# The Impact of Credit Counseling on Consumer Outcomes: Evidence from a National Demonstration Program

Stephen Roll<sup>1</sup> John Glenn College of Public Affairs The Ohio State University

Stephanie Moulton<sup>2</sup> John Glenn College of Public Affairs The Ohio State University

February 1, 2016

# WORKING DRAFT

#### Abstract:

Despite purported benefits, relatively little is known about credit counseling's impact on consumer outcomes. This analysis leverages data on more than 6,000 clients completing credit counseling through a national demonstration program implemented by the National Foundation for Credit Counseling. Administrative data is linked to quarterly credit report data for 18 months post completion of counseling services. In partnership with Experian, a matched comparison group is generated through Coarsened Exact Matching (CEM). We estimate a series of differences-in-differences models to trace the evolution of credit outcomes for the counseling group relative to the matched comparison group. The results demonstrate that counseling clients have reductions in both total debt and revolving debt relative to the matched comparison group. These reductions hold even when accounting for client bankruptcies, foreclosures, debt charge-offs or participation in a debt management plan (DMP). Clients with weaker credit profiles also demonstrate improvements in payment delinquency metrics relative to the comparison group.

This manuscript has been prepared as part of an evaluation of the Sharpen Your Financial Focus program, which is being jointly conducted by The Ohio State University and the National Foundation for Credit Counseling.

<sup>&</sup>lt;sup>1</sup> Doctoral candidate; roll.48@osu.edu

<sup>&</sup>lt;sup>2</sup> Associate professor; moulton.23@osu.edu

# 1. Introduction

Credit counseling has been available in the U.S. since the 1960s through a network of nonprofit credit counseling organizations. Credit counseling agencies started to increase in number in the 1990s following a period of increased household access to credit markets, eventually reaching millions of people per year in the 2000s (Loonin & Plunkett, 2003). These agencies typically target individuals going through an unexpected financial shock or who are looking to resolve general credit or debt payment difficulties. Services include individualized budget and debt counseling, financial education, access to community resources, and enrollment in debt management plans (DMPs).

Despite purported benefits, relatively little is known about credit counseling's impact on consumer outcomes. To date, there has only been one systematic evaluation of credit counseling, which found modest improvements in the credit scores of high-risk consumers, while the results were more mixed for the general counseling population (Elliehausen, Lundquist, & Staten, 2007). That evaluation, however, only focuses on credit indicators at two points in time (the year a client received counseling and three years after they received counseling), which may ignore critical shorter-term changes in consumer credit profiles. It also does not separate the impact of credit counseling from the impact of debt management plans or debt write-offs (e.g. from bankruptcy, foreclosure, or debt charge-offs by creditors), which are often associated with credit counseling.

This study addresses these gaps in the literature through an evaluation of a nationwide credit counseling program called Sharpen Your Financial Focus, an initiative launched by the National Foundation for Credit Counseling (NFCC) in September of 2013.<sup>3</sup> The Sharpen initiative builds upon and enhances the standard counseling model implemented by NFCC affiliate agencies. Specifically, credit counseling offered by affiliate agencies via the Sharpen initiative incorporates three major steps: A financial stress test aimed at increasing clients' awareness of their own financial activities and overall financial health; a financial review with an NFCC-certified financial professional to help clients establish goals and action plans; and a targeted education or "deep dive" intervention that provides additional information on a financial area of interest or concern to the client.

As of March 2015, more than 40,000 consumers have received credit counseling services under the Sharpen Initiative. For this analysis, we leverage data on more than 6,000 clients enrolling during the first quarter of the initiative, for whom administrative data can be linked to quarterly credit report data for 18 months post completion of counseling services. In partnership with Experian, a matched comparison group is generated through Coarsened Exact Matching (CEM). We estimate a series of differences-in-differences models to trace the evolution of credit outcomes for the counseling group relative to the matched comparison group, from a pre-counseling baseline period to six quarters post-counseling. In addition to estimating the impact of counseling, our data and modeling approach allow us to account for other time-varying credit interventions post-counseling, including bankrupticies, charge-offs and foreclosures. In an alternative specification, we trace outcomes separately for counseling clients enrolling in DMPs.

<sup>&</sup>lt;sup>3</sup> The NFCC is an umbrella membership organization representing more than 80 affiliate nonprofit financial and credit counseling agencies nationwide.

The results indicate that Sharpen clients enter the counseling program at times of substantial financial distress, as indicated by higher rates of account delinquencies and declines in credit scores around the time of counseling. This is corroborated by administrative data tracking the reasons clients give for entering counseling, in which they frequently indicate seeking counseling because of job loss or an unexpected increase in expenses. After the initial decline in credit outcomes at the time of counseling, clients' credit scores and debt payment behaviors return to their pre-counseling levels about one year after counseling and begin to exceed their pre-counseling levels by the end of the evaluation period.

Relative to the comparison group, Sharpen clients make significant reductions in their debt balances after counseling. Specifically, Sharpen clients have reductions in both total debt and revolving debt relative to the matched comparison group. These reductions hold even when accounting for client bankruptcies, foreclosures, debt charge-offs or participation in a debt management plan (DMP). Clients participating in agency-sponsored DMPs experience even greater reductions in debt balances relative to the comparison group. Further, Sharpen clients' available credit (as a percent of their revolving credit limit) increases post-counseling at a significantly higher rate than for the comparison group, indicative of improved borrowing capacity. Clients with weaker credit profiles also demonstrate improvements in payment delinquency metrics relative to the comparison group, though this improvement is not present across all Sharpen clients. These findings have implications for both research and policy.

# 2. Credit Counseling Background

Services offered by nonprofit credit counseling agencies tend to fall in three areas: financial education, credit and budget counseling, and debt management (Loonin & Plunkett, 2003; Samuelson & Stiller, 2012). Educational programming informs consumers about core financial issues such as general money management, credit or debt, and/or provides customized information about decisions at specific life stages (i.e. teaching high school students about using their first credit card, assisting first-time homebuyers through the purchase process, or informing senior citizens about potential fraudulent schemes or reverse mortgages).

While financial education tends to be more generic, credit and budget counseling is tailored to the individual. Counselors review specific financial information for a household, including inflows and outflows of money, and provide advice regarding financial decisions (such as reducing expenses, liquidating assets, or closing existing credit accounts). Credit counseling typically culminates in the creation of an action plan, where clients work with counselors to set short and long-term goals.

Debt management is the final major component of credit counseling services, including the administration of a debt management plan (DMP). Under a DMP, the credit counseling agency attempts to negotiate a payment arrangement with the client's creditors to get their debt payments, interest rates, and fees down to a level manageable by the household. In exchange, the client commits to make a monthly payment to the credit counseling agency (who then distributes payments to the client's creditors), and live within the budget established with the agency's help (Samuelson & Stiller, 2012).

Non-profit credit counseling agencies have a substantial client base in the United States, but one that is highly variable and unsurprisingly dependent on the overall state of the economy. Stronger economies and high levels of employment lead to less need for counseling services, while high unemployment or

economic uncertainty leads to increased demand for these services. In terms of overall reach, non-profit credit counseling agencies have provided services to between 1.5 and two million clients in 2013 and 2014, and at the height of the recession these agencies serviced around four million clients in total (Keating, 2013; NFCC.org, 2014).<sup>4</sup>

# 3. Literature Review

Research on the impact of credit counseling initiatives is limited. However, there are several existing streams of literature in financial education, counseling and coaching more broadly. This section will provide a brief review of credit counseling and related research.

### 3.1 Credit Counseling Research

While the credit counseling industry has been around for a long period of time, relatively little is known about the impacts of credit counseling on household outcomes. Indeed, much of the financial counseling literature is focused less on credit counseling explicitly and is instead focused on targeted education or counseling programs such as pre- or post-purchase homeownership counseling. Results from these targeted programs are mixed, with some studies on homeownership counseling showing positive and significant improvements among counseling clients on mortgage default rates (Agarwal, Amromin, Ben-David, Chomsisengphet, & Evanoff, 2010; Ding, Quercia, & Ratcliffe, 2008; Hartarska & Gonzalez-Vega, 2005), and other studies showing only limited changes in client outcomes (Agarwal, Amromin, Ben-David, Chomsisengphet, & Evanoff, 2009; Quercia & Spader, 2008). Outside of these targeted programs, there have also been evaluations of general financial inclusion initiatives that include a counseling component. For example, a study of a randomized intervention to provide bank account access with financial counseling found that the program was associated with improvements in debt payment behaviors and financial planning behaviors (Wiedrich, et al., 2014).

There are a few studies which seek to measure the outcomes of credit counseling, specifically. Kim, Garman, and Sorhaindo (2003) use pre- and post-counseling surveys and find that while enrollment in a credit counseling program has no direct effects on financial behaviors, credit counseling participants do have a lower propensity to experience future financial stressor events like collection calls or foreclosures, and that those who remain active in DMPs have better self-assessed financial outcomes than those who do not. Bagwell (2000) uses a similar research design and finds that credit counseling participants report improved financial behaviors post-counseling relative to their pre-counseling behaviors, and also show improvements in financial stress levels one year after counseling. Barron and Staten (2011) do not test the overall impacts of credit counseling, but rather explore the relative effectiveness of "technology-assisted" counseling (counseling done over the phone or online) versus in-person counseling using the change in credit scores from pre-counseling to post-counseling and find few differences between the modes of delivery on client outcomes. While these studies can provide descriptive insights, they lack a comparison group against which to compare the outcomes of credit counseling clients—which is necessary for evaluating impact.

<sup>&</sup>lt;sup>4</sup> These numbers have historically been much higher when including clients served at any credit counseling agencies, rather than just non-profit agencies. In 2003, for example, it was estimated that around nine million total clients sought credit counseling in any agency (Loonin & Plunkett, 2003).

One exception is a study on credit counseling conducted by Elliehausen, Lundquist, & Staten (2007). Using credit bureau data, Elliehausen, Lundquist and Staten (2007) construct a comparison dataset of consumers who did not receive credit counseling, matched to be otherwise similar at baseline to a sample of consumers receiving credit counseling from NFCC member agencies in 1997. They employ a two-stage least squares model to first predict selection into the credit counseling program, and then use a selection-corrected model to predict the impact of the receipt of counseling on an array of credit indicators. While they find that the impact on credit scores is relatively minimal once selection is taken into account, they do find positive impacts from credit counseling on debt levels, accounts held, and bank card use (as well as more general positive effects for those with the weakest credit profiles prior to counseling).

