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A snowball's chance: Debt snowball vs. debt avalanche

Evan McAllister

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Abstract

Traditional mathematical analysis states that the most efficient way to pay off interest-bearing consumer debt is to pay the individual debts in order from largest to smallest interest rate. In doing this, the debtor will eliminate the largest sources of interest first, thus shortening the overall time-to-pay. This method is known as the “Debt Avalanche.” The “Debt Snowball” method, popularized in large part by investor-author David Ramsey, recommends that consumers pay debts in order from smallest to largest, regardless of interest rate. In this paper, I conduct an empirical analysis of the Federal Reserve’s Survey of Consumer Finance (SCF), calculating time-to-pay for several thousand households’ worth of financial data using a simplified mathematical model of snowball and avalanche models. This paper concludes that though the avalanche is more effective in the majority of cases, the snowball method is a very close competitor that offers debtors additional psychological benefits in motivation and habit-forming.

I – Introduction

Overwhelmingly, American consumers are in debt – automobile, medical, credit card, mortgage, and others. A commonly-repeated statistic has it that an individual with $10 and no debt is wealthier than 25% of Americans, and 15% of American households put together. From the Federal Reserve Bank of New York:

> "We estimate that 15.1 percent of the households in the U.S. population have net wealth less than or equal to zero, while 14.0 percent have strictly negative wealth."

This should not come as a surprise. The advent of readily-available credit and financing for nearly every major consumer purchase has made it dramatically easier to become indebted while removing much of the stigma (and repercussions) *for* becoming indebted. Also unsurprising is the inevitable backlash to this economic trend. Strategies for debt reduction have become increasingly popular.

One of the most prominent voices in the realm of debt-relief is financial advisor David Ramsey, author of multiple influential books[1] on the subject of consumer debt relief. Among other things, Ramsey frequently recommends a method he refers to as the "debt snowball": similar to the idea of a snowball gradually getting larger and larger as it rolls downhill, consumers are advised to order their debts smallest to largest, and pay them off in this order. Continuing the metaphor, money previously used to pay the smallest debt is then "rolled" into the next debt, and the pattern continues until all debts are paid.

[1] The most prominent and commonly cited of these is *The Total Money Makeover: A Proven Plan for Financial Fitness.*

Ramsey's "snowball" recommendations are intriguing, mathematically. Traditional economic analysis recommends that the debtor pays ordered debts from largest to smallest interest rate, thus removing the *largest* interest payment first and (theoretically) significantly reducing the overall time-to-pay for the total debt. Nevertheless, the snowball method continues to be immensely popular with consumers and analysts alike. This paper will explore the relative efficiency of the snowball and avalanche approaches for debt reduction via a simple computer-assisted mathematical model using consumer debt and income data from the 2016 Survey of Consumer Finance (SCF). Section II will provide a brief, simplified economic analysis of the two methods for debt relief. Section III will survey relevant literature related to both methods and the efficiency of various other debt reduction strategies. Sections IV - V will provide an overview of the methodology and findings of this paper's analysis of the Survey. Section VI will discuss the implications of these findings and conclude.

II – A Short Illustration of Three Debt Relief Strategies

Before continuing on to the literature survey, it may be useful to provide a comparison of the two debt-payment strategies described here. Imagine a theoretical consumer with *x* debts. Each is independent of the rest, and has its own corresponding rate of interest due at the end of every period: I_1, I_2, $I_3 \ldots I_x$ respectively. Each debt also incurs a flat minimum payment for each period, or the smallest amount of money the consumer can pay toward the debt without incurring additional penalties: Min_1, Min_2, $Min_3 \ldots Min_x$.

The consumer's complete debt at the end of *n* periods is:

$$D_{total} = (D_1)(1+I_1)^n + (D_2)(1+I_2)^n + (D_3)(1+I_3)^n + \cdots + (D_x)(1+I_x)^n$$

For a short illustration of the relative efficiency of the three methods, assume that a consumer has three debts. For this consumer with *x* = 3, the formula is:

$$D_{total} = (D_1)(1 + I_1)^n + (D_2)(1 + I_2)^n + (D_3)(1 + I_3)^n$$

Interest rates, debts sizes and minimum payments:

$$D_1 = 4000,\ D_2 = 1000,\ D_3 = 2500$$

$$I_1 = 0.05,\ I_2 = 0.04,\ I_3 = 0.06$$

$$Min_1 = Min_2 = Min_3 = 25$$

Under these assumptions, the consumer's debt at the end of n periods would be:

$$D_{total} = (4000)(1.05)^n + (1000)(1.04)^n + (2500)(1.06)^n$$

If we assume a payment of P = 500 was made toward the total debt for each period, we can examine how long it takes the three debts to be paid with the three competing methods. Ordering the debts from largest to smallest interest rate (avalanche) results in a time-to-pay of twenty-eight periods, and a total paid of $14,000. Conversely, ordering the debts from smallest to largest dollar value (snowball) results in a time-to-pay of thirty periods, and a total paid of $15,000.[2]

Method	Periods	Total
Avalanche	28	$14,000
Snowball	30	$15,000

Of the two strategies – snowball and avalanche – avalanche was the fastest and snowball the slowest. In nearly all circumstances, the avalanche method would be the fastest method of achieving zero debt, contingent on size of outstanding debts (in dollar amount) and size of relevant interest rates. However, for this example, avalanche was faster than snowball, but not *dramatically* faster. If the snowball method were to have additional consumer benefits, the small difference in overall time-to-pay might be mitigated. Additional consumer benefits are discussed in Section III, and the results of real-world calculations are explored in sections IV – VI.

