Selecting the Optimal Credit Card Portfolio

Project Outline

ECO 6935 – Capstone in Business Analytics I

Remco A. Scheepmaker

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1 Introduction and Motivation

Credit cards are an important part of the American economy and culture. According to the Consumer Financial Protection Bureau (CFPB, 2023), consumers spent $3.2 trillion on purchases using credit cards in 2022. Total credit card debt recently passed $1 trillion, 82 percent of which is revolving (i.e. bearing interest, the remaining 18 percent is paid by the due date without being charged interest). The combination of income from interest, interchange fees and annual fees makes credit cards very profitable for the major banks, but they can also be profitable for a certain fraction of their users. A key feature of many credit cards is their rewards structure, which returns a percentage of the user's spend back to the user in the form of cash back, reward points, or miles.[1] Credit card rewards programs are designed by banks to attract new customers and improve their loyalty, as well as to increase income through interchange fees and interest by stimulating (over)spending. The CFPB estimates that the total dollar value of the rewards earned in 2022 exceeded $40 billion, and the average rewards-earning account redeemed $167.[2] These "earnings" are, of course, much less than the $130 billion charged to consumers in interest and fees, making credit cards such a profitable enterprise for banks.

[1] I consider points and miles to be the same for this project. Both can generally be redeemed for cash, statement credit, or used to book travel, either by transfering to loyalty programs of travel partners, or by booking flights and hotels directly through the bank's own travel portal.

[2] According to Experian, the average American has 3.9 credit card accounts (https://www.experian.com/blogs/ask-experian/average-number-of-credit-cards-a-person-has/, accessed June 1, 2024).

As we will see in more detail in the next section, credit card rewards work partially through what is called the "reverse Robin Hood" mechanism, since to some extend it is the poor who, by paying interest and fees, subsidize the rewards of the rich (The Wall Street Journal, 2010). More accurately, it is primarily the financially naïve who are sponsoring the financially sophisticated, where the level of sophistication seems best measured by credit scores from the Fair Isaac Corporation (FICO), as opposed to income (Agarwal, Presbitero, Silva, and Wix, 2023). For those interested in travel using credit card points, or just saving some money through cashback rewards, it is therefore crucial to learn good financial habits and eventually become part of the financially sophisticated demographic with high FICO scores.

Once credit card rewards are a net benefit, it might be worthwile to explore how we can optimize one's choice of credit cards to maximize this benefit. Which credit cards should different consumers select, and is there an optimal number before the marginal benefit of adding more cards becomes too small? These are the topics I would like to study in this project. My personal credit card portfolio has expanded from two to eleven credit cards over the last five years, increasing my net benefit from below two to about five percent of my entire annual spend. With this project, I aim to turn this experience into an optimization algorithm that can be applied at scale to different types of consumers. This might result in some interesting insights, and perhaps an online tool, that could benefit many sophisticated credit card users who would like to stretch their budgets, travel more, or who simply enjoy optimizing their personal finances.

2 Literature

The latest "Consumer Credit Card Market" report from the CFPB (2023) contains a wealth of information about how Americans use their credit cards, separated by FICO credit scores according to the levels shown in Table 1. The CFPB reports that more than 90 percent of the purchase volume is on rewards cards, and that the average rewards-earning account contained \$156 in 2022. But, as we can see in Fig. 1, accounts with high credit scores have considerably higher rewards balances compared to accounts with low credit scores. The CFPB also finds that people with prime plus or superprime credit scores keep zero, or very low, revolving balances, while their purchase volumes and payment rates are actually the highest. This is consistent with practicing good financial habits

	CFPB	Agarwal *et al.* (2023)
deep sub-prime	< 580	
sub-prime	580–619	< 660
near-prime	620–659	660–719
prime	660–719	720–779
prime plus	720–799	
super-prime	> 799	> 779

Table 1: FICO score thresholds used by the CFPB and Agarwal et al. (2023).

in order to enjoy the benefits of credit card rewards and reach a high FICO score.[3] The most important habit regarding rewards is to pay off statement balances *in full* by the due date each month (so no interest on revolving balances is paid). This implies only using credit cards for purchases that you can afford to pay off completely the next month.

