, the independent exposure variables: CurrentCreditScore, NumberHomesPurchased, RefinancedDuringLifetime, Age1streditCard, PurchasedNoMortgage, RelationshipStatus1stHome, InterestRate1stHome, MarketPrice1stHome, and ForclosedLifetime, all had correlations with the dependent variable consistent with the theory—just not driving any noticeable changes. For example the relation between interest rate at time of first purchase and EGB was inversely proportional, showing the theorized relation that an increase in interest rates lowers EGB, just not statistically significant enough to determine is a true-unbiased indicator of EGB.

5. Discussion

Exponential Growth bias plays a major role in influencing the decisions of American households causing them to underestimate compound savings growth and debt financing payments. In day to day life, debt and saving decision facing individuals are so common, that a percentage of are bound to treat these financial decisions with increased triviality. Because financing and spending money is an essential part of life, there will always be the framework for an implicit bias among the consumer—most often presenting itself through an overdeveloped scene of confidence and by perpetuating false experience. In this scene the bias is extremely damaging. When unrecognized the victim will often build on inaccuracies, treating bad financial decisions as real money experiences. They then disseminate these distorted realities in day to day life through and gain confidence in their own bias.

Because of its infectious nature, exponential growth bias places hidden restraint on household finances. Millions of Americans are in a constant battle with debt and begin saving for retirement years too late. American culture continues to have an obsession with convenience that encourages fast thinking to questions that really need to be deliberated.

My research contributes to the study of exponential growth bias in that it models the bias to identify the main influencers. My research helps to identify distinguishing factors that highlight who is at highest risk for the bias, and address techniques for how these individuals can recognize its presence, and make positive financial life-style changes. This is the most important application as it sparks conversation about solving the issue of the bias rather than simply highlighting its existence.

In our main model I determine the variable effects of 6 lifetime housing decisions to an individuals calculated exponential growth bias score and find that in many housing market experience and exposure reduces the likelihood of exponential growth bias later in life.
I find that the number of homes an individual purchases in a lifetime, the market price of their first home purchase, their income bracket, and their level of education all have statistically significant negative correlations with exponential growth bias. Our model shows identifies the relationships that the more homes you purchase, the more you spend on your first house, the more income you make per year, and the more education you have received, will all result decreased predicted values of current exponential growth bias score. These finding support our initial hypothesis that home-purchasing experience, housing market exposure, and disposable income are highly responsible for influencing an individual's current exponential growth bias.

The remaining variables in the model (Number of times foreclosed during lifetime, and number of times refinanced during lifetime) where not shown to be statistically significant but showed marginal coefficient relationships still consistent with my theory. Each showed indication that positive exposures in the housing market (i.e. more times refinancing, fewer times foreclosed) would result in slight but observable decreases to predicted current exponential growth bias values. While the model could not state with a high degree of confidence that these correlations where significant, it is encouraging that the marginal relationships where trending in the theorized direction. This observation alone encourages me that these confidence lacking variable relationships within my model would likely become more significant with a significantly larger sample size.

Interestingly, our model highlights how solutions and fixes to exponential growth bias are directly related to housing experiences, and previous education. This means that the solution to treating underlying exponential growth bias of Americans is less objective than one might expect, and more experiential. Our model shows how significantly positive housing experiences can tame exponential growth bias later in life subconsciously, but at the same time shows how detrimental poor exposures can be causing false experience to perpetuate.

When it comes to money, everybody deserves to understand how to invest and save in the least damaging ways. There should be no competition around understanding simple savings and debt equations, seeing as increased disposable income in the pockets of everyone is beneficial to the collective economy. When I consider exponential growth bias and break it down to its most fundamental level, it feels more like a right of happiness to have the proper understanding than a privilege. Financial literacy competition in the marketplace is no doubt a productive, but we cannot consider exponential growth bias of the individual as a mere subset of financial literacy. We must not be complacent with its uneven distribution in our society.

Often times those most susceptible to exponential growth bias, and those most infected are most unaware that small lifestyle adjustments to facilitate proper experiences can make the world of a difference. My model showed how education level and experience is key driver of exponential growth bias eluding the fact that the bias can perpetuate through society a tragedy of the commons. An ideal free market society would be devoid of exponential growth bias. In a sense it feels that to address this tragedy of the commons exponential growth bias must essentially be insured against, much similar to health care. Those most healthy, most aware, and most adequately experience, have the responsibility to support those unhealthiest. There should be incentive among American economist and politicians to insuring that those with the most severe exponential growth bias are able to recognize and address their bias.