[2] See Appendix A for full table of calculations for both methods.

III – Survey of Literature

Academia provides a vast literature on the subject of debt – national, international, governmental, consumer and more. Little empirical investigation into the efficacy of Ramsey's snowball, however, appears to be present in the literature, much of which deals with sources and distribution of debt. Much of what does investigate or reference Ramsey, furthermore, is purely psychological research.

Amar and Ariely (2011) find that when presented with debt-payment games in an experimental setting, participants regularly choose to pay off the smallest debts first. The researches approach this with the expectation that the interest-ordered payment strategy would be the most efficient in an economic sense. Citing previous studies that find that consumers demonstrate poor estimations of how debt compounds over time with interest and that poorly-understood mechanics are rarely utilized in decision-making (Eisenstein & Hoch 2005, Hsee 1996, and others) they argue that consumers engage in a phenomenon known as "debt account aversion". When presented with a difficult task, individuals will tend to break the task into subgoals and focus on these – the task at hand being debt payment. The trouble with this strategy, they find, is that these subgoals can diminish motivation to focus on superordinate goals (Amar & Ariely 2011). Additionally, while many consumers seem to take Ramsey's heuristic approach to debt management, this debt-aversion phenomenon may lead consumers astray when debts have both large dollar values and larger interest rates.

Brown and Lahey (2014) also examine psychological factors related to the debt snowball, and how consumers prefer certain payment methodologies over others. Citing Ramsey's common mantra that the snowball method is a good way for debt procrastinators to form habits of debt payment,[3] they agree with other studies that the method does have an established track record of successful debt relief, likely due to behavioral and psychological factors. Brown and Lahey also note that many experimental setups demonstrating the relative efficiency of the traditionalist and snowball methods do not account for motivational boosts accrued in real life, since experimental motivational investment is usually somewhat low. They end on a cautionary note: while significant motivational effects are produced by the snowball method, these may not overshadow the negative effects of the additional interest produced by high-interest debts that are not immediately dealt with (Brown & Lahey 2014).

Gal and McShane (2012), in examining task efficiency and the tendency of initial success and task breakdown to predict future success also touch upon Ramsey's financial recommendations:

> "Our findings also direcly address how consumer psychology affects consumer behavior with respect to debt management. Consumers seem to believe that closing off debt accounts, regardless of balance size, is important in motivating them to persist in the coal of eliminating their debts…the popular personal finance guru Dave Ramsey, while acknowledging that 'the math' steers toward paying off higher-interest-rate accounts first, claims that his experience reveals that eliminating debts is '20 percent head knowledge and 80 percent behavior' and that people need 'quick wins in order to stay pumped enough to get out of debt completely'. Our finding that closing off debt accounts…is predictive of eliminating debts hits that this intuition has a basis in reality." (Gal & McShane 2012)

In modeling other relevant factors, they also determine that "substantial" increases to consumer chances of paying off debt occur as a result of the snowball method, and provide a limited

[3] "The reason we list smallest to largest is to have some quick wins…When you start the Debt Snowball and in the first few days pay off a couple of little debts, trust me, it lights your fire…When you pay off a nagging medical bill or that cell-phone bill from eight months ago, your life is not changed that much mathematically yet. You have however, begun a process that works, and you have seen it work, and you will keep doing it because you will be fired up about the fact that it works." (David Ramsey, *The Total Money Makeover.* 1998)

recommendation to advisory institutions to offer the snowball method as a potential viable method for debt relief (Gal & McShane 2012).

While these sources (Amar & Ariely 2011, Eisenstein & Hoch 2005, Hsee 1996, Brown & Lahey 2014, Gal & McShane 2012) are certainly not the only ones available treating on the subject of psychological factors related to debt, much of the rest of the literature treats only with the subject of debt as a phenomenon and how it occurs in the first place, rather than the efficacy of payment methods. They also serve to illustrate two important points. First, psychological factors related to initial success and the breakdown of complex or overwhelming tasks can be incredibly important in providing a morale boost for the debt-riddled consumer. Paying off a large debt first may be too daunting a task for the compulsive debtor, despite its repeatedly-demonstrated economic efficiency. Second, habit-formation becomes important when a task is long and difficult, and it can be difficult to quantify the benefits to the consumer accrued by making a habit of paying debts; this habit-formation becomes exponentially easier when the process has tangible results, as Ramsey argues. Brown and Lahey's cautionary note that large, high-interest debts may provide a counteracting effect of dramatically higher later payments is a strong counterargument; nonetheless, the simplified model provided in this paper provides some evidence that it may not actually increase time-to-pay by a significant margin in the majority of cases. This possible conclusion is discussed further in sections V and VI.