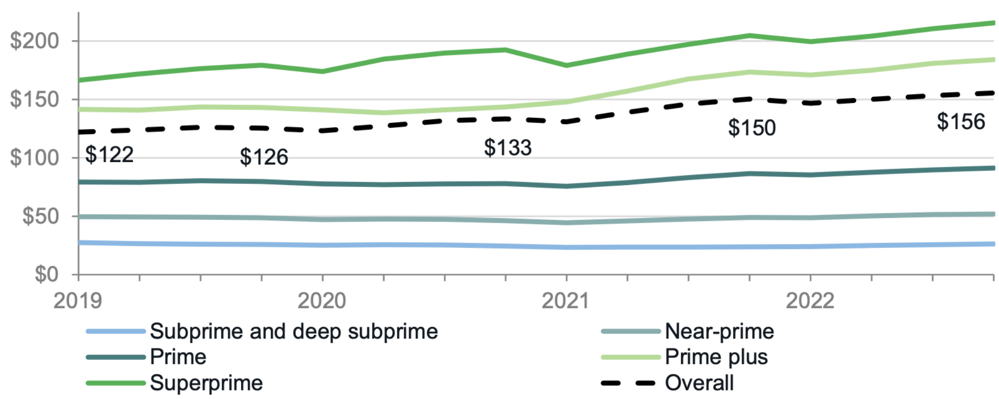

Figure 1: Quarterly dollar value of average rewards balances for different credit scores. Source: CFPB (2023).

While it is true that applying for new credit cards results in the banks "pulling" the applicant's credit report, lowering the credit score, it is important to note that this effect is only temporary. In the long run, opening many credit cards to optimize rewards can actually have a positive impact on credit scores, as the "utilization ratio" per card is lowered (the amount of spending on the card as a percentage of the credit limit). As an example, Fig. 2 shows a time series of my personal credit scores with the dates of nine credit card applications marked. Even with this above-average number of credit card applications, the overall trend in credit scores is positive.

Regarding the payment structure of rewards programs, Fumiko Hayashi (2009) shows a good

[3] Although the exact algorithm is proprietary, there are many online resources that explain what a FICO score consists of, and how one can improve it, e.g. `https://www.myfico.com/credit-education/credit-scores`.