Thankfully, addressing systematic exponential growth bias in America seems slightly easier to address than similar collective tragedies we face today such as racism, and xenophobia. This is because the issue is not partisan in nature and not divisive. There is no strong counterargument to having a recognizing and taming the bias and therefore addressing the issue not likely to receive backlash. The existing problem is simply one of ignorance in which those lacking exponential growth bias don't understand the extent to which it plagues other Americans, and vice versa.

With this in mind, Americans are in dire need of some form of campaigning to spread awareness of exponential growth bias. It seems like a good primary step would be to target those with relatively low cases of exponential growth bias, educate them on the prevalence and the detriment of exponential growth bias on disposable income and market stimulation. Using moral persuasion, a team could be developed to pressure their state legislators into addressing unknowingly silenced population suffering from exponential growth bias. We need to keep in mind here that systematically redefining a widespread bias is going to require incredible time and funding. For this reason, any grassroots movement from the citizens alone will be unsuccessful. This is an issue of non-partisan disconnect, and economically speaking would be a positive investment for the economy and the American people.

A widespread campaign could build on implications of out model to meet meet the highest risk Americans at the highest risk times. For example, our model shows that those with less education and with no home-purchase history are more likely to be underestimate compound saving and debt domain interest growth. In this case, a simple government mandate could enforce banks to help reduce bias by educating when an individual fitting the description files for a mortgage plan on their first home. A fix could be as simple as providing inexperienced, low educated individuals, with a printed copy of debt formulas. The same mandate could be made for credit card companies issuing their first card. Possible applications extend all the way to mandating verbal reminders making brokers explicitly explain exponential growth rather than assume participant knowledge when creating a savings account.

All these marketing possibilities drawing from the implications of my model should be remodeled for efficiency, reported, and refined accordingly. It is important however, to keep in mind that these are just initial suggestions sparking the conversation about addressing exponential growth bias as a result of experience. Before any widespread actions can be implemented effectively, there is present a large continued call for research. Continued modeling of housing exposures on exponential growth bias is essential as well as expanding the theory realm of my model to incorporate how different market sector financial exposure may have a different effect on exponential growth bias.

I hope to re-run this model in the future with significantly larger sample size and perhaps expand my theory to incorporate automotive purchasing exposure and aspects of household consumption exposure. It would be interesting to learn how a new families price point decision for a necessity goods budget, or a young student’s financial sophistication decision to lease their first vehicle, would subconsciously impact their personal exponential growth bias.

6.1 APPENDIX A*:*

Thank you for taking the time and interest with our study. This survey will be split into three sections. Sections 1 and 2 are primarily focus on background, informational questions, and Section 3 is mainly critical thinking problems. Please begin with section one below. Further instructions will be provided as you go.

Section 1: Please answer the following questions.

1. Date of birth: __/__/____

2. Personal profession/field of work: ________
   (i.e. finance, publishing, real estate, food services, etc)

3. Previous level of education:
   a. No schooling completed
   b. Nursery school to 8th grade
   c. Some high school, no diploma
   d. High school graduate, diploma or the equivalent (for example: GED)
   e. Some college credit, no degree
   f. Trade/technical/vocational training
   g. Associate degree**,** *what was your major?:* ________
   h. Bachelor's degree, *what was your major?:* ________
   i. Master's degree, *what was your major?*:________
   j. Professional degree, *what was your major?:* ________
   k. Doctorate degree, *what was your major?:*________

4. Marital status:
   a. Single, never married
   b. Married or domestic partnership
   c. Widowed
   d. Divorced
   e. Separated

5. Current employment status:
   a. Employed for wages
   b. Self-employed
   c. Out of work and looking for work
   d. Out of work but not currently looking for work
   e. A homemaker
   f. A student

g. Military
h. Retired
i. Unable to work

6. What yearly income bracket do you fall under?
    a. Less than $20,000
    b. $20,000 to $34,999
    c. $35,000 to $49,999
    d. $50,000 to $74,999
    e. $75,000 to $99,999
    f. $100,000 to $149,999
    g. $150,000 to $199,999
    h. $200,000 or more

6.2 APPENDIX B

Section 2: Please answer the following questions to the best of your recollection. Provide your best estimates when appropriate.