IV – Methodology

To perform an analysis of the relative efficacy of the avalanche and snowball methods for debt payment, this paper utilizes a simple mathematical model and data from the 2016 Survey of Consumer Finances (SCF). The Survey provides a comprehensive overview of a random sample of American households, and includes, among many other variables, household income and several types of debt: home, car, credit, and others. Data analysis was conducted in Mathworks' Matrix Laboratory software (MATLAB), using the following process:

1. Import data from SCF raw data, provided in Excel spreadsheet format.
2. Collect and average multiple-entry data for all SCF households into a single array.[4]
3. Sort debts and income array by size of debt for each consumer.
4. Calculate household monthly income.
5. Calculate time-to-pay for debts, using traditionalist method.
6. Calculate time-to-pay for debts, using snowball method.
7. Calculate time-to-pay for debts, using avalanche method.
8. Analyze time-to-pay for all debts at various consumer income fractions.

(See Appendix B for code)

The SCF provides an enormous amount of data for each household, but only income, payment and debt values are relevant for the analysis performed. As such, the MATLAB software imports debts, payments and incomes for each of the 6248 households, ignoring the rest. The software then constructs a large array of values, pairing income with debts and payments for each household. This array is used to calculate how long it would take each individual household to pay off its debt using the three methods surveyed. For each period (one month), a fraction of the household's monthly income is subtracted from the next debt in the payment scheme. This fraction is first used to make the minimum payment on each of the remaining outstanding debts for the current consumer, with the remainder being applied to the next debt in the list. Every twelve periods, each debt grows by its respective percentage. Calculation continues until all

[4] The 2016 SCF provides data for 6248 households, but uses quintuple-entry bookkeeping for maximum precision. The MATLAB code used here includes a custom function written to remedy this that averages each set of five entries into one, importing the result. This brings the original number of Excel rows from the 31,240 present in the raw SCF data to the 6248 show in this paper's data.

debts are paid, and the number of elapsed months is recorded. This calculation is repeated for different fractions of total household income, ranging from 5% to 80%. While the far ends of this spectrum are unrealistic estimates of the actual amounts of money a consumer could put towards their debt (5% being prohibitively low and 80% being unrealistically high), the analysis covers a large range of potential values for the sake of illustration and completeness. Descriptive statistics for the original Survey of Consumer Finance data are provided below.

	Income	Card	Education	Car	Mort	Other
Mean	799817	2429	6929	17274	109828	48939
Standard Error	68986	100	316	7550	4979	22192
Median	69062	0	0	0	0	0
Mode	30379	0	0	0	0	0
Std. Dev.	5452944	7874	24999	596774	393564	1754158
Kurtosis	1334	154	71	5102	365	5499
Skewness	30	9	7	69	15	72
Range	289132000	200000	465400	44760000	13080000	134304000
Minimum	0	0	0	0	0	0
Maximum	289132000	200000	465400	44760000	13080000	134304000
Count	6248					

The SCF statistics are unusual, but not unexpected for a publication of a very large cross-sectional survey. In nearly all cases, the largest values in each category and the frequency for which a given debt is zero lead to a skewed distribution. Further, the SCF disproportionally represents wealthy families; this is a deliberate choice on the part of the National Opinion Research Center. Additional wealthy households are added to the sample to accurately survey financial trends across a demographic that would be underrepresented in a truly random sample (SCF Codebook).[5] This weighting explains the unusually high average values exhibited across several of the categories. Further, several extremely high values in certain categories (Car and

[5] Members of the Forbes 400 are excluded from this sample.

Other)[6] may have a pronounced effect on the overall distribution. In examining the data used for the analysis, however, such high values are very, very uncommon and likely the product of a few outliers. They are not expected to change the overall conclusions of this analysis, as each household is calculated independently of the others.

Calculations were performed with rough estimates of different interest values for the consumers surveyed. These interest values were estimated from available national averages for 2016, since the SCF does not include individual percentages for households.

Data Point	Value	% Value
Year	2016	N/A
Fraction of Disposable Monthly Income	0.05 - 0.8	5 - 80%
Mortgage Interest Rate	0.037	3.7%
Car Loan Interest Rate	0.045	4.5%
Credit Debt Interest Rate	0.15	15%
Student Loan Interest Rate	0.043	4.3%

Likewise, monthly minimum payments were also estimated using reasonable assumptions (where necessary) and 2016 averages (where available):

Variable	Value
Minimum Card	$25
Minimum Student	$50
Minimum Car	$479
Minimum Mortgage	0.5%
Minimum Other	$25

[6] The "car" variable actually tracks overall *vehicular* debt. The one very high value in this category (about $44 million) is theorized to be a very expensive yacht or personal aircraft, or else the debt of a compulsive collector.