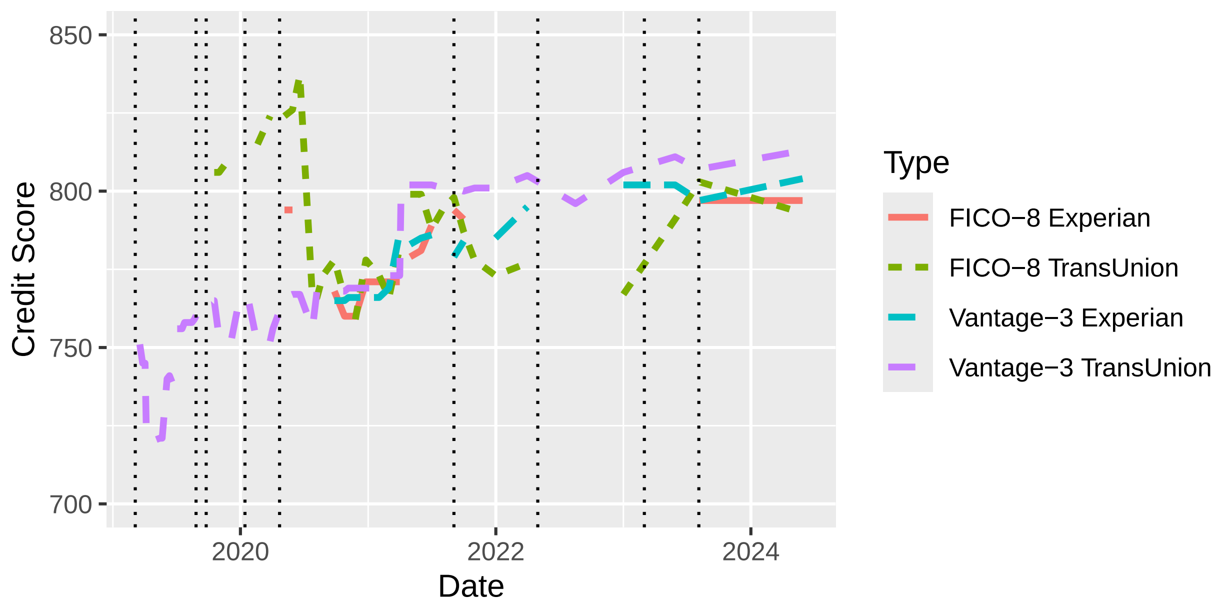

Figure 2: Time series of my personal credit scores. The vertical dotted lines mark the dates when new credit card accounts were opened.

overview of the payment fee flows between the merchant, the merchant acquirer (the bank that processes card payments for the merchant), the card issuer (the cardholder's bank) and the cardholder. In an example where the cardholder makes a $100 purchase, the merchant receives $97.50. The $2.50 in fees is split between the merchant acquirer ($0.50) and an interchange fee of $2.00 that is paid from the merchant acquirer to the card issuer. The card issuer pays a fraction of the interchange fee (say $1.00) as a reward to the cardholder, and also pays the card network (such as Visa or MasterCard), who set the interchange fees.[4] The merchant is likely to pass on these fees as higher retail prices to the consumer (regardless of the payment method). Hayashi (2009) concludes that it is not completely clear who ultimately pays for the rewards programs, but it seems likely that credit card rewards programs are not efficient markets.

Schuh, Shy, and Stavins (2010) find that it is cash-using households who are paying for the rewards of card-using households, which, due to the positive correlation between income and use of credit cards, translates to lower incomes paying for the rewards of higher incomes (the "reverse Robin Hood" mechanism). However, Agarwal, Presbitero, Silva, and Wix (2023) show that this

[4]American Express transactions work differently, as American Express operates its own network and simultaneously acts as both card issuer and merchant acquirer.

redistribution takes place from low to high FICO scores *regardless* of income. As Fig. 3 shows, it is primarily the super prime cardholders who have positive monthly net rewards, while the sub-prime and near-prime cardholders pay the most for using rewards cards. Interestingly, high-income, super-prime cardholders benefit the most ($20.1 in net rewards per month), primarily at the expense of *high-income* cardholders with low credit scores.