1. Have you purchased a home?
    a. Yes
    b. No

2. How old were you when you purchased your first home? As best you can recollect, what was the date?
    a. ________ years old, __/__/____

3. What type of mortgage did you have?
    a. Adjustable
        i. 1 year ARM
        ii. 10/1 ARM
        iii. 2-Step ARM
        iv. 5/5 ARM
        v. 5/1 ARM
        vi. 5/25 ARM
        vii. 3/3 ARM
        viii. 3/1 ARM
        ix. Other
        x. Unsure
    b. Fixed
        i. 10 year Fixed
        ii. 15 year Fixed
        iii. 30 year Fixed
        iv. Other
        v. Unsure
    c. Balloon
    d. No mortgage

4. Do you remember the initial interest rate you paid on your first home? If so, around what was it?
    a. Yes, __%.
    b. No.
5. What was the total market purchase price of your first home?
    a. $1-$50,000
    b. $50,000-$100,000
    c. $100,000-200,000
    d. $200,000-$300,000

e. $300,000-$500,000
f. $500,000-$700,000
g. $700,000-$900,000
h. $900,000-$1,100,000
i. $1,100,000$1,400,000
j. $1,400,000-$1,800,000
k. $1,800,000-$2,200,000
l. $2,200,000-$3,000,000
m. $3,000,000-$5,000,000
n. $5,000,000+

6. What was your initial percentage you put down for the purchase of your first home?
    a. __%

7. About what was your initial starting monthly payment on the first home you purchased?
    a. $____.__

8. Did you finance the purchase of your first home with one loan, 2 loans, or 2+ loans?
    a. Single loan
    b. Multiple loans
        i. 2
        ii. 2+

9. How many homes have you purchased in your lifetime?
    a. 0-2
    b. 2-4
    c. 2-6
    d. 6+

10. Have you ever completely purchased a home without mortgaging?
    a. Yes
    b. No

11. How is your mortgage payment set up?
    a. Payment transferred directly out of bank account
    b. Manually write a check out for each payment

12. Have you ever paid of a mortgage completely?
    a. Yes, applies to my current home.
    b. Yes, in purchase of a past home.
    c. No.

13. Have you ever refinance the rates on your mortgage?
    a. Yes, about __ times.
    b. No

14. When you purchased your first home did were you:
    a. Single
    b. Married

15. How old where you when you first got a credit card.
    a. ______ years old.
16. Has any home of yours ever been foreclosed? If so, what year.
    a. Yes, ____.
    b. No.
17. How would you say your current credit score is?
    a. Bad
    b. Average
    c. Good
    d. Perfect
    e. Don't know

6.3 APPENDIX C

Section 3: Please answer the following questions to the best of your knowledge. Provide your best possible estimate, closest to the correct answer. We encourage you to use a pen/pencil and paper on each question, however, we ask that you please do not use a calculator or ***any external aid.***

1. The interest rate on your savings account is 2% / year and inflation is 3% / year. After one year, would the money in the account buy more than it does today, exactly the same or less than today.
    a. More
    b. Less
    c. The same
    d. I don't know

2. What happens to bond prices if interest rates rise?
    a. They fall
    b. They rise
    c. The remain the same
    d. Bond prices and interest rates are not related.
    e. I don't know

3. True or False? A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage but the total interest over the life of the loan will be less.
    a. True
    b. False

4. Assume over the next 10 years that the prices you pay for the paper towels you buy will double. Suppose your income doubles as well. Will you be able to buy less than you can buy today, the same, or more?
    a. Will be able to buy more
    b. Will be able to buy the same
    c. Will have to buy less

5. Your goal is to have $100,000 in your savings account 30 years from today. Today, you will invest an initial amount of money in your savings account for 30 years at a constant interest rate of 2% per year. *Assume no additional deposits or withdrawals. Interest is compounded annually and reinvested into the account.*
    a. How much do you need to invest today in order to reach your savings goal in 30 years? Please provide your best estimate: $______.__

6. Your goal is to have $175,000 in your savings account 50 years from today. Today, you will invest an initial amount of money in your savings account for 50 years at a constant interest rate of 5% per year. *Assume no additional deposits or withdrawals. Interest is compounded annually and reinvested into the account.*
   a. How much do you need to invest today in order to reach your savings goal in 50 years? Please provide your best estimate: $______.__

7. You currently have a balance of $10,000 in your account. You leave this money in your savings account for 30 years at a constant annual interest rate of 3%. *Assume no additional deposits or withdrawals. Interest is compounded annually and reinvested into the account.*
   a. Based on the above information, estimate your total account balance after 30 years. Please provide your best estimate: $______.__

8. You currently have a balance of $10,000 in your account. You leave this money in your savings account for 30 years at a constant annual interest rate of 3%. *Assume no additional deposits or withdrawals. Interest is compounded annually and reinvested into the account.*
   a. Based on the above information, estimate your total account balance after 30 years. Please provide your best estimate: $______.__
9. Did you use a calculator or external aid on any of the problems at all. Of course there is no penalty for doing so, however the integrity of our results requires that your be honest and let us know if you gave into the pressure! It’s okay! Don’t worry! But please explain.
   a. No, I followed intsructions completely.
   b. I gave into the difficulty, and used external help!
      i. Please briefly explain.

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