The limitations of the available data and assumptions for both percentage values and minimum payment values are discussed in Section V.

Finally, the results of these calculations were also scanned for the following noteworthy occurrences in the time-to-pay (TTP) calculations:

1) **(Large)** TTP for least efficient method(s) is extremely large – 100 years or more.[7]
2) **(Immediate)** TTP is extremely small for least efficient method(s) – 0 or 1 months.
3) **(Equal)** No difference between fastest and slowest methods.
4) **(Similar)** Very small difference between fastest and slowest methods (3 months or fewer difference).
5) **(Different)** Large difference between fastest and slowest methods (12+ months).
6) **(Very Different)** Extreme difference between fastest and slowest methods (100 years for snowball, "normal" range for traditionalist).
7) **(Fastest Method)** Which of the two methods is the fastest with for a given income fraction.

Results and analysis are provided in Section V.

V – Results / Discussion

The output produced by the MATLAB analysis was surprising, and contradictory to expectations of a significantly faster time-to-pay for the avalanche approach. The table below contains the findings of the MATLAB analysis, with sub-sections devoted to each variable. All values are in number of overall households out of the complete sample size (N = 6248) exhibiting the relevant behavior for a given fraction of consumer income (5% to 80%). No values overlap – that is to

[7] 1200 month TTP used as cutoff value in program. If a given household will not pay off its debt (under given assumptions about monthly disposable income) in 100 years, then the author feels it is reasonably safe to conclude that they will not be out of debt in the next hundred either, unless something in household income or household spending changes.

say, a household will not be in multiple categories, excluding the measure of which method is fastest.

Fraction	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40
Infinite	1863	1093	630	379	224	153	117	93
Small	1729	1729	1729	1729	1729	1729	1729	1729
Equal	1221	1627	1994	2268	2518	2740	2912	3052
Similar	383	663	878	1023	1070	1038	1029	996
Different	731	697	555	436	351	255	181	145
Very Different	0	0	0	0	0	0	0	0
Snowball Fastest	927	751	481	311	201	142	98	75
Avalanche Fastest	1114	1009	907	771	644	537	427	350
Fraction	**0.45**	**0.50**	**0.55**	**0.60**	**0.65**	**0.70**	**0.75**	**0.80**
Infinite	84	76	69	61	57	52	50	48
Small	1729	1729	1729	1729	1729	1729	1729	1729
Equal	3151	3297	3365	3398	3469	3563	3650	3663
Similar	991	916	898	896	864	801	738	731
Different	101	68	58	49	35	31	28	23
Very Different	0	0	0	0	0	0	0	0
Snowball Fastest	54	41	38	33	26	21	18	16
Avalanche Fastest	281	225	178	154	124	99	79	76

Infinite (Impossible to Pay)

This variable tracks how many of the SCF households would be unable ever to pay off their outstanding debts, using a cutoff point of 100 years. This statistic starts out very high, then drops exponentially as income fractions rise from 5% to 25%, decreasing steadily from there.

Small (Immediate Payment)

This variable tracks how many households would pay all of their debts in a month or less. Of the households surveyed, 1729 (27.6%) had no outstanding debt, or so little debt that for any given fraction of consumer income (5% - 80%), their individual time-to-pay was immediate. The number of such households remained constant for any debt fraction values used, supporting the hypothesis that these households were debt-free to being with.

Equal (Same Time-to-Pay)

This variable indicates how many households have exactly the same time-to-pay. The number starts out large, increasing steadily as consumer income shares increase. This trend in the data indicates that for larger values of consumer disposable income, time and interest differences between the avalanche and snowball methods decrease accordingly. For very large shares of consumer income (50% - 80%), more than 50% of all households had an equal time-to-pay between the two methods.

Similar (< 3 months difference)

Of all the data points, the number of households for which the avalanche and snowball methods produce a similar (but not equal) time-to-pay seems to be the most variable. The overall number climbs quickly between income fractions of 5% and 25%, but declines from there, making small resurgences between 35-40% and 50-55%. One likely explanation for this tendency is that increasing amounts of disposable income means that more and more households are being absorbed into the “Equal” category, as the relative difference between the two methods evaporates.

Different (12+ months difference)

“Different” households are ones where there is a large difference between the efficiency of the avalanche and snowball methods – a year or more. This number begins relatively large (about 10% of all households), but becomes almost negligible around the 40-50% income mark. Few households appear to be very strongly affected by the choice between either method. For the households that are, the avalanche method is obviously a much better overall strategy than the snowball.

Very Different

This analysis found no evidence of households for which the difference between the avalanche and snowball methods was very large – the theoretical maximum of 100 years for the snowball method versus a more finite amount for the avalanche method. From this, it is reasonable to conclude that any households reaching the 100 year mark for debt payment will do so regardless of which method is used. This result did not change with income fraction.