Despite its strengths relative to other existing analyses, the Elliehausen, Lundquist, and Staten (2007) study does not account for debt reductions stemming from charge-offs or bankruptcies (rather than client or program-driven debt reductions), and does not investigate the differences between DMP participants and those not recommended into DMP plans. Further, the study of outcomes is limited to one point in time, three years after the initial counseling session compared to credit characteristics at baseline (prior to counseling). This does not allow for the investigation of dynamic patterns in credit changes over time.

Finally, outside of analyses on the relationship between counseling and client outcomes, work has also been done on the nature of individuals who seek credit counseling. In a series of in-depth interviews with counseling clients and counselors themselves, Wang (2010) presents two narratives underpinning the decision to seek credit counseling. The first is that clients find themselves in an ever-worsening cycle of debt from overconsumption. These individuals take on debt to finance luxuries or other items they feel will help maintain their self-image or status, even if they cannot afford them. This leads to high amounts of debt and unsustainable debt payments, sometimes accompanied by less favorable borrowing terms which exacerbate their debt problem. The other narrative for credit counseling clients is that of the person driven into debt by some income or expense shock. Rather than using credit cards to finance conspicuous consumption, these individuals take on credit card debt in response to job losses, divorce, unanticipated health problems and the associated medical bills, or other unforeseen issues.

#### 3.2 Evidence from Related Programs

While this study is concerned with evaluating the impact of credit counseling, there are other related studies that inform how behaviorally-oriented financial interventions relate to individual outcomes. In particular, there has been a relatively large body of research on the impact of financial education interventions, and there is a new and growing literature on the impact of financial coaching programs. Though credit counseling differs from interventions focused purely on education or coaching, counseling services have components which share many commonalities with these types of programs. For example, many agencies offer supplemental targeted education and general financial advice to improve clients' money management; providing guidance, information, and resources on how to handle key financial issues like building emergency savings funds, budget management, and saving for retirement (Wang, 2010). Agencies also typically work with clients to develop detailed action plans and help them stabilize their finances, often following up with clients to address any financial concerns, provide encouragement, and keep clients on track with their financial goals (Wang, 2010), practices in-line with the processes embedded in financial coaching programs.

Formal financial education programming, aimed at increasing consumer financial literacy, has been touted as having a large number of personal and social benefits. Lusardi & Mitchell (2014) notes that only 30 percent of people in the United States can answer three basic questions on personal finance (regarding inflation, investment diversification, and interest) correctly, and ties financial illiteracy to paying higher fees in financial transaction and an increased propensity to use high-cost services like payday lending or rent-to-own schemes. The authors also demonstrate that sub-optimal borrowing behaviors such as late bill payments, going over credit limits, or paying minimum amounts on credit card debt are associated with lower levels of financial literacy.

There is little consensus as to whether or not financial education actually improves household financial outcomes. On a macro-level, early evidence for the efficacy of financial education programs was shown by Bernheim, Garrett, & Maki (2001), which used survey data to determine that there was a link between having received a state-mandated financial education curriculum in high school and savings rates in later years. However, this study was later contradicted by Cole & Shastry (2010), which used analysis of census data to show that states which had high savings and investment rates due to economic growth were more likely to impose a financial education mandate, indicating that the imposition of mandates which the Bernheim, Garrett, & Maki paper assumed were exogenous were actually endogenous to economic factors.

In terms of specific financial education programs, the evidence is similarly mixed. There have recently been two quantitative meta-analyses of financial education research which systematically assess the potential impacts of these programs. Miller et al. (2014) review 188 articles and find that a majority of studies report positive financial outcomes for participants in education programs including increased savings and improved financial skills, but that these positive impacts notably diminish when only looking at programs delivered in a randomized, controlled setting. Similarly, Fernandes, Lynch, and Netemeyer (2014) found that interventions aimed specifically at improving financial literacy had little effect, particularly when controlling for psychological variables like impulsivity and other behavioral variables like the length of planning horizons. They do, however, find evidence that "just-in-time" financial education programs, which target people at specific moments in their life (such as opening a 401(k) or buying a house), have the potential to improve financial literacy and financial outcomes.

Among the "just-in-time" programs identified by Fernades, Lynch, and Netemeyer (2014) are financial coaching programs. While there exists a relatively large body of research on financial education, financial coaching research is still relatively new and rigorous evaluations of financial coaching programs are only beginning to emerge. Financial coaching has grown out of the more general field of "coaching" (other examples of which include life coaching and health coaching) and has a variety of attributes including monitoring and evaluating progress and providing feedback, being collaborative and client-driven (rather than expert-oriented) in nature, and focusing on the development of a client's strengths. It is this client-oriented and iterative process that largely differentiates financial coaching from services like credit counseling, which is often more expert-oriented and less collaborative (Collins & O'Rourke, 2012).

There have only been a handful of studies which have evaluated the impact of coaching on financial outcomes. Collins & O'Rourke (2012) detail three small field studies in financial coaching, which include a coaching program for community college students, a program for low-income clients in New York City who sought nonprofit help in filing their taxes, and a general financial coaching program implemented in a number of sites across the United States. These studies found, respectively, that coaching could improve the self-reported ability to follow a budget, assist in the development of a financial goal, and improve the self-reported likelihood of engaging in positive financial behaviors like setting money aside for savings or paying more than the minimum balance on a credit card. However, these studies were relatively limited in scope and relied on non-randomized samples and self-reports, which limits the strength of their findings.

By contrast, Collins (2013) assesses a randomly-delivered coaching program for low-income individuals on public assistance and found a positive relationship between coaching and self-reported indicators such as paying bills on time, budgeting, and saving. Moulton et al. (2015) investigated the impact of financial coaching on the likelihood of default for new homebuyers within the context of a randomized, controlled study, and found positive and significant treatment effects. Similarly, an experimental evaluation by the Urban Institute (Theodos et al., 2015) on the impact of financial coaching found that coaching was associated with positive impacts on savings amounts, making timely debt payments, debt reduction, and the use of high-cost lenders. The receipt of coaching was also associated with improved budgeting behaviors and coaching clients also reported reduced financial stress and increased confidence.

# 4. The Relationship between Counseling and Outcomes

Taken together, the existing literature on credit counseling and related interventions allows us to specify expected mechanisms by which counseling can drive changes in counseling clients. Here, we focus specifically on two components: budget counseling and debt management plans.

Client behavioral changes from budget counseling sessions may be driven in part by increased client awareness of their expenses. This increased awareness may help them shift their behaviors to be more inline with their financial goals. In providing budget counseling, counselors often help clients develop an action plan for strengthening their financial circumstances, which clients are expected to follow. The action plan developed for clients may reduce some of the stress of making hard financial decisions on what expenses to cut. Research has shown that people operating under stress or financial scarcity often face high degrees of drain on their cognitive resources which limits their willpower and prevents them from thinking about longer-term goals (Baumeister, 2002; Mullainathan & Shafir, 2013). Given that clients in credit counseling agencies are likely operating under relatively high levels of stress from debt burdens or other financial circumstances (burdens which likely drove them to seek counseling services), having a concrete plan to make concrete changes may reduce some of the cognitive stress and increase the likelihood they change their financial behaviors.

Budget counseling may also drive changes in behaviors by providing a type of behavioral monitoring. Counseling clients, who commit to following their action plans to reduce expenses (and make make explicit commitments in the case of DMP enrollment), may feel accountable to the counselor if they do not adhere to their action plans, and this sense of accountability may lead to better adherence to the plan (Lerner & Tetlock, 1999). Additionally, agencies often follow up with clients at set interval to check in on their progress and overall financial condition, which provides an additional source of external monitoring and may contribute to this sense of accountability on the part of the client.

Debt management plans (DMPs) offer an additional intervention that may directly and indirectly influence client outcomes. Directly, DMPs may lower a household's debt burden. Through a DMP, counseling agencies negotiate with creditors to lower interest rates or waive fees for clients, making an individual's overall debt situation more sustainable and increasing the likelihood of successful debt repayment (Bagwell, 2000). Indirectly, DMPs may also reduce client stress. By acting as an intermediary between creditors and their clients, DMPs may eliminate the overall burden on clients by allowing them to only engage with one organization (the counseling agency) instead of multiple creditors, and also reduces debt collection calls (Elliehausen et al., 2007). Finally, by consolidating multiple debt streams into one, DMPs eliminate the need for clients to manage multiple payments; they no longer have to track multiple due dates and differing payment requirements for each debt stream. This reduction in complexity may enhance the propensity for clients to successfully pay off their debts.

Through budget counseling and DMPs, credit counseling services may improve targeted financial behaviors. These behaviors include managing expenses to avoid unsustainable debt burdens, paying down debts in a way that avoids high interest payments, making on-time payments, and avoiding high-cost financial products like payday loans and check cashing services. In the long-term, these changes should result in stronger credit profiles, and may lead in an increase in credit indicators such as borrowing liquidity and credit scores. Other longer-term changes in client conditions may stem from this as well, such as an improved sense of financial well-being and more confidence in managing financial issues.

Though this evaluation does not explore credit counseling's relationship to all potential changes in client outcomes, it does explore client outcomes along several key indicators of financial health: (1) revolving debt and total debt levels; (2) available liquidity and balance-to-credit ratios; and (3) credit scores and payment delinquencies. In addition, it will explore how several of these outcomes are shaped by debt management plan enrollment; the presence of bankruptcies, charge-offs, and foreclosures; and an individual's credit risk profile prior to counseling.

# 5. Data and Methods

## 5.1 Counseling Sample Construction

This study employs data from a nationwide Sharpen Your Financial Focus credit counseling program, which is being conducted over three years beginning in September of 2013 and, at the time of this writing, has reached over 40,000 households. The initiative features what is referred to as a "Three-Step Personal Financial Stabilization Program" consisting of: (1) a financial stress test (named MyMoneyCheckUp) which is a self-administered test asking clients a variety of questions about different aspects of their financial health such as their debt levels, budgeting and savings behaviors, and financial confidence, and then assesses the various strengths and weaknesses of their financial state; (2) a customized financial review, which is designed to help clients set financial goals, create a budget, and develop a feasible plan for accomplishing a variety of goals; and (3) targeted education courses (referred to as "deep dives") which provide additional resources and education on specific areas of interest or concern to a client.