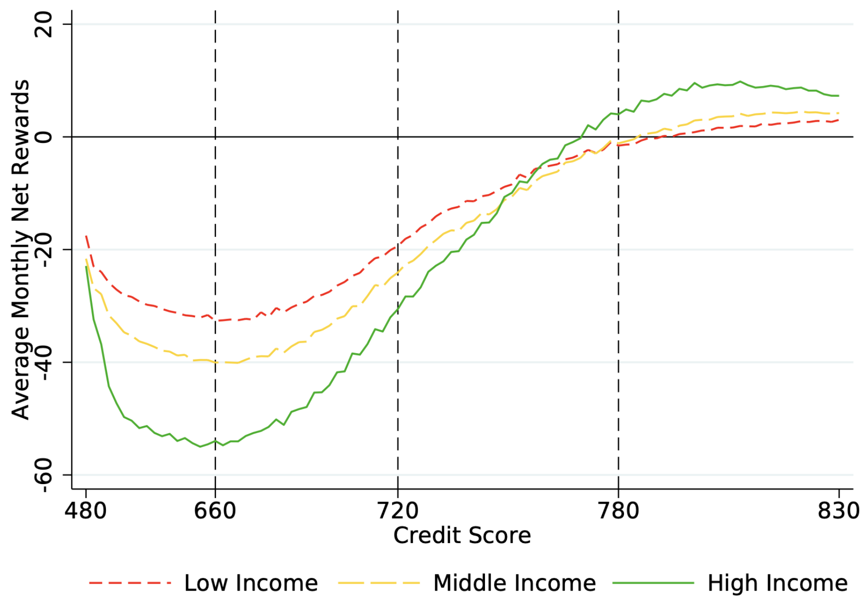

Figure 3: Average monthly net rewards by income and credit score. Source: Agarwal et al. (2023).

Agarwal, Presbitero, Silva, and Wix (2023) use FICO scores as a proxy for financial sophistication, and conclude that "sophisticated individuals profit from reward credit cards at the expense of naïve customers." They also estimate the aggregate annual redistribution to be $15 billion and find that the this redistribution takes place from less to more educated, poorer to richer, and high to low minority areas, widening existing disparities.

Even though in this project I do not have access to detailed data on people's income, zip codes, and credit card usage, it will be interesting to compare some of these results to a modeling exercise that accounts for different types of credit card users.

3 Theoretical Model

Above we have seen that, in order to maximize the net benefits of credit card rewards, we should show "sophisticated" financial behavior. Assuming we have such a sophisticated credit card user who never pays interest, and who spends her entire discretionary budget (staying within her means) on rewards credit cards, I will model the maximum net benefit for a different number of credit cards and for different types of users (e.g. users who will redeem credit card points for travel versus users who are only interested in cashback).

All reward credit cards come with certain point multipliers in specific categories, that will be multiplied with the spend in that category to calculate the number of points. For cashback rewards, the value of a point is per definition one cent, but for certain cards the value of a point can vary between a lower value (base value) and a higher value when redeemed for travel. Cards might also have an annual fee, or come with certain static benefits such as airport lounge access, travel or food credits, and discounts toward certain subscriptions such as Disney^{+}. In this project I will ignore sign-up bonuses (SUBs), which were 9.1 percent of total reward earnings in 2022 (CFPB, 2023), since these high (but one-time) SUBs will always result in a very high marginal benefit for relatively little spend. Including them would lead to the conclusion that it is always beneficial to open another account with a SUB into perpetuity.[5]

The problem of optimizing a credit card portfolio can be considered a *Dynamic Program*, since it requires an algorithm that uses simpler subproblems and stores intermediate solutions before the final solution is constructed. If we consider selecting K credit cards from a dataset of N possible cards, we start with a single card and add more cards later on, but only if this increases the net benefit. Therefore, the first subproblem is to the select the best single card and use it for all our spending categories. For adding an additional card, we have to iterate over all remaining possible cards and compare the value for each spending category to the previous card that we had already selected. If the total net benefit is higher, we keep the card in our portfolio and update the best card to use for each category. To select K cards, we have to repeat the search through all N possible cards K times, making this an algorithm with complexity $\mathcal{O}(N)$.

[5] People who keep opening new credit card accounts just for the SUB are known as *churners*.

4 Empirical Specification

The theoretical model described in Sect. 3 can be broken down into the following empirical specification. For every credit card k we have for the value earned per spending category c:

$$y_{kc} = x_{kc} m_{kc} \left[\eta v_{t,k} + (1 - \eta) v_{b,k} \right], \tag{1}$$

where x_{kc} is the spend on card k in category c, m_{kc} is the card multiplier for that category, $v_{t,k}$ and $v_{b,k}$ are the card's highest and lowest point redemption values, and η quantifies which fraction of the points are used for the higher-valued travel redemptions (a user-specific variable). The total value from spending is simply found by summing over the C possible categories:

$$s_k = \sum_{c=1}^{C} y_{kc}. \tag{2}$$

For the total benefit we add the static benefits b_k multiplied with the fraction of their use θ, subtract the annual fees f_k, and sum over all the K cards in our portfolio:

$$Y(\mathbf{X}, K, \eta, \theta | \mathbf{M}, \mathbf{v_t}, \mathbf{v_b}, \mathbf{b}, \mathbf{f}) = \sum_{k=1}^{K} (s_k + \theta b_k - f_k). \tag{3}$$