Fastest Method

For all analyzed income fractions, the avalanche method proved to be consistently more efficient than the snowball method in overall number of households. The number of households for which one was definitively faster than the other dropped quickly with increasing income fraction. Interestingly, even as the number of definitive households dropped, the overall ratio of one method to the other increased significantly, in favor of avalanche.

Overall

The preceding sections tell a compelling story – while there appears to be an overall greater efficiency of the avalanche method over the snowball, this efficiency is not large. If 40-50%[8] disposable income is used as a realistic example of consumer behavior, about half (48.8 - 52.7%) would have an equal time-to-pay whichever method they used, and of the remaining households, about one-third would have a difference of less than three months, with only 1-2% having a large (12+ months) difference in time-to-pay.

These conclusions do rely on a number of assumptions, as detailed in the previous section. First, this analysis relies on a simplified model. Only included in this model are overall household income, overall debt, and several generous assumptions about interest rates and

[8] Per the commonly-used 50/30/20 heuristic, where 50% of one's income goes toward debts and basics,

minimum payments for 2016. Second, this model assumes a clockwork regularity on the part of each consumer in debt payment – that is, missed payments or monthly fluctuations are not part of the data. Third, the SCF does not provide the interest rates for individual consumer debts. All yearly (or monthly) interest rates were estimated from the averages from 2016. Fourth, minimum payment values were also estimated from 2016 averages (or federal minimums for certain loan types), and are likely underestimated in some cases. Fifth, certain categories, as noted previously, have a number of large outlier values that may produce odd results here and there.[9] Finally, this data applies certain assumptions universally, and does not account well for households where the "other" or "car" debt categories are unusually large or households with unusual overall income-debt ratios.[10]

VI – Conclusion

Despite the limitations mentioned, the robustness of the analysis' conclusions should not be underestimated. For nearly all changes and refinements made to the project code over time, the overall consensus did not vary: while the Debt Avalanche is obviously the numerically superior method in the vast majority of cases, Ramsey's Debt Snowball is a very close competitor. Further, the avalanche method does not offer significant psychological benefits to the consumer – if anything, the prospect of paying a very large debt is much more daunting than paying a smaller one. If the goal is for the individual consumer to simply pay off their debts the most quickly, and the consumer has no motivational or habitual issues that might complicate this,

[9] Though, as also noted previously, these are so uncommon as to be statistically insignificant (< 0.2% of households).

[10] An appreciable number of household in the Survey had significant outstanding debt with no income, very large debt for small income or unusually-large debt in the "other" category, for which a $25 minimum monthly payment would be realistically inadequate. While it is expected that these would fall into the outlier categories above, they are still a complicating feature of the data.

the avalanche (or the traditionalist approach) will nearly always be the superior choice. If poor habits of personal finance or motivation are a complicating factor in the consumer's life, on the other hand, then the analysis here would lend credence to Ramsey's recommendations to use the snowball method. This conclusion is much weaker for very small overall fractions of consumer income disposable toward debt, but becomes much stronger at realistic fractions and higher.

Overall, this analysis provides compelling evidence in favor of the debt snowball as a viable method for debt relief. When applied to a very large, very meticulous sample of real-world data, the snowball's empirical performance was equal or very close to the debt avalanche in a large majority of cases. Further, the psychological benefits discussed in Section III[11] recommend it strongly to debt-ridden consumers, as the avalanche method can be daunting to households facing a very large debt to pay up front before moving on to the next source. The effects of cyclical economic variables, random variance, population and geography (county, state, country, etc.) on the efficacy of the two methods were not included as part of the analysis, but may be addressed in a future publication. The author would like to conclude by recommending further explanation into this subject based on additional data sets,[12] especially ones with more specific per-consumer data on individual debts' minimum payments, interest rates, and behavior patterns relating to debt.

[11] By Amar & Ariely 2011, Eisenstein & Hoch 2005, Hsee 1996, Brown & Lahey 2014 and Gal & McShane 2012, among others.
[12]

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Survey of Consumer Finance

Appendix A – Theoretical Times-To-Pay (from Section II)