Despite being managed at the national level by the National Foundation for Credit Counseling, the Sharpen program is implemented through a network of more than 80 affiliated non-profit counseling agencies which operate at either the local, state, or regional levels. Member agencies have some discretion in how they implement the Sharpen program. To receive reimbursement from the NFCC under the Sharpen initiative, agencies were required to document implementation of the first two components for each client. The "deep dive" component was left to the discretion of the agencies.

As of the end of March, 2015, 43,072 clients had enrolled in the Sharpen initiative across all member agencies. This evaluation was conducted using clients from 13 of the non-profit member agencies, which submitted proposals to the NFCC in order to be selected for the evaluation. The 13 agencies have enrolled a combined total of 18,829 clients as of March, 2015. We further limit the evaluation population to 10,925 clients enrolling in the Sharpen initiative during the first quarter of the program, from September 1, 2013- November 30, 2013. This allows for eighteen months of data post counseling for all households in the sample. Finally, the analysis sample is limited to those consumers with complete credit data (n=8,963), for whom a match could be generated during the baseline period, resulting in 6,094 counseled clients. Appendix A provides a visual diagram of the sample construction for this analysis. Appendix B provides a comparison of the administrative characteristics for the sample of consumers counseled by the member agencies included in this analysis, relative to the full population of Sharpen participants.<sup>5</sup>

Data on counseled clients is generated from two sources. Administrative data is compiled by counseling agencies, measuring client demographic and financial data as well as reasons for seeking counseling and the number of different steps of the Sharpen program experienced by each client. Longitudinal credit report data is provided by Experian, which includes a variety of credit indicators including credit score, revolving and installment balances, debt payment delinquencies, and indicators for charge-offs, bankruptcies and foreclosures. The administrative data is cross-sectional and recorded at the time clients enroll in counseling, while the credit data is pulled at quarterly intervals across six quarters beginning with August of 2013.

On average, clients in this credit counseling program tend to be female, white, unmarried (either single, widowed, or divorced), and middle aged. They also tend to be relatively well educated with around two-thirds reporting some education beyond high school, and come from relatively small households. However, they also tend to be relatively low-income, with an average monthly income of around \$3,000. Their savings levels are also particularly anemic, with an average of \$500 saved; the median Sharpen client has no savings whatsoever. Tables 1 and 2 outline the counseling motivations and summary statistics of this sample

[Insert Tables 1 & 2 Here]

<sup>&</sup>lt;sup>5</sup>All metrics except clients' average monthly income are significantly different between the groups; however, the differences are not substantively large. In terms of the demographic characteristics, clients in both agency groups are roughly similar, though clients in non-participating agencies are more likely to have a high school diploma or four year college degree. There are some notable differences in the financial characteristics between agencies. While the average monthly income and monthly housing expenses are relatively similar, clients in participating agencies had fewer debt-related expenses, more tangible assets, less in liquid savings, and more liabilities.

#### 5.2 Matched Comparison Sample Construction

The comparison group was drawn using Experian's credit database which contains credit information for all households in the United States. From this database, a five percent random sample of U.S. individuals was generated and comparison group members were selected based on their similarity to counseled individuals across the matching covariates referenced above.

Specifically, comparison group members were identified using Coarsened Exact Matching (CEM), a method of data processing which uses Monotonic Imbalance Bounding to match treated and untreated observations and allows for causal analyses using a variety of estimation approaches. This technique is similar to more traditional propensity score matching, but has been found to improve the balance, error, and efficiency of traditional propensity score matching methods (Iacus, King, & Porro, 2012). In CEM, data is first "coarsened" into categories for treatment and comparison groups (i.e. credit score might be coarsened into categories of <520, between 520 and 560, 561 and 620, 621 and 660, 661 and 720, and >720), and subsequently matches observations between treated and untreated groups based on the presence of an exact match between these groups. Any individuals from the treatment or comparison groups who do not have an equivalent match in the other group are excluded from the analysis. Weights for each observation are calculated as the number of comparison observations in a matching "stratum", which contains every observation in the treated and untreated groups with identical coarsened covariates, divided by the number of counseled observations in that strata.

Credit indicators used to construct the match include revolving debt levels,<sup>6</sup> bankruptcy history, the age of the oldest trade, mortgage debt levels, the presence of any payment delinquencies 60 days or greater in the past 12 months, the presence of any mortgage payment delinquencies 90 days or greater in the past 24 months, the balance-to-credit ratio, the credit score, and the state of residence.<sup>7</sup> These indicators were selected for the matching process because they represent a diverse array of elements which may impact a person's short and long-term credit outcomes. A history of delinquent payments may indicate a higher propensity have future delinquencies; debt levels may impact the rate at which a person pays down their debts (this may also be influenced by the type of debt); bankruptcy impacts a person's access to future credit; the age of accounts serves as a proxy for a person's experience with credit and plausibly captures certain life cycle factors that can affect debt levels, savings, income, etc.; and the state of residence serves to capture specific macroeconomic or institutional factors which may be relevant, such as the employment conditions of a state.

Out of 8,963 counseling clients, matches were found for 6,297, or 70 percent.<sup>8</sup> Of these matched clients, 137 observations were dropped from the comparison group because they had received credit counseling

<sup>&</sup>lt;sup>6</sup> Specifically, individuals in the comparison and counseled groups were matched on *open* revolving debt, which does not include balances on accounts voluntarily closed by consumers. This debt measure is a very good proxy for total revolving debt, and as can be seen from Table 3, the comparison and counseled groups are still extremely well matched on total revolving debt.

<sup>&</sup>lt;sup>7</sup> Matching was also attempted on the first three digits of the zip code rather than the state of residence, but this resulted in too few matches so the geographical scope was broadened to the state level.

<sup>&</sup>lt;sup>8</sup> As a supplemental analysis, the demographics of the unmatched counseling clients were compared to those for whom matches were available. Overall there were very few substantial differences between the matched and unmatched counseling clients, though matched clients were somewhat less likely to be white, married, and have a

and were in the counseling sample. After excluding any observations with data issues, 6,094 Sharpen clients remained matched with 6,005 non-counseled individuals.<sup>9</sup>

In order to assess the accuracy of the matching process, differences in the means of each matching variable between the counseled and comparison groups at baseline were calculated. Ideally, the resulting samples will be completely balanced, with little to no difference in baseline characteristics between groups. These results can be seen in Table 3. At baseline, consumers from both the counseled group and the matched comparison group have credit scores just under 600, open revolving debt levels of around \$10,000, installment debt levels around \$21,000, mortgage debt around \$45,000, around 0.3 bankruptcies on average, an oldest account around 15 years old, 0.6 payments 60 days delinquent or more in the last year, 0.1 delinquent mortgage payments in the last two years, and a balance to credit ratio of 0.5.

Table 3 also reports the standardized differences of baseline variables, which are a function of the differences in the variable mean between the groups divided by the total standard deviation of the combined sample (Austin, 2009). Per the Institute of Education Sciences (2014) best practices, any variable with a standardized difference below 0.05 between groups is considered to be well-balanced, as is the case with all the matching variables employed in this study. The standardized differences for the matching variables range between 0.01 and 0.04. Thus it is appropriate use a straightforward difference of means when comparing the evolution of credit indicators between counseling and comparison groups.

Additionally, several variables are included in Table 3 that were not matching variables but are dependent variables used in the analysis: total revolving debt (including closed accounts), total overall debt (including installment, revolving, and mortgage debt), the number of payments 60 days delinquent or more in the last six months, and the available open credit ratio (the amount of available credit across all open accounts divided by the amount of total potential credit across those accounts). Even though these metrics were not used in matching, counseling clients and the comparison group are still very similar across these variables, having around \$16,500 in total revolving debt, over \$80,000 in total debt, around 0.45 sixty day payment delinquencies in the last six months, and an available open credit ratio of 0.5.

[Insert Table 3 Here]

#### 5.3 Methods

We track key credit indicators at quarterly intervals for both the counseled and comparison groups. Specifically, we track the change in indicators from quarter to quarter within the counseled group and compare this change to changes within the comparison group of non-counseled individuals; a differencein-difference comparison. The analysis starts in the baseline quarter, which is the period prior to a client

four-year degree. They also had less average monthly income than counseling clients for whom no match was available.

<sup>&</sup>lt;sup>9</sup> 137 clients were dropped from the analysis because they appeared in both the counseling and comparison groups, and 66 were dropped because of missing data in one or more periods. Specifically, of the counseling clients in the matched analysis, 31 had to be dropped due to missing data for the client, and 35 had to be dropped due to missing data for the comparison individual. Additionally, a very small portion of the sample (120 from the comparison group, 35 from the counseled group) did not have credit scores available in certain periods, and those individuals have been omitted from any analyses of credit scores in this evaluation.

enrolling in counseling. The baseline quarter for all clients in the full analysis is August, 2013. This baseline captures any clients enrolling in Sharpen between September and November of 2013.

For this analysis, we estimate differences using a fixed effects panel regression model, where the credit outcome of interest is measured at baseline and for six subsequent quarters for each individual, as follows:

 $y_{it} = a_i + \pi Counseling_{it} + \lambda Quarter_t + \delta (Counseling_{it} * Quarter_t) + \beta_i x_{it} + \epsilon_{it}$ 

where y is the credit outcome of interest, the coefficient  $\pi$  captures the overall impact of receiving counseling (coded 0 for all individuals in the baseline period and 1 for counseling clients after they receive counseling),  $\lambda$  measures the quarterly changes in outcomes for the comparison group,  $\delta$  measures the quarterly changes for the treatment group,  $\beta$  measures the impact of j time varying control variables (several models in this study control for bankruptcies, charge-offs, foreclosures, and changes in HELOC debt),  $\varepsilon$  is the error term of the model, and  $\alpha$  is a constant which represents the average value of the variable for the full sample. The model is estimated using a fixed effects panel regression with standard errors clustered on each individual.

In addition to estimating the model with the full sample, supplemental analyses are conducted for subgroups of analytical interest. These subgroups includes clients in the bottom 50<sup>th</sup> and 25<sup>th</sup> credit percentiles at baseline, clients holding debt at baseline, and clients either recommended or not recommended into DMP plans. To construct these subgroups within the context of the Coarsened Exact Matching analysis, counseled clients were only compared to comparison group individuals who were matched to them in the full analysis.

#### 5.4 Dependent Variables

This analysis traces the evolution of a number of different key credit metrics, including credit scores, revolving debt levels, total debt levels, and payment delinquencies. The credit score used in this analysis is the Vantage 3.0 scoring metric, which is a similar metric to the more traditional FICO credit score<sup>10</sup> and spans an identical range to the FICO score (300 to 850). This score is used here as it is the primary credit reporting metric of the credit data provider for this study (Experian).