Here it is made explicit that the total benefit Y depends on user-specific variables $\mathbf{X}$ (the budget matrix with spending per card and category), K (the number of cards), η (the fraction of travel redemptions), and θ (the fraction of benefits used), and the card-specific parameters $\mathbf{M}$ (a matrix with the multipliers per card and category), $\mathbf{v_t}$ (a vector with travel point values), $\mathbf{v_b}$ (a vector with base values), $\mathbf{b}$ (a vector with benefits), and $\mathbf{f}$ (a vector with annual fees). The goal of this project is to study Y as a function of its variables, given the parameters.

5 Data

The empirical specification from Sect. 4 (Eq. 3) implies that we need data on rewards credit cards point multipliers, point values, benefits, and fees, as well as budget data for our credit card users.

5.1 Credit Card Data

There are many websites writing about rewards credit cards, their perks, and points structure. I mainly used the website allcards.com[6] to manually scrape the information on point multipliers and their caps (limits) from the most popular rewards credit cards from the seven major banks (American Express, Chase, Bank of America, Citi, Capital One, US Bank, and Wells Fargo). The bank websites were used to find some missing information, if needed. This resulted in a list of 27 unique credit cards.[7] However, some of the cards have a "custom" bonus reward category that can be chosen by the user (e.g. 5x points on groceries, or gas, or home improvement up to $6000 per year). These cards were treated as a separate credit card for each bonus category, bringing our total number of cards to 37.

For this project I will ignore the credit cards that are dedicated to users of very specific stores, hotels, or airlines, as well as cards with rather exotic or variable reward categories (such as "3x points on all mobile wallet payments", or "5x points on quarterly changing categories"), since these categories are impossible to map to our average budget that will be discussed in the next section. The results on total benefits should therefore be considered *lower limits*, as there are many cards that can bring additional benefits to loyal users of certain brands. In case the (prototype) model of this project is successful, I will consider adding other categories and credit cards, in combination with an online tool where a user can adjust a standard budget to his or her own spending patterns. The algorithm will then suggest the top cards to use to maximize the benefit for that specific budget.

A list of 18 common card spending categories was taken from the website cardpointers.com,[8] with the modification of removing "warehouse clubs" and "ride sharing", and adding "streaming" and "travel (other)", to facilitate a mapping of all the items on our budget to a spending category (see Sect. 5.2). The list of categories can be found in the first column of Table 2.

Annual fees were also collected for all the cards in the dataset, as well as an estimate for the static benefits. If a card has a travel or food credit, this credit was taken as a benefit at full value. A $100 "Global Entry / TSA Precheck" credit every five years was assumed as a $20 yearly benefit.

[6] `https://www.allcards.com` (accessed between June 3–9, 2024).

[7] Two cards, the "Citi Double Cash" and "Wells Fargo Active Cash" have identical multipliers and are included as a single card.

[8] `https://www.cardpointers.com/app/` (accessed between June 3–9, 2024).

Airport lounge access was valued at $40, which is approximately the value of two free meals with drinks.

For the base and travel values of the credit card points, I used the table from the Nerdwallet (2024) website. Finally, a boolean was added to indicate if the card is cash-back only (TRUE), or if the card allows for higher-valued travel redemptions (FALSE). This could potentially be used to filter for certain user preferences. All these credit card data were manually recorded in a Google Sheet and finally saved to the file `CreditCards.csv`. An exerpt of this file is shown in Fig. 4.