Method	Avalanche			Snowball		
Period	D1	D2	D3	D1	D2	D3
0	2500	4000	1000	1000	2500	4000
1	2200	4175	1015	590	2625	4175
2	1882	4358.75	1030.6	163.6	2757.5	4358.75
3	1544.92	4551.688	1046.824	-279.856	2618.094	4551.688
4	1187.615	4754.272	1063.697		2300.18	4754.272
5	808.8721	4966.985	1081.245		1963.19	4966.985
6	407.4044	5190.335	1099.495		1605.982	5190.335
7	-18.1513	5406.7	1118.474		1227.341	5424.851
8		5202.035	1138.213		825.9812	5671.094
9		4987.137	1158.742		400.5401	5929.649
10		4761.494	1180.092		-50.4275	6150.704
11		4524.568	1202.295			5958.239
12		4275.797	1225.387			5756.151
13		4014.587	1249.403			5543.958
14		3740.316	1274.379			5321.156
15		3452.332	1300.354			5087.214
16		3149.948	1327.368			4841.575
17		2832.446	1355.463			4583.654
18		2499.068	1384.681			4312.836
19		2149.022	1415.068			4028.478
20		1781.473	1446.671			3729.902
21		1395.546	1479.538			3416.397
22		990.3237	1513.72			3087.217
23		564.8398	1549.268			2741.578
24		118.0818	1586.239			2378.657
25		-351.014	1273.675			1997.589
26			824.6215			1597.469
27			357.6064			1177.342
28			-128.089			736.2094
29						273.0199
30						-213.329

Note that this table assumes a total paid of 500 for each period, with a minimum payment of 25 subtracted for each unpaid debt. The first column assumes 450 paid to its debt, with 25 to the second and third columns of each section. The second column assumes a payment of 475, and the third column assumes 500. A negative debt is immediately rolled into the next debt, or the cell to its immediate right.