With regard to debt measurement, there are a number of different debt indicators which can be used to assess consumer financial health. The level of consumer revolving debt and total debt can be used to get a sense of the consumer's overall debt profile. Revolving debt includes balances on credit cards (open and closed) and home equity lines of credit (HELOCs). The total debt measure includes debt from any revolving, mortgage, and non-mortgage installment accounts updated within the last year. While revolving debt measures are presumed to be the most sensitive to counseling interventions and subsequent behavioral changes, understanding how counseling clients' total debt profiles change provides a more robust sense of their overall financial state.

In addition to debt levels, we consider two debt ratio measures: (1) the open revolving credit ratio, which measures available revolving credit as a percent of the credit limit on revolving accounts, and (2) the total

<sup>&</sup>lt;sup>10</sup> Key differences are that paid collections are not counted against consumers under the VantageScore, and that VantageScores can be calculated with less of a credit history (Credit.com, 2015).

revolving balance to credit ratio, which measures the total balance on all revolving accounts (open and closed), as a percent of the high credit limit. The first ratio can be viewed as an indicator of liquidity, where a higher ratio indicates that the consumer has a higher level of available credit from which to borrow. Access to liquidity has been described as a type of financial "slack" allowing individuals a degree of flexibility in managing their finances (Mullainathan & Shafir, 2009, 2013). The second ratio includes balances on both open and closed revolving accounts, and is thus an indicator of overall revolving debt burden.

Finally, the number of debt payment delinquencies for both counseling and comparison groups will be explored. While the counseling and comparison groups were matched based on the number of payments 60 days delinquent within the last 12 months (to capture a longer history of potential delinquency), this study presents the number of delinquencies in the last six months in order to provide more sensitivity to any changes in payment behaviors. When analyzed at quarterly intervals, the number of delinquent payments in the last six months can be understood as a moving average of delinquent payments over time, which means immediate reductions in the number of delinquent payments will take time to fully manifest.<sup>11</sup>

## 5.5 Control Variables

Given that the Coarsened Exact Matching procedure produced strongly balanced samples across a wide array of metrics at baseline, the need for control variables is limited. However, this study will control for three time varying covariates which may drive differences in outcomes between the two groups in the post-counseling period: Bankruptcies, debt charge-offs, and foreclosures. The logic behind the inclusion of these controls is that they may occur after counseling and influence the dependent variables of interest in this study. For example, credit counselors may suggest bankruptcy as a possible strategy for their clients to manage their debts (indeed, bankruptcy counseling has been a rapidly growing service offered by credit counseling agencies; Wilshusen, 2011), and this may lead to a higher propensity to declare bankruptcy for counseling clients.

Alternately, if clients seeking credit counseling are experiencing financial distress not captured in their pre-counseling credit data (i.e. from the loss of a job), this may result in a greater likelihood for experiencing debt charge-offs or foreclosures. In these cases, clients experiencing these events would show declines in their debt levels, but these declines are not necessarily driven by improved financial behaviors like prudent debt management and paying off balances. As such, these controls help isolate the behavioral components driving changes in credit outcomes. Each of these variables are coded as 0 if a client does not have an increase in the number of bankruptcies, charge-offs, or foreclosures in the post-counseling period, and 1 if they do. Once these variables are coded as 1, they remain coded as 1 for all remaining quarters as the impacts of these events on consumer credit profiles are likely long-lasting.<sup>12</sup>

<sup>&</sup>lt;sup>11</sup> Given the quarterly nature of this analysis, the ideal would be to track the number of delinquent payments made within the last three months. However, these data were not available.

<sup>&</sup>lt;sup>12</sup> Other specifications of these variables were also tested, including only coding them as 1 in the quarter when they happened and simply controlling for the number of these events in each quarter. Regardless of the specification, results were similar.

# 7. Results

# 7.1 Overall Outcomes

Table 4 reports the estimated impact of counseling on four different debt indicators.<sup>13</sup> Across all the debt metrics explored, the counseled client group experiences significant improvements relative to the comparison group. Notably, Sharpen clients have significantly lower *levels* of debt by the end of the evaluation period. Compared to their matched non-counseled individuals, the counseled group reduces their revolving debt (Model 1) by an average of around \$3,600 and reduces their total debt (Model 2) by around \$11,300. In terms of available revolving credit (Model 3), Sharpen clients show a significant improvement relative to the comparison group, with their open credit ratio increasing five percent more than the comparison group by the end of the evaluation period. In addition, Sharpen clients show significant reductions in the balance-to-credit ratio (Model 4) on *any* revolving accounts, including closed accounts.

Though the results are not included here, there is also evidence that Sharpen clients are closing their open revolving accounts at higher rates. By the end of the evaluation period, Sharpen clients have on average reduced their number of open revolving accounts by 0.4 relative the comparison group (p<0.01).<sup>14</sup>

### [Insert Table 4 Here]

In addition to overall debt levels, we track the impact of counseling on credit score as well as debt payment delinquencies. While examining the overall change in outcomes is instructive, the trends in certain metrics can provide additional detail around the dynamics driving these changes. To this end, Figures 1 and 2 explore this by examining the evolution in credit scores and 60 day payment delinquencies over the evaluation period.

## [Insert Figures 1 & 2 Here]

Figure 1 reveals a marked difference in the credit score trends between the counseled clients and the comparison group. Though the two groups begin with very similar scores, the counseled group faces a steep drop of about 13 points in their credit score between the pre-counseling quarter and the first post-counseling quarter which persists through the second quarter. The comparison group however has a modest upward trend over this same interval, and this trend persists across all quarters. The counseled group begins to recover in the third quarter after the receipt of counseling. By the sixth post-counseling quarter the counseled group has a slightly higher credit score (601) than they did when they began, but the overall increase in their credit score is still 6.8 points lower than the comparison group's credit score increase.

Similarly, we plot the trends in 60 day delinquencies over time. Figure 2 shows an inverted pattern to the development in credit scores. The baseline delinquencies between the two groups are roughly identical

<sup>&</sup>lt;sup>13</sup> This section of the analysis does not control for the presence of bankruptcies, charge-offs, and foreclosures, which likely impacts the debt levels held by consumers. Sub-Section G excludes these consumers to provide a more detailed examination of the debt metrics.

<sup>&</sup>lt;sup>14</sup> This impact remains significant when controlling for bankruptcies and charge-offs over the evaluation period.

(~0.45 delinquent payments on average for each person in the sample). Post-counseling, there is a spike in payment delinquencies for the counseling group (the delinquencies for the comparison group stay roughly flat over the entire period) which peaks in the second post-counseling quarter before declining substantially over the study period. By the sixth post-counseling quarter, payment delinquencies fall below their pre-counseling levels and are at parity with the comparison group.<sup>15</sup>

There are two noteworthy points of discussion here. The first is the initial drop in credit score and spike in payment delinquencies for counseled clients. Though the drop in credit score is evident in the first quarter after counseling, this should not be read as evidence that counseling caused drops in credit scores. Rather, the evidence is in-line with a counseled client experiencing a debt- or income-based shock (such as a hospitalization or the loss of a job) around the time of counseling (perhaps motivating them to seek counseling), resulting in a downward trend in their credit score that persists for the first quarter after counseling. There is some evidence of a shock driving participation into counseling, as indicated on Table 4 of this report. The majority of clients (almost two-thirds) reported seeking counseling because of reduced income, while another ~30 percent reported facing increased expenses. When Figures 6 and 7 are paired together, it appears that the drop in credit score appears to be driven by clients' inability to meet their debt payment obligations.

Table 5 investigates client outcomes relative to the comparison group for credit score and debt payment measures. When measured as total change over the evaluation period, receiving counseling is negatively associated with the change in credit score (Model 1),<sup>16</sup> and there is no significant difference between counseling and comparison groups in terms of having payments 60 days or more delinquent. This is not unexpected, in light of the dynamic time trend analysis that shows an initial shock in both indicators shortly after the baseline period.

#### 7.2 Subsample Analysis: Outcomes for Debt-Owning Clients

For this portion of the analysis we examine the evolution of revolving debt indicators only for those individuals who *had debt at the baseline period*. Given the nature of credit counseling, debt-owning households are likely a more relevant target population than those households who have no debt in the period prior to receipt of counseling. It is also possible that debt-owning clients seek credit counseling for different reasons than those without debt (for example, they may seek counseling to deal with high debt burdens as opposed to an inability to make debt payments). For reference, approximately one in six counseling clients does not have debt in the quarter prior to the receipt of counseling, and slightly over one out of five matched clients do not have revolving debt in the baseline period. Table 6 presents the results for debt-owning Sharpen clients compared to their debt-owning matched comparison individuals. Models 1 and 4 explore the change in total revolving debt for those with revolving debt at baseline, while Model 2 looks at the change in total debt including only those who had *any* debt at baseline, and Model 3

<sup>&</sup>lt;sup>15</sup> The number of payments 60 days delinquent in the last six months can be understood to be a moving average of the number of payment delinquencies over time (since any delinquencies in the past six months are counted). To get a more dynamic read on what is happening with payment delinquencies, the number of payments *currently* 60 days or more delinquent in any quarter was also investigated. Though the graphical analysis is not featured here, the payment delinquency spike for current delinquent payments is over by the third post-counseling quarter and by the fifth post-counseling quarter the level of current delinquencies is actually *lower* than it was at baseline.

<sup>&</sup>lt;sup>16</sup> Throughout this analysis, the base size for credit score models will be slightly lower than for models investigating other credit indicators, as credit scores were not available in all periods for a small subset of clients.

examines the change in the available credit (as a ratio of total credit) for those who had any open revolving credit *or* debt at baseline.

#### [Insert Table 6 Here]

By the end of the evaluation period, debt-owning counseling clients experience improvements across all four metrics relative to the comparison group. Indeed, the results here are relatively similar to those in Table 4, although the magnitude of the difference between counseling and comparison groups are greater. This is perhaps most notable in the case of the available credit ratio (Model 3) and the total revolving balance to credit ratio (Model 4). Excluding any individuals who did not have any debt at baseline causes the magnitude of the change between counseling and comparison groups to almost double. Taken together, these results show that credit counseling clients are reducing their total amount of revolving debt faster than the comparison group, while developing access to liquidity on their existing open accounts at higher rates as well.