5.2 User Data

For our credit card users we need a vector $\mathbf{x}$ with the amount of spend per category. The optimization algorithm will allocate the spend for each category to the credit card with the highest multiplier, turning the vector $\mathbf{x}$ into a sparse matrix $\mathbf{X}$. Although detailed credit card account data from real users would be very valuable for this project, regulations and privacy concerns make these data practically unavailable for researchers outside of the banking sector. I will therefore have to make a realistic estimate of the average spending of Americans, for which I will use the 2022 Consumer Expenditure Survey (CES) from the Bureau of Labor Statistics (BLS, 2023).

According to the CES, the average annual expenditures in 2022 were $72,967 (after savings), from an average income before taxes of $94,003. To approximate the amount that can be spend on credit cards, I subtracted from the $72,967 the expenses on shelter (such as mortgage, rent, property taxes), vehicle purchases, health insurance, education, cash contributions, personal insurance, and pensions. The resulting budget totals to $38,576 or 41 percent of the average gross income. The remaining CES items were then mapped to the credit card spending categories according to Table 2. Note that some items were split 50/50 over multiple credit card categories, to make sure that all the categories were populated with some reasonable spend. For example, I assumed that the CES item “Apparel and services” is split 50/50 between the “Online shopping” and “Department store” credit card categories.

Category	Expenditure [$]	%	Consumer Expenditure Survey Items
Everything else	7,786	20.18	Household operations, Vehicle finance charges, Maintenance and repairs, Vehicle insurance, Medical services and supplies, Reading, Tobacco, Miscellaneous
Groceries	6,362	16.49	Food at home, Laundry and cleaning supplies, Other household products
Dining	4,222	10.94	Food away from home, Alcoholic beverages
Gas	3,120	8.09	Gasoline, other fuels, and motor oil
Utility	3,117	8.08	Utilities, fuels and public services
Home improvement	2,606	6.76	Household furnishings and equipment
Online shopping	1,881	4.87	50% Apparel and services, Pets, toys, hobbies, and playground equipment
Drug store	1,481	3.84	Drugs, Personal care products and services
Travel (other)	1,460	3.78	50% Other lodging, 50% Vehicle rental, leases, licenses and other charges, 50% Public and other transportation
Phone	1,431	3.71	Telephone services
Streaming	1,020	2.64	Audio and visual equipment and services
Department store	973	2.52	50% Apparel and services
Entertainment	833	2.16	Fees and admissions
Cable internet	698	1.81	Other entertainment supplies, equipment, and services
Hotel (portal)	644	1.67	50% Other lodging
Airline (portal)	423	1.10	50% Public and other transportation
Car rental (portal)	394	1.02	50% Vehicle rental, leases, licenses and other charges
Office supplies	128	0.33	Postage and stationery
Total	38,576	100.00	

Table 2: The average credit card budget as derived from the 2022 BLS Consumer Expenditure Survey.