Appendix B – MATLAB Code

(Original code available from author upon request. Several minute runtime, depending on machine.)

```
%---------------------------------------------------------------------------
% Title:              SCFcalc.m
% Author:             Evan McAllister
% Last Updated:       12/13/18
%
% Description:
% This file imports data from an Excel spreadsheet of the Survey of
% Consumer Finance and uses it to calculate the length of time it would
% take for individual consumers to pay off their various debts, using both
% the traditional and "debt snowball" models for debt payment. Output of
% findings is put into an additional Excel spreadsheet.
%---------------------------------------------------------------------------

% Note: This code relies on the Spreadsheet provided in the 2016 SCF.
%       Column values are hardcoded under "SCF DATA IMPORTS" below.

%---------- VARIABLES -----------------------------------------------------
%
% Variable Name - (Type)          Description
% -------------   ------          ------------
% INPUT_NAME    - (String)        Name of input file
% OUTPUT_NAME   - (String)        Name of output file
%
% rCAR          - (Double)        2016 Car loan rate
% rEDU          - (Double)        2016 Education loan rate
% rCARD         - (Double)        2016 Credit card debt rate
% rMORT         - (Double)        2016 Mortgage rate
% rOTHER        - (Double)        2016 Estimated rate for other debts
% DIS           - (Double)        Fraction of yearly income paid to debt
%
% income        - (Double Array)  SCF incomes
% cardDebt      - (Double Array)  SCF credit card debts
% eduDebt       - (Double Array)  SCF education debts
% carDebt       - (Double Array)  SCF car debts
% mortDebt      - (Double Array)  SCF mortgage debts
% otherDebt     - (Double Array)  SCF other debts
% otherDebt2    - (Double Array)  SCF additional other debts
%
% rows          - (Int)           Number of rows in SCF arrays
% debtArr       - (Double Array)  3D array of all debts and rates
% tempArr       - (Double Array)  Temporary copy of debtArr
% sorted        - (Double Array)  Sorted first layer of debtArr
% index         - (Int Array)     Index of sorted
% level2        - (Double Array)  Sorted second level of array
% level3        - (Double Array)  Sorted third level of array
% ii            - (Int)           Loop index variable (reused)
% jj            - (Int)           Loop index variable (reused)
% kk            - (Int)           Loop index variable (reused)
```

```
% month          - (Int)           Time (in months) to pay off all debt
% monthIncome    - (Double)        1/12 yearly income multiplied by DIS
% monthPay       - (Double)        Monthly income after minimum payments
%
% avTime         - (Int Array)     Array of "avalanche" payoff times
% snowTime       - (Int Array)     Array of "snowball" payoff times
% finArr         - (Int Array)     Combination of quickTime and snowTime
% statArr        - (Int Array)     Data distribution for DIS values
%
% tpLarge        - (Int)          # of data points equal to 1200
% tpSmall        - (Int)          # of data points equal to 0 or 1
% tpEqual        - (Int)          # of data points equal to each other
% tpSimilar      - (Int)          # of data points similar to each other
% tpDiff         - (Int)          # of data points dissimilar
% tpVeryDiff     - (Int)          # of data points very dissimilar
% avFast         - (Int)          # of times Avalanche fastest
% snowFast       - (Int)          # of times Snowball fastest
% col            - (Int)          location in statArr for current DIS
% ------------------------------------------------------------------------

%---------- CONSTANT VALUES ----------

clc;
clear;
format bank;

% EXCEL FILE NAMES
INPUT_NAME = 'SCFP2016';
OUTPUT_NAME = 'Results';

% RATES (Estimated)
rCAR    = 0.045;    % Simple est. 2016 auto loan rate
rEDU    = 0.043;    % Simple est. 2016 education loan rate
rCARD   = 0.150;    % Simple est. 2016 card loan rate
rMORT   = 0.037;    % Simple est. 2016 mortgage rate
rOTHER  = 0.050;    % Assuming 5% for other debts.

%---------- CALCULATIONS ----------

% SCF DATA IMPORTS
income     = xlsread(INPUT_NAME, 'W:W');        % Yearly household income
cardDebt   = xlsread(INPUT_NAME, 'IG:IG');      % Card balance
eduDebt    = xlsread(INPUT_NAME, 'IK:IK');      % Education debt
carDebt    = xlsread(INPUT_NAME, 'IJ:IJ');      % Vehicle debt
mortDebt   = xlsread(INPUT_NAME, 'HM:HM');      % Primary mort. debt
otherDebt  = xlsread(INPUT_NAME, 'IR:IR');      % Other debt
otherDebt2 = xlsread(INPUT_NAME, 'IM:IM');      % Other installment debt

fprintf('\nData Imported');

% AVERAGE/COMBINE MULTIPLE-INPUT DATA FROM SCF
income     = reduceAvg(income, 5);
cardDebt   = reduceAvg(cardDebt, 5);
eduDebt    = reduceAvg(eduDebt, 5);
carDebt    = reduceAvg(carDebt, 5);
```

```matlab
mortDebt   = reduceAvg(mortDebt, 5);
otherDebt  = reduceAvg(otherDebt, 5);
otherDebt2 = reduceAvg(otherDebt2, 5);

rows = length(income);

% COMBINE OTHER DEBTS
for ii = 1:1:rows
    otherDebt(ii) = otherDebt(ii) + otherDebt2(ii);
end

fprintf('\nData Averaged & Combined');

% CREATE DEBT ARRAYS
debtArr = zeros(rows, 5, 3);
avArr = zeros(rows, 5, 3);

for ii = 1:1:rows
  % Array for snowball calculations.
  debtArr(ii, 1, 1) = cardDebt(ii);
  debtArr(ii, 2, 1) = eduDebt(ii);
  debtArr(ii, 3, 1) = carDebt(ii);
  debtArr(ii, 4, 1) = mortDebt(ii);
  debtArr(ii, 5, 1) = otherDebt(ii);

  debtArr(ii, 1, 2) = rCARD;
  debtArr(ii, 2, 2) = rEDU;
  debtArr(ii, 3, 2) = rCAR;
  debtArr(ii, 4, 2) = rMORT;
  debtArr(ii, 5, 2) = rOTHER;

  debtArr(ii, 1, 3) = 25;
  debtArr(ii, 2, 3) = 50;  %Min student loan payment 2016
  debtArr(ii, 3, 3) = 479; %Avg Monthly Car Payment 2016
  debtArr(ii, 4, 3) = 0.005 * debtArr(ii, 4, 1); %0.5% of mortgage
  debtArr(ii, 5, 3) = 25;