Figures 3 and 4 respectively trace the evolution in total revolving debt and the available open credit ratio for counseling clients and comparison individuals. Both figures show that debt and the available credit ratio track closely with the comparison group through the first post-counseling quarter before diverging slightly in the second. For total revolving debt, the comparison group continues to reduce its revolving debt level by around \$200 to \$600 a quarter, while the counseling group exhibits a much more rapid and statistically significant decline which peaks in the third post-counseling quarter and continues through the sixth post-counseling quarter. In total, the counseling group reduces their debt by about 35 percent while the comparison group reduces their debt by 13 percent. Similarly, the ratio of available credit for counseled clients grows at a higher rate than the comparison group after the first post-counseling quarter, and is 19 percent higher than the comparison group six quarters after counseling.

## [Insert Figures 3 & 4 Here]

#### 7.3 Subsample Analysis: Bottom 50th Credit Percentile

This section and the following will explore key credit indicators for two different sub-groups defined by their baseline credit score. This section covers those in the bottom  $50^{\text{th}}$  percentile of initial credit scores (which translates to a credit score at or below 601), and the following section covers those in the bottom  $25^{\text{th}}$  percentile of credit scores. The purpose of these analyses is to explore how credit indicators evolve for clients with relatively weak or distressed credit profiles at the time of counseling (even above and beyond the relatively weak profile of counseling clients generally). There are 2,668 counseled clients in the bottom  $50^{\text{th}}$  percentile of baseline credit scores, and 2,574 individuals in the comparison group.

Table 7 shows the outcomes for counseling clients in this subgroup relative to the non-counseled comparison group across several key metrics. The amount of total revolving debt for counseling clients declines by almost \$2,000 relative to the comparison. In absolute terms, this is less than the reduction seen in the full matched sample, but individuals in the bottom 50<sup>th</sup> credit percentile also have less than half the revolving debt of the full sample at baseline.<sup>17</sup> The change in credit score for counseling clients is positive but insignificant for this subgroup, though counseling clients show significant improvements in their number of 60 day payment delinquencies relative to the comparison group.

<sup>&</sup>lt;sup>17</sup> This can be seen in comparing the constants for the full sample and 50<sup>th</sup> credit percentile subsample.

#### [Insert Table 7 Here]

For those in the bottom 50<sup>th</sup> credit percentile at baseline, the pattern in credit scores (shown in Figure 5) looks somewhat different than for the full sample: These clients do not appear to have as much of a shock in their credit scores around the time of counseling as their scores stay roughly flat from baseline to the first post-counseling quarter, and by the end of the evaluation period their scores are equal to those of the comparison group.

#### [Insert Figure 5 Here]

#### 7.4 Subsample Analysis: Clients in the Bottom 25th Credit Percentile

This portion of the analysis covers clients and comparison group individuals who fall in the bottom 25<sup>th</sup> percentile of the baseline credit distribution (a credit score at or below 540). For this subgroup, there are 1,315 counseled clients and 1,243 individuals in the comparison group.

Table 8 presents the results for this subgroup. There are two notable differences between this analysis and the analysis of the  $50^{\text{th}}$  credit percentile above. First, while counseling clients do reduce their revolving debt by over 500 dollars relative to the comparison group, this change does not reach statistical significance. This is perhaps driven in part by the fact that individuals with such low credit scores at baseline do not have high levels of revolving debt to begin with (relative to the general counseling population). The other major change is that counseling clients experience positive and statistically significant growth in their credit scores relative to the comparison group over the evaluation period. By the sixth post-counseling quarter, counseling clients' credit scores have grown 7.5 points higher relative to the comparison group's scores (p<0.01). The delinquency metrics both improve for this group, and the change on these metrics is similar to the  $50^{\text{th}}$  credit percentile group.

#### [Insert Table 8 Here]

Figure 6 traces the change in credit scores for clients in the bottom 25<sup>th</sup> credit percentile at baseline. Interestingly, the credit scores for this high-risk group grow roughly parallel to the comparison group for the first three post-counseling periods before diverging, with the counseling group experiencing more rapid growth in their credit scores in the final quarters of the evaluation period than the comparison group.

[Insert Figure 6 Here]

#### 7.5 Controlling for the Credit "Shock"

As detailed above, the credit scores and payment delinquencies for both the counseled and comparison groups start off roughly similar in the baseline period before diverging quickly. The most obvious explanation for this is that counseled clients are driven to take up counseling services due to some shock experienced around the time of counseling (or in the periods prior to counseling), and that this is reflected on their credit report data in the first quarter after counseling.<sup>18</sup> Indeed, this explanation tracks with the

<sup>&</sup>lt;sup>18</sup>The quarterly nature of the credit data in the study means that the baseline observation of credit data for a household may have occurred anytime in the range of 0-90 days prior to counseling. Thus, the baseline credit data may not pick up on the shock experienced by the household that drove them to counseling. Further, there is likely a

reasons clients give for seeking out counseling: The majority of clients are facing job losses, income reductions, or sudden expenses which may make it difficult to meet their debt obligations.

To better understand how credit scores evolve for clients who undergo an income or expense shock, a subsample was constructed to compare clients who appear to have experienced a shock directly to comparison group members who also appear to have experienced a shock. To do this, the analysis looks at the change in credit score and payment delinquencies from pre-counseling to the first quarter post-counseling for the counseling group, and defines a shock as having a credit score which *decreased* by more than one standard deviation from baseline to the first or second post-counseling period, <sup>19</sup> or having payment delinquencies which *increased* by more than one standard deviation over the same time period. This allows us to isolate the counseling clients who were undergoing exceptional credit shocks around the time of counseling, and match them to comparison group individuals going through similarly exceptional shocks.<sup>20</sup> To quantify this, a person was identified as having gone through a shock if their credit score dropped by 48 points, or if their number of payment delinquencies 60 days past due increased by more than 1.2. The results of the analysis for only individuals going through shocks can be seen in Table 9.

#### [Insert Table 9 Here]

The number of observations in this leg of the analysis is relatively small: 321 for the counseling group and 313 for the comparison group. This is due to the low prevalence of comparison group individuals who underwent credit shocks in this time period—the number of counseled clients who went through a shock *and* could be matched with similar comparison individuals who also went through a shock was relatively low. What this evidence points to is that credit scores are slow to recover for both groups if they went through shocks, and while there is some directional evidence that counseled clients may recover at a higher rate in later periods, this difference is not significant.

Figure 7 outlines the trends in credit scores between counseling and comparison groups for those undergoing credit shocks. What the relative trends between these two groups show is that even when comparing individuals going through credit shocks (as we have defined them in this analysis), the shocks experienced by the counseling group are still more extreme, as their credit scores drop substantially more than the comparison group in the first two post-counseling quarters. Despite this, their scores recover quicker and, as shown in Table 9, end up higher than the comparison by the end of the evaluation period.

[Insert Figure 7 Here]

lag in the time that it takes a shock experienced by a household to impact the credit report; e.g., a loss of a job in a particular month may not result in delinquent payments until subsequent months.<sup>19</sup> The reason for selecting this time period stems from the fact that a shock could take time to manifest. Most

<sup>&</sup>lt;sup>19</sup> The reason for selecting this time period stems from the fact that a shock could take time to manifest. Most households who underwent a credit shock did so in the period between the baseline and the first post-counseling quarter, while about a third went through a shock between the first and second post-counseling quarters. The delay in the shock could be due to such factors as having existing liquid assets or other financial support to buffer the shock of job loss or increased expenses, and thus delayed any missed payments made by these clients.

<sup>&</sup>lt;sup>20</sup> A number of other methods of creating a "shocked" comparison group were explored, including alternate specifications of the changes in credit score and payment delinquencies, matching on post-counseling attributes, and matching on trends in credit scores. Regardless of the definition of the shock, the results were largely similar to this analysis.

Additionally, an analysis on the credit score trend controlling for variables which might be correlated with a credit shock (charge-offs, bankruptcies, and foreclosures) was conducted, but the inclusion of these controls did not notably alter the credit score outcomes for counseling clients seen in Table 9. Without controlling for these factors, the credit score for counseling clients drops by 6.8 points relative to the comparison group. Controlling for these factors, the credit score drops by 6.4 points (p<0.01).

### 7.6 Exploring the Dynamics of Consumer Debt

Another aspect of consumer outcomes is the evolution of revolving debt for both the counseled and comparison groups. While overall debt is declining among counseled clients, this decline can be attributed to behavioral changes, debt reductions from interventions (such as the debt management plan), creditors charging off severely delinquent debts, or consumer bankruptcy. To explore these debt dynamics, this section will re-estimate the models for revolving and total debt, controlling for the initiation of a bankruptcy, charge-off or foreclosure over the evaluation period. The next section will explore debt outcomes based on DMP status.

Table 10 presents the results when controlling for any bankruptcies or charge-offs, or foreclosures. Specifically, Models 1 and 2 estimate changes in revolving debt, while controlling for new bankruptcies and charge-offs, while Models 3 and 4 estimates changes in total debt, controlling for bankruptcies, charge-offs, and foreclosures (since total debt includes mortgage debt). Even controlling for debt write-offs, the decline in these debt metrics for the counseled group is greater than for the comparison group. Controlling for bankruptcies and charge-offs, revolving debt declines by around \$2,000 for the counseling group relative to the comparison, and this increases to around \$2,700 when only including individuals with revolving debt at baseline. Controlling for bankruptcies, charge-offs, and foreclosures, the counseling group still decreases their total debt relative to the comparison group by around \$6,600 relative to the comparison and this increases to a \$7,600 decline when only including those who had any debt at baseline.

## [Insert Table 10 Here]

A separate set of models were also developed controlling for the amount of HELOC debt in each quarter as well as the presence of bankruptcies, charge-offs, or foreclosures (as in Table 10). These models found that including HELOC debt lessened the reduction in debt by about \$200 in each model (there was no change in the significance of any variable), though the R-squared for the revolving debt models did increase substantially when including HELOCs, from 0.08-0.10 in Table 10 to 0.53-0.54 when including HELOCs.