id	bank	name	fee	benefits	cash_only	base_value	travel_value	travel_other	travel_other_cap	airline_portal	airline_portal_cap	hotel_portal	hotel_portal_cap	car_portal	car_portal_cap	groceries	groceries_cap
1	Amex	Blue Cash Preferred	95	84	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	6	6000
2	Amex	Blue Cash Everyday	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	3	6000
3	Amex	Everyday Preferred	95	0	FALSE	0.01	0.02	1	0	2	0	2	0	2	0	3	6000
4	Amex	Everyday	0	0	FALSE	0.01	0.02	1	0	1	0	1	0	1	0	2	6000
5	Amex	Green	150	229	FALSE	0.01	0.02	3	0	3	0	3	0	3	0	1	0
6	Amex	Gold	250	240	FALSE	0.01	0.02	3	0	3	0	1	0	1	0	4	25000
7	Amex	Platinum	695	1044	FALSE	0.01	0.02	5	500000	5	500000	5	0	1	0	1	0
8	Chase	Freedom Unlimited	0	0	TRUE	0.01	0.01	1.5	0	5	0	5	0	5	0	1.5	0
9	Chase	Sapphire Preferred	95	50	FALSE	0.0125	0.026	2.1	0	5.1	0	5.1	0	5.1	0	1	0
10	Chase	Sapphire Reserve	550	360	FALSE	0.015	0.027	3	0	10	0	10	0	10	0	1	0
11	Chase	Amazon Prime	0	0	TRUE	0.01	0.01	1	0	5	0	5	0	5	0	1	0
12	BoA	Premium Rewards	95	120	TRUE	0.01	0.01	2	0	2	0	2	0	2	0	1.5	0
13	BoA	Travel Rewards	0	0	FALSE	0.01	0.01	1.5	0	3	0	3	0	3	0	1.5	0
14	BoA	Unlimited Rewards	0	0	TRUE	0.01	0.01	1.5	0	1.5	0	1.5	0	1.5	0	1.5	0
15	BoA	Customized Cash Dining	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	2	10000
16	BoA	Customized Cash Online	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	2	10000
17	BoA	Customized Cash Gas	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	2	10000
18	BoA	Customized Cash Home	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	2	10000
19	BoA	Customized Cash Drug	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	2	10000
20	Citi / Wells Fargo	Double/Active Cash	0	0	TRUE	0.01	0.01	2	0	2	0	2	0	2	0	2	0
21	Citi	Strata Premier	95	0	FALSE	0.01	0.015	3	0	10	0	10	0	10	0	3	0
22	Citi	Custom Cash Gas	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	1	0
23	Citi	Custom Cash Groceries	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	5	6000
24	Citi	Custom Cash Dining	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	1	0
25	Citi	Custom Cash Streaming	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	1	0
26	Citi	Custom Cash Drugs	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	1	0
27	Citi	Custom Cash Home	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	1	0
28	Citi	Custom Cash Entertainment	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	1	0
29	CapOne	Venture X	395	460	FALSE	0.01	0.017	2	0	5	0	10	0	10	0	2	0
30	CapOne	Venture	95	20	FALSE	0.01	0.017	2	0	2	0	5	0	5	0	2	0
31	CapOne	Venture One	0	0	FALSE	0.01	0.017	1.25	0	1.25	0	5	0	5	0	1.25	0
32	CapOne	Savor	95	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	3	0
33	CapOne	Savor One	0	0	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	3	0
34	US Bank	Altitude Connect	95	90	TRUE	0.01	0.01	4	0	4	0	5	0	5	0	2	0
35	US Bank	Altitude Go	0	15	TRUE	0.01	0.01	1	0	1	0	1	0	1	0	2	0
36	Wells Fargo	Autograph Journey	95	50	FALSE	0.01	0.015	3.5	0	4	0	5	0	3	0	1	0
37	Wells Fargo	Autograph	0	0	FALSE	0.01	0.015	3	0	3	0	3	0	3	0	1	0

Figure 4: Exerpt of the file `CreditCards.csv` with all the 37 credit cards shown, but only 5 of the 18 categories with multipliers and their corresponding caps.

The CES also provides expenditures separated by nine income levels. I have repeated the above construction of the average budget also for these nine income bins separately, and saved the results in the file `BudgetIncome.csv`. This allows for selecting the most appropriate budget as a function of the user's income (before taxes). Our model will then predict the total credit cards benefit as a function of this income, as well as η, θ, and the number of credit cards K (see Sect. 4). Initially I will assume the average budget of Table 2 (that corresponds to an average income of \$94k), as well as the budgets corresponding to an income of \$45k (low) and \$160k (high). For η and θ I will assume values of 0, 0.5 and 1. These values can easily be adjusted, however, so I might include other values in my sensitivity analysis, in case more granularity is required.

If successful, the prototype model will be expanded to a Monte Carlo Simulation by making many draws (with replacement) from an income distribution taken from the U.S. Census Bureau, in combination with sampling η and θ from uniform distributions. Such a simulation should give a reasonable estimate of the average net benefit and standard deviation for Americans who use an optimized credit card portfolio.

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