  % Array for avalanche (traditionalist) calculations.
  avArr(ii, 1, 1) = cardDebt(ii);
  avArr(ii, 2, 1) = otherDebt(ii);
  avArr(ii, 3, 1) = carDebt(ii);
  avArr(ii, 4, 1) = eduDebt(ii);
  avArr(ii, 5, 1) = mortDebt(ii);

  avArr(ii, 1, 2) = rCAR;
  avArr(ii, 2, 2) = rOTHER;
  avArr(ii, 3, 2) = rCARD;
  avArr(ii, 4, 2) = rEDU;
  avArr(ii, 5, 2) = rMORT;

  avArr(ii, 1, 3) = 479;
  avArr(ii, 2, 3) = 25;
  avArr(ii, 3, 3) = 25;
  avArr(ii, 4, 3) = 50;
  avArr(ii, 5, 3) = 0.005 * avArr(ii, 5, 1);
```

```
end

% SORT SNOWBALL ARRAY & RATES
[sorted, index] = sort(debtArr, 2);
level2 = zeros(size(sorted,1), size(sorted,2));
level3 = zeros(size(sorted,1), size(sorted,2));

for ii = 1:(size(sorted,1))
    for jj = 1:(size(sorted,2))
        level2(ii,jj) = debtArr(ii, index(ii, jj), 2);
        level3(ii,jj) = debtArr(ii, index(ii, jj), 3);
    end
end

% Replace 2nd and 3rd layers with matching original layers.
sorted(:,:,2) = level2;
sorted(:,:,3) = level3;

debtArr = sorted;

fprintf('\nDebt-Rate Array Created & Sorted\n');

% Prepare Array of Descriptive Stats
% (# of variables, 16 fractions + 1)
statArr = zeros(9,17);

% Future Note: Apply overpaid "rollover" money to next period.

% Very Large Loop
for DIS = 0.05:0.05:0.8

    avTime   = zeros(rows, 1);
    snowTime = zeros(rows, 1);

    % CALCULATE TIME TO PAYMENT (Largest Interest First) (Avalanche)
    tempArr = avArr;
    for ii = 1:rows

        month = 1;
        monthIncome = (income(ii) / 12) * DIS;

        for jj = 1:1:size(tempArr,2)
            while (tempArr(ii,jj) > 0)

                monthPay = monthIncome;

                for kk = jj:1:size(tempArr, 2)

                    if (tempArr(ii,kk,1) > 0)
                        monthPay = monthPay - tempArr(ii,kk,3);
                        tempArr(ii,kk,1) = tempArr(ii,kk,1)...
                        - tempArr(ii,kk,3);
                    end
```

```
            end

            if (monthPay < 0)
                monthPay = 0;
            end

            tempArr(ii,jj) = tempArr(ii,jj) - monthPay;
            month = month + 1;

            if (mod(month,12) == 0)
                for kk = 1:size(tempArr,2)
                    tempArr(ii,kk) = tempArr(ii,kk)...
                        + tempArr(ii,kk) * tempArr(ii,kk,2);
                end
            end

            if (month >= 1200) %100 years
                break
            end

        end

        if (month >= 1200) %100 years
            break
        end
    end

    avTime(ii) = month;
end

% CALCULATE TIME TO PAYMENT (SMALL --> LARGE) (SNOWBALL)
tempArr = debtArr;
for ii = 1:rows

    month = 1;
    monthIncome = (income(ii) / 12) * DIS;

    for jj = size(tempArr,2):-1:1
        while (tempArr(ii,jj) > 0)

            monthPay = monthIncome;

            for kk = size(tempArr, 2):-1:jj

                if (tempArr(ii,kk,1) > 0)
                    monthPay = monthPay - tempArr(ii,kk,3);
                    tempArr(ii,kk,1) = tempArr(ii,kk,1)...
                    - tempArr(ii,kk,3);
                end

            end

            if (monthPay < 0)
                monthPay = 0;
```

```
            end

            tempArr(ii,jj) = tempArr(ii,jj) - monthPay;
            month = month + 1;

            if (mod(month,12) == 0)
                for kk = 1:size(tempArr,2)
                    tempArr(ii,kk) = tempArr(ii,kk)...
                        + tempArr(ii,kk) * tempArr(ii,kk,2);
                end
            end

            if (month >= 1200) %100 years
                break
            end

        end

        if (month >= 1200) %100 years
            break
        end
    end

    snowTime(ii,1) = month;
end

finArr = [avTime, snowTime];

tpLarge = 0;        % 1200
tpSmall = 0;        % 0 or 1
tpEqual = 0;        % equal
tpSimilar = 0;      % diff. < 3
tpDiff = 0;         % diff. > 12
tpVeryDiff = 0;     % small vs. 1200
snowFast = 0;       % how many times Snowball was fastest
avFast = 0;         % how many times Avalanche was fastest

for ii = 1:rows

    lg = max(finArr(ii,:));
    sm = min(finArr(ii,:));

    % Fill in stat variables
    if (lg == 1200)
        tpLarge = tpLarge + 1;
    elseif (sm <= 1 && lg <= 1)
        tpSmall = tpSmall + 1;
    elseif (lg == sm)
        tpEqual = tpEqual + 1;
    elseif ((lg - sm) <= 3)
        tpSimilar = tpSimilar + 1;
    elseif ((lg - sm) >= 12)
        tpDiff = tpDiff + 1;
    elseif (lg == 1200 && (lg - sm) <= 3)
        tpVeryDiff = tpVeryDiff + 1;
```

```
        end

        % Count which one is consistently faster
        if ((lg - sm) > 3)
            if (sm == finArr(ii,2))
                snowFast = snowFast + 1;
            else
                avFast = avFast + 1;
            end
        end

    end

    col = round((DIS/0.05) + 1);

    statArr(1, col) = DIS;
    statArr(2, col) = tpLarge;
    statArr(3, col) = tpSmall;
    statArr(4, col) = tpEqual;
    statArr(5, col) = tpSimilar;
    statArr(6, col) = tpDiff;
    statArr(7, col) = tpVeryDiff;
    statArr(8, col) = snowFast;
    statArr(9, col) = avFast;

    fprintf('Calculations complete for DIS = %0.2f\n', DIS);
end

xlswrite(OUTPUT_NAME, statArr);
fprintf('\nProgram Complete\n');


% ---------- FUNCTIONS -----------

% (Reduce Average) SCF data is entered five times per household.
% This function takes the average of each set of n-numbered
% consecutive entries and returns a new, smaller array of
% their averages, evening out discrepancies.
function ret = reduceAvg(arr, n)

   len = length(arr);
   step = n;
   count = 0;
   total = 0;
   newArr = zeros(1,(len / step));

   for ii = 1:1:(len / step)
       for jj = 1:1:step
           total = total + arr(count * step + jj);
       end

       total = (total / step);
       newArr(ii) = total;
       total = 0;
```

```
        count = count + 1;
    end

    ret = newArr;
end
```