## 7.7 Client Outcomes Based on DMP Status

Finally, Table 11 presents the results examining the relative changes in credit and debt outcomes based on client DMP status. While this analysis cannot track who entered into a DMP, we do have information on which clients were *recommended* into a DMP. To analyze client outcomes based on DMP status, this analysis separates DMP and non-DMP clients into two separate models, with DMP clients only compared to their matched equivalents (as are the non-DMP clients).<sup>21</sup> As can be seen in Table 11, in the models

<sup>&</sup>lt;sup>21</sup> As a note, the DMP client sample models contain 3,801 clients recommended for DMPs (and 3,926 comparison individuals); the non-DMP client sample contains 2,293 clients not recommended for DMPs (and 2,442 comparison

with no controls (Models 1 and 2), the non-DMP group actually reduces their debt more than the DMP group. However, there appears to be evidence that more of the debt reduction for non-DMP clients stems from bankruptcies and charge-offs, as controlling for these factors (Models 3 and 4) leads to greater debt reductions for DMP clients than non-DMP clients.

[Insert Table 11 Here]

# 8. Discussion

Sharpen households are uniquely distressed at baseline relative to households with similar profiles. The presence of expense or income shocks from events like major illnesses or the loss of a job likely leads these Sharpen clients to seek help for their debt obligations. The finding that many Sharpen clients (and likely credit counseling clients in general) appear to seek counseling as their credit profiles have already begun to deteriorate may indicate that future counseling approaches should be oriented toward stemming these short-term declines as a supplement to the longer-term orientation of other credit counseling offerings (such as the DMP).

The central focus of this matching analysis is measuring what happens to these households after they enroll in the Sharpen Your Financial Focus credit counseling program. By tracing what happens to Sharpen clients' key credit indicators relative to a matched comparison group, this evaluation allows us to approximate a counterfactual outcome for Sharpen clients and compare client outcomes to this counterfactual.

The primary outcome explored here is the change in debt for Sharpen clients relative to the comparison group. In this evaluation, debt is measured in two ways: the total amount of revolving debt, and the amount of total debt (revolving and installment, including mortgages). Regardless of the type of debt examined, the results are similar. While debt reductions are present and significant for the full sample in this analysis, the results are most stark when considering those who held debt in the baseline period. For total revolving debt (which includes debt on closed accounts and HELOCs), Sharpen clients have about 26 percent less revolving debt than the comparison group at the end of the evaluation period and their balance-to-credit ratio on this debt is about 16 percent lower. For the total debt level including revolving and installment debt, Sharpen clients reduce their debt by around \$13,000 relative to the comparison group over the evaluation period. Additionally, counseling clients also exhibit comparatively rapid growth in their available credit (as a percentage of total credit), indicating that they are building available liquidity at a significantly faster rate than the comparison group.

While debt unambiguously declines for the counseling group relative to the comparison group, the question of what drives this decline is less clear. To explore the answer this question, this study checked for two potential sources of debt reduction (in addition to the effects of general credit counseling): Debt write-offs from charge-offs, bankruptcies or foreclosures, or program-related debt reductions from DMP enrollment. Overall, the results show that both of these sources contribute significantly to client debt reduction. When controlling for bankruptcies, charge offs and foreclosures over the study period, the

individuals). The combined number of comparison individuals between DMP and non-DMP models slightly exceeds the total number of comparison individuals because comparison individuals could be matched to both DMP and non-DMP clients within strata, leading to some slight overlap in comparison individuals between models.

relative difference in debt levels is smaller, but is still significant. It is worth noting here that client bankruptcies do not exist in isolation from credit counseling. Sharpen clients can, as part of the counseling process, be recommended for bankruptcy and even undergo separate bankruptcy counseling. From the perspective of the client, bankruptcy may be the best option for them to manage their debts, so excluding bankrupt individuals from the analysis may understate the realized benefit to clients from credit counseling. When looking at the relative debt reduction for DMP and non-DMP Sharpen clients, we see that both groups experience significant revolving debt reductions even when controlling for bankruptcy or charge offs, and DMP clients exhibit higher rates of debt reduction than those not recommended for DMPs.

For client credit scores, the results are mixed. For the full sample of counseled individuals, we observe a substantial credit decline which only begins to recover in the third post-counseling quarter. The comparison group, however, experiences a modest upward trend in credit scores over the evaluation period and has a significantly higher credit score than the counseled group at the end of the evaluation period. In the final quarters of the evaluation, Sharpen clients' credit scores are growing at faster rates than that of the comparison group. However, it is unclear if this is due to Sharpen or from the fact that lower credit scores have more room to grow (a "regression to the mean" effect). Additional credit data for these households over a longer study period may help resolve this, as credit scores tend to be "sticky" and may not fully reflect changes in financial behaviors (i.e. making payments on time, improving debt ratios, etc.) which may emerge as a result of counseling. When only looking at counseling clients and comparison group individuals who went through major credit shocks, there is a directional improvement in credit scores for counseling clients relative to the comparison group, but this difference is not significant.

Though credit scores for the counseled group remain consistently lower than credit scores for the comparison group, the story changes slightly when looking at more financially distressed households. For those who had credit scores in the *bottom half* of the credit distribution (a credit score at or below 601) at baseline, counseled households see their credit scores first lag behind the comparison group before exceeding them by the end of the evaluation period. This may be due to the fact that clients in this subset do not experience as much of a credit decline in response to a debt or income shock, as their credit was already substantially lower to begin with. An additional possibility is that these clients experienced a debt or income shock further back in their credit history (i.e. six months or a year prior to counseling). This would imply that clients who had lower credit scores due to a shock may be matched with comparison group individuals with chronically low credit, and the increased gains relative to the comparison group reflect this difference. Yet given that the comparison group's credit scores are growing persistently over time as well, it is difficult to characterize the comparison group as simply having persistently low credit. For those in the *bottom quartile* of the credit distribution at baseline (a credit score at or below 540), Sharpen clients actually end up with somewhat higher credit scores than comparison individuals, and there is evidence that their growth over the evaluation period is significant. However, it remains unclear if the increased credit gains relative to the comparison group are due to the counseling program or from factors outside of counseling.

Notably, clients in the bottom credit quartile do not appear to have a credit shock during the study period, which may indicate that they had a shock prior to the evaluation period. The absence of a shock could also possibly be because clients with relatively low credit scores seek credit counseling due to a desire to

improve their persistently poor credit profile rather than due to a credit shock of some sort. Indeed, supplemental analysis reveals that clients in the bottom quarter of the credit distribution report seeking counseling for "bad credit" at twice the rate of the general Sharpen clientele (though overall their motivations appear largely similar). Summarizing these results, we can say that there is some evidence that Sharpen clients with relatively distressed credit profiles improve their credit scores relative to non-counseled individuals, though the exact mechanisms for this improvement remain unclear.

Finally, there is also evidence that clients recommended for DMPs see stronger improvements in their credit scores than those clients not recommended for DMPs. While credit scores for both groups decline relative to the comparison group, the DMP group experiences a substantially smaller decline in credit scores. While this difference may be attributable to inherent differences between DMP and non-DMP groups, the fact that this difference holds when controlling for bankruptcies and charge-offs post-counseling may indicate that DMPs themselves drive improvements in credit scores.

Turning to credit payments rather than credit score, relatively distressed Sharpen clients exhibit improvements in making on-time payments. Relative to the comparison group, clients in both the bottom half and bottom quartile of credit scores at baseline similarly exhibit improvements in their propensity to fall 60 days or more behind on payments relative to the comparison group. Generally speaking, Sharpen clients as a whole experience spikes in payment delinquencies around the time of counseling which recover by the end of the evaluation period, though as with the credit score metric it is not clear if counseling specifically plays a role in driving this recovery.

Overall, this evaluation demonstrates that clients receiving credit counseling have statistically significant improvements in debt reduction relative to a comparison group, and it has provided evidence that relatively credit-distressed counseling clients (defined as those in the bottom 50<sup>th</sup> or 25<sup>th</sup> percentiles of the credit distribution prior to counseling) experienced more substantial credit gains post-counseling than the general counseling population. In this, the study has somewhat similar results to a separate analysis of credit counseling conducted by Elliehausen, Lundquist, and Staten (2007). Examining credit outcomes three years after counseling, that analysis found that counseling was associated with very modest credit improvements for consumers in the bottom credit quartile, and also found substantial reductions in debt for this segment.

A few cautions should be noted when interpreting the results from this analysis. First, there may be unobserved differences between households who are counseled and the matched comparison group, limiting the ability of the study to estimate causal impact. The gold standard approach to identify causality is a randomized control trial, where a subset of consumers is randomly assigned to the intervention. Given the nature of the counseling industry, it is unlikely that counseling services would be withheld from a random subset of consumers in distress, which would be necessary to establish a randomized control group. While our alternative of creating a matched comparison group allows us to approximate a counterfactual outcome, the only traits of the counseled and comparison groups on which we can match are those traits we can observe for both groups. This means that we cannot match on motivational or behavioral traits. Further, individual demographic characteristics and employment characteristics (including recent job loss) are not provided in credit data. Inasmuch as these characteristics influence the decision to seek credit counseling, our estimate of the counterfactual outcomes is incomplete.

Relatedly, caution should be exercised when interpreting the evolution of credit and payment delinquency indicators. Many counseling clients appear to go through some form of shock impacting their credit indicators around the time of counseling. Ideally, one would construct a comparison group of consumers experiencing a similar shock, who did not receive counseling. Future analyses could address this by using a "dynamic baseline" approach, wherein counseling clients would be matched with comparison group individuals based on multiple pre-counseling periods. This would allow for individuals to be matched based on the *trends* in their credit indicators as well as the indicators themselves, and would potentially allow the analysis to match clients experiencing deteriorating credit scores with non-counseled individuals experiencing a similar credit decline.

Another limitation arises from the limited sample of credit counseling agencies used in this analysis. A subset of 13 NFCC affiliated credit counseling agencies volunteered and was selected to participate in the credit analysis. As such, the results presented here are specific to the sample examined from these participating agencies and may not reflect outcomes across other credit counseling agencies. To assess potential differences between agencies participating in the credit analysis and those not participating, client characteristics between participating and non-participating agencies were compared. Though not featured in this essay, this analysis shows that clients in participating and non-participating agencies are demographically similar, and while the financial profiles do differ somewhat between these groups the differences are not substantial enough to draw any strong conclusions.

Finally, the strength of this analysis is limited by the matching procedure. As this study drew the comparison group from a credit database of millions of individuals, the matching procedure was likely as robust as it possibly could be. Even so, based on our matching criteria we still were unable to find a match for a portion of counseled clients. Almost by definition, clients for whom there was no match likely have more unique credit circumstances, so by excluding these clients for lack of a match it is also possible we are failing to capture Sharpen's impacts on these relatively idiosyncratic clients. A comparison of the characteristics and credit outcomes between matched and unmatched clients (not presented in this essay) shows that unmatched counseling clients are relatively distressed compared to the matched counseling clients, with lower credit scores and higher debt levels; however trends in credit scores and debt levels for the unmatched group are similar to those of the matched counseling clients. This analysis partially addresses Sharpen's impact on households in exceptional states of financial distress by looking at outcomes for subsets of clients with relative low credit scores and found positive results, but the possibility that the matching analysis is failing to capture outcomes for uniquely vulnerable clients remains.

# 9. Conclusion and Policy Implications

As individuals continue to struggle with high debt levels, employment volatility, low savings levels, and inadequate assets for retirement, both policymakers and creditors are examining a variety of options for addressing these problems and their associated risks. This study provides evidence that consumer credit counseling, a decades-old service that has nevertheless been under-researched, can provide a means of improving consumer financial outcomes, particularly for those undergoing substantial financial distress. Of particular interest is the behavioral impact of counseling on credit indicators for these clients, or the degree to which counseling itself (rather than bankruptcy, charge-offs, or debt management plans) may impact people's financial behaviors and thus their long-term outcomes. This study has taken a number of

steps to isolate this behavioral component by isolating the reduction in debt when accounting for bankruptcies, charge-offs, foreclosures, or DMP enrollment status. Regardless of the steps taken, the positive impact of counseling (particularly on the levels of revolving debt held by clients) remains.

What this analysis cannot explain, however, is the exact source of this change. Perhaps counseling's function of calling attention to financial problem areas and providing concrete action plans causes clients to focus more on their own behaviors and manage their money better; perhaps the check-ins and payment monitoring done by counseling agencies reminds clients of their obligations and drives their actions; perhaps the credit counseling agency acts as a hub to provide clients with additional resources such as other non-profit or public programs to assist them with job-training or high debts. It is also possible that some of this reduction stems from intrinsic characteristics also associated with the motivation to seek counseling. By virtue of being the type of person to seek counseling, one may also be the type of person likely to responsibly manage their debts. Yet the fact that many people are driven to seek these services due to exogenous shocks rather than internal desire may lessen any impact that selection effects like these have on the total outcomes. Individuals in crisis seek out likely seek out counseling based on the severity of their crisis and their awareness of the service and its purported benefits, factors likely unassociated with any selection mechanism. Regardless, these issues remain a concern for this and many other studies where randomization is not possible or feasible.

From the policymaker's perspective, the benefits demonstrated in this study are important to enhancing overall social welfare. Reductions in overall debt levels mean less money is being spent on interest payments and more money is being put towards savings or consumption. Further, lower debt levels likely mean less propensity to declare bankruptcy, which can prevent individuals from making larger purchases that can enhance personal welfare such as cars, houses, or college tuition. Increases in liquidity provide safety nets for individuals which can give them a means of weathering a crisis without relying on public assistance, and also provide them with the financial slack necessary to avoid using high-cost options such as payday lenders to weather short-term crises. Enhanced credit scores for the most credit distressed individuals means those individuals may become credit-worthy sooner, and thus will not be prevented from accessing a wide variety of potentially beneficial financial instruments including mortgages.

From the creditor's perspective the results are more mixed. Having individuals paying down debt more rapidly may be seen as a net loss, but having individuals with unsustainable levels of debt that they may eventually have to write-off is a larger loss still. Inasmuch as credit counseling provides a path for clients to reach a more manageable debt situation, in the long-term creditors may be better off *vis a vis* these clients, as decreased debt and increased liquidity mean clients can qualify for more financial products and afford to make debt-financed purchases.

In addition to the benefits from the core counseling service, credit counseling also provides a means to pursue more targeted programs. As clients come through the doors of credit counseling services, specific needs can be identified (such as a need to save for retirement or the need to responsibly take on student loans) and steps can be taken above and beyond the core counseling services to address those needs. These steps can involve additional targeted financial education (which is already being pursued in many counseling agencies), access to appropriate public or non-profit programs, or the provision of specific savings or debt products generated through partnerships with financial firms. As the positive impact of credit counseling has been established through this and the limited number of other studies in this field,

the next steps for this research involve determining how to build on this general counseling framework through additional program enhancements. In particular, future research will explore how the use of text and email reminders for financial goals and payment obligations can impact long-term financial outcomes.

# References

- Agarwal, S., Amromin, G., Ben-David, I., Chomsisengphet, S., & Evanoff, D. D. (2010). Learning to cope: Voluntary financial education and loan performance during a housing crisis. *American Economic Review*, 100(2), 495–500.
- Agarwal, S., Amromin, G., Ben-David, I., Chomsisengphet, S., & Evanonff, D. D. (2009). *Do financial counseling mandates improve mortgage choice and performance? Evidence from a legislative experiment* (No. WP 2009-07).
- Bagwell, D. C. (2000). *Work and personal financial outcomes of credit counseling clients*. Virginia Polytechnic Institute and State University, Blacksburg: Unpublished doctoral dissertation.
- Barron, J. M., & Staten, M. E. (2011). *Is technology-enhanced credit counseling as effective as in-person delivery?* DIANE Publishing.
- Bernheim, B. D., Garrett, D. M., & Maki, D. M. (2001). Education and savings: The long-term effects of high school financial curriculum mandates. *Journal of Public Economics*, 80(3), 435–465.
- Cohen-Cole, E., Duygan-Bump, B., & Montoriol-Garriga, J. (2009). Forgive and forget: Who gets credit after bankruptcy and why? *EFA 2009 Bergen Meetings Paper*.
- Cole, S., & Shastry, G. (2010). Is high school the right time to teach savings behavior? The effect of financial education and mathematics courses on savings.
- Collins, J. M. (2013). The impacts of mandatory financial education: Evidence from a randomized field study. *Journal of Economic Behavior & Organization*, 95, 146–158.
- Collins, J. M., & O'Rourke, C. (2012). *Still holding out promise: A review of financial literacy education and financial counseling studies* (No. 2012-WP-02).
- Courchane, M. J., & Zorn, P. M. (2005). Consumer literacy and creditworthiness.
- Visa, U.S.A. (1999). Credit counseling: Debt management plan analysis.
- Credit.com. (2015). What is VantageScore? Retrieved January 1, 2015, from https://www.credit.com/credit-scores/vantagescore/
- Ding, L., Quercia, R. G., & Ratcliffe, J. (2008). Post-purchase counseling and default resolutions among low- and moderate- income borrowers. *Journal of Real Estate Research*, *30*(3), 315–344.
- Elliehausen, G., Lundquist, E., & Staten, M. E. (2007). The impact of credit counseling on subsequent borrower behavior. *Journal of Consumer Affairs*, 41(1), 1–28.
- Fernandes, D., Lynch Jr, J. G., & Netemeyer, R. G. (2014). Financial Literacy, Financial Education, and Downstream Financial Behaviors. *Management Science*, (June 2015), 1–23. http://doi.org/10.1287
- Gross, D. B., & Souleles, N. S. (2002). Do liquidity constraints and interest rates matter for consumer behavior? Evidence from credit card data. *The Quarterly Journal of Economics*, 117(1), 149–185.
- Hartarska, V., & Gonzalez-Vega, C. (2005). Credit counseling and mortgage termination by low-income households. *The Journal of Real Estate Finance and Economics*, *30*(3), 227–243.
- Haushofer, J., & Fehr, E. (2014). On the psychology of poverty. Science, 344(6186), 862-867.
- Haushofer, J., Schunk, D., & Fehr, E. (2013). Negative income shocks increase discount rates. *University* of Zurich Working Paper.
- Iacus, S. M., King, G., & Porro, G. (2012). Causal inference without balance checking: Coarsened exact matching. *Political Analysis*, 20(1), 1–24.

Keating, S. (2013). 2013 state of the credit counseling and financial education sector.

- Kim, J., Garman, E. T., & Sorhaindo, B. (2003). Relationships among credit counseling clients' financial well-being, financial behaviors, financial stressor events and health, 75–87.
- Laibson, D. (1997). Golden eggs and hyperbolic discounting. *The Quarterly Journal of Economics*, *112*(2), 443–477.
- Loonin, D., & Plunkett, T. (2003). Credit counseling in crisis: The impact on consumers of funding cuts, higher fees and aggressive new market entrants.
- Lusardi, A., & Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *Journal of Economic Literature*, 52(1), 5–44.
- Meier, S., & Sprenger, C. (2010). Present-biased preferences and credit card borrowing. *American Economic Journal: Applied Economics*, 2(1), 193–210.
- Miller, M., Reichelstein, J., Salas, C., & Zia, B. (2014). Can You Help Someone Become Financially Capable ? A Meta-Analysis of the Literature (No. 6745).
- Moulton, S., Collins, J. M., Loibl, C., & Samak, A. (2015). Effects of monitoring on mortgage delinquency: Evidence from a randomized field study. *Journal of Policy Analysis and Management*, 34(1), 184–207.
- Mullainathan, S., & Shafir, E. (2009). Savings policy and decision-making in low-income households. In *Insufficient funds: Savings, assets, credit, and banking among low-income households* (pp. 140–42).
- Mullainathan, S., & Shafir, E. (2013). *Scarcity: Why Having Too Little Means So Much*. New York: Times Books.
- Muraven, M., & Baumeister, R. F. (2000). Self-regulation and depletion of limited resources: Does self-control resemble a muscle ?, *126*(2), 247–259.
- Nfcc.org. (2014). Urban Institute study raises the question of why people are not reaching out for financial help. Retrieved January 1, 2015, from https://www.nfcc.org/press/multimedia/news-releases/urban-institute-study-raises-the-question-of-why-people-are-not-reaching-out-for-financial-help/
- Quercia, R., & Spader, J. (2008). Does homeownership counseling affect the prepayment and default behavior of affordable mortgage borrowers? *Journal of Policy Analysis and Management*, 27(2), 304–325.
- Samuelson, W., & Stiller, M. (2012). The credit counseling industry--Distinguishing between the reputable and the less reputable. *Research Foundation Publications*, 2012(3), 71–84.
- Shah, A., Mullainathan, S., & Shafir, E. (2012). Some consequences of having too little. *Science*, 338(6107), 682–685.
- Spears, D. (2011). Economic decision-making in poverty depletes behavioral control. *The B.E. Journal of Economic Analysis & Policy*, 11(1), 1–42.
- Theodos, B., Simms, M., Treskon, M., Stacy, C., Brash, R., Emam, D., ... Collazos, J. (2015). An Evaluation of the Impacts and Implementation Approaches of Financial Coaching Program.
- Wang, J. J. (2010). Credit counseling to help debtors regain footing. *Journal of Consumer Affairs*, 44(1), 44–69.
- Wilshusen, S. M. (2011). *Meeting the demand for debt relief. Federal Reserve Bank of Philadelphia Payment Cards Center Discussion Paper.*

## FIGURES



Figure 1: Difference-in-Difference Analysis: Change in Credit Score

Source: Experian Credit Data



Figure 2: Difference-in-Difference Analysis: Change in 60 Day Payment Delinquencies

n=12,099 Source: Experian Credit Data



Figure 3: Difference-in-Difference Analysis: Change in Revolving Debt (For Those with **Debt at Baseline**)

Source: Credit Attributes Data





n=9,008 Source: Credit Attributes Data



Figure 5: Difference-in-Difference Analysis: Change in Credit Score (Bottom 50<sup>th</sup> Credit Percentile)

Figure 6: Difference-in-Difference Analysis: Change in Credit Score (Bottom 25<sup>th</sup> Credit Percentile)



*n*=2,558 Source: Credit Attributes Data





n=634 Source: Credit Attributes Data

	Mean
Gender, Female	69%
Status, Single	39%
Status, Separated	6%
Status, Divorced	13%
Status, Married or Living with a Partner	39%
Status, Widowed	3%
Race, Asian	3%
Race, Black	22%
Race, White	64%
Race, Other	12%
Ed, Less than High School	3%
Ed, High School Graduate	30%
Ed, Two Year College/Technical School	34%
Ed, Four Year Degree	21%
Ed, Graduate Degree	12%
Region, Midwest	18%
Region, Northeast	25%
Region, South	30%
Region, West	26%
Age	42.8
Average Monthly Income	\$3,093.2
Savings	\$559.0
Household Size	2.5
Children Under 18	0.8

 Table 1: Summary Statistics, Administrative Data

n=6,094 credit counseling clients Source: NFCC Administrative Data

Table 2. Reasons for Seeking Counseing		
	#	%
Reduced Income	4,804	79%
Domestic Conflict	390	6%
Un/underemployment	1,762	29%
Other	2,652	44%
Increased Expenses	1,321	22%
Costs of death in family	35	1%
Creditors increased interest rates	148	2%
Increased family size	128	2%
Medical/Disability expenses	404	7%
Other	606	10%
Other Reasons	1,350	22%
Bad credit	149	2%
Previous bad experience	45	1%
Other	1,156	19%

# **Table 2: Reasons for Seeking Counseling**

n=6,094 credit counseling clients

Source: NFCC Administrative Data

\*Respondents could select multiple reasons for seeking counseling

Mataking Variable	Counseled Mean	Comparison Mean	% Difference (Treatment/	Dolonoo*
	(St. Dev)	(St. Dev)	Comparison)	Balance*
Credit Score (Vantage 3.0)	594	597	-1%	0.04
	(77.1)	(80.3)		
Open Revolving Debt (\$)	10,582	10,248	3%	0.02
	(15,346)	(14,947)		
Total Revolving Debt $(\$)^{\dagger}$	16,612	16,453	1%	0.00
	(35,612)	(38,893)		
Total Installment Debt (\$)	20,425	21,113	-3%	0.02
	(34,647)	(44,461)		
Mortgage Debt (\$)	44,021	46,565	-5%	0.02
	(104,449)	(131,740)		
Total Debt $(\$)^{\dagger}$	81,059	84,130	-4%	0.02
	(129,829)	(159,032)		
Number of Bankruptcies	0.30	0.29	3%	0.01
	(1.6)	(1.6)		
Age of Oldest Account (Months)	182	183	-1%	0.01
	(105.4)	(109.5)		
Payments 60 Days Delinquent (Last 12				
Months)	0.58	0.59	-1%	0.01
Dermanta 60 Davis Delinguant (Last 6	(1.6)	(1.7)		
$\operatorname{Months}^{\dagger}$	0.46	0.45	1%	0.00
	(14)	(1.5)	- / -	
Mortgage Payments 90 Days Delinquent	(11.1)	(110)		
(Last 24 Months)	0.11	0.12	-8%	0.01
	(1.2)	(1.4)		
Available Open Credit Ratio <sup>†</sup>	0.48	0.49	-1%	0.01
	(0.4)	(0.4)		
Balance to Credit Ratio on Revolving Debt	0.52	0.52	1%	0.01
	(0.4)	(0.4)		
Observations	6,094	6,005		

Table 3: Summary Statistics for Treatment and Comparison Groups (CEM)

Source: Credit Attributes Data

\*Balance is calculated as a function of the absolute difference between the counseled and comparison means, divided by the standard deviation for the full sample.

†These variables were not used in the matching procedure, but are dependent variables used in the differences-in-differences analysis.

Model (Standard Errors in				
Parentheses)	1	2	3	4
	Total		Open Credit	Total Balance-
Dependent Variable	Revolving Debt	Total Debt	Ratio	to-Credit Ratio
Counseling Client	-3,637.18***	-11,341.00***	0.05***	-0.04***
-	(341.88)	(1,368.07)	(0.01)	(0.01)
Quarter Indicators (Baseline	as Reference)			
1Q Post Counseling	-493.93***	512.71	0.03***	-0.03***
	(94.55)	(657.35)	(0.00)	(0.00)
2Q	-1,031.38***	1,735.79**	0.05***	-0.05***
	(198.23)	(694.10)	(0.00)	(0.00)
3Q	-1,516.85***	1,288.81*	0.08***	-0.08***
	(209.31)	(776.91)	(0.00)	(0.00)
4Q	-1,791.68***	1,391.67*	0.09***	-0.09***
	(220.78)	(836.38)	(0.00)	(0.00)
5Q	-2,032.59***	2,420.78***	0.09***	-0.09***
	(227.78)	(868.70)	(0.01)	(0.01)
6Q	-2,098.07***	2,808.70***	0.10***	-0.10***
	(239.86)	(968.64)	(0.01)	(0.01)
Treatment Quarter Interaction	ons (Final Quarter a	as Reference)		
Counseling	3,918.54***	12,014.93***	-0.05***	0.05***
C	(329.36)	(1,266.27)	(0.01)	(0.01)
Treatment*20	3,378.52***	9,290.58***	-0.03***	0.03***
	(252.74)	(1,167.90)	(0.01)	(0.01)
Treatment*3Q	2,074.04***	6,277.40***	-0.02***	0.02***
-	(226.10)	(1,047.73)	(0.01)	(0.01)
Treatment*4Q	1,059.97***	4,075.49***	-0.02***	0.02***
	(177.01)	(864.83)	(0.01)	(0.01)
Treatment*5Q	456.61***	1,540.19**	-0.01*	0.01*
	(122.36)	(700.31)	(0.00)	(0.00)
Constant	16,532.97***	82,582.95***	0.48***	0.52***
	(100.20)	(406.35)	(0.00)	(0.00)
R-squared	0.04	0.01	0.04	0.03
Observations				
(Individuals*Quarters)	84,693	84,693	84,693	84,693
Unique Individuals	12,099	12,099	12,099	12,099

#### Table 4: Differences-in-Differences Analysis, Debt Indicators

This table presents the results for a fixed effects panel regression with standard errors clustered by observation. The Counseling Client indicator measures the difference in outcomes for counseling clients relative to a matched non-counseled comparison group.

Source: Credit Attributes Data

\* $p{<}0.1$ ; \*\* $p{<}0.05$ ; \*\*\* $p{<}0.01$ 

Model (Standard Errors	•	
in Parentheses)	1	2
		Payments 60 Days
Dependent Variable	Credit Score	Delinquent (Past 6 Months)
<b>Counseling Client</b>	-6.76***	-0.01
	(1.23)	(0.03)
Constant	595.12***	0.46***
	(0.39)	(0.01)
R-squared	0.03	0.01
Observations		
(Individuals*Quarters)	82,859	84,693
Unique Individuals	11,837	12,099

#### Table 5: Differences-in-Differences Analysis, Credit Indicators

This table presents the results for a fixed effects panel regression with standard errors clustered by observation. The Counseling Client indicator measures the difference in outcomes for counseling clients relative to a matched non-counseled comparison group. Output for the quarter indicators and counseling/quarter interactions is suppressed.

Source: Experian Credit Data

\* p<0.1; \*\* p<0.05; \*\*\* p<0.01

Model (Standard Errors in				
Parentheses)	1	2	3	4
			Open	Total Revolving
	Total Revolving		Revolving	Balance-to-Credit
Dependent Variable	Debt	Total Debt	Credit Ratio	Ratio
<b>Counseling Client</b>	-4,814.77***	-12,725.78***	0.09***	-0.09***
	(449.98)	(1,477.65)	(0.01)	(0.01)
Constant	22,051.75***	90,989.41***	0.31***	0.70***
	(131.75)	(439.66)	(0.00)	(0.00)
R-squared	0.05	0.01	0.10	0.10
Observations				
(Individuals*Quarters)	63,105	77,217	63,056	63,105
Unique Individuals	9,015	11,031	9,008	9,015

#### Table 6: Differences-in-Differences Analysis, Debt Indicators (For Those with Debt at Baseline)

This table presents the results for a fixed effects panel regression with standard errors clustered by observation. The Counseling Client indicator measures the difference in outcomes for counseling clients relative to a matched non-counseled comparison group. Output for the quarter indicators and counseling/quarter interactions is suppressed.

Source: Credit Attributes Data

\* p<0.1; \*\* p<0.05; \*\*\* p<0.01

Model (Standard			
Errors in Parentheses)	1	2	3
	Total Revolving		Payments 60 Days Delinquent
Dependent Variable	Debt	Credit Score	(Past 6 Months)
<b>Counseling Client</b>	-1,973.05***	0.86	-0.13**
	(404.15)	(1.82)	(0.06)
Constant	7,195.09***	526.27***	0.96***
	(115.89)	(0.55)	(0.02)
R-squared	0.03	0.08	0.02
Observations			
(Individuals*Quarters)	37,135	36,694	37,135
Unique Individuals	5,305	5,242	5,305

# Table 7: Differences-in-Differences Analysis, Credit Indicators (50th Credit Percentile at Baseline)

This table presents the results for a fixed effects panel regression with standard errors clustered by observation. The Counseling Client indicator measures the difference in outcomes for counseling clients relative to a matched non-counseled comparison group. Output for the quarter indicators and counseling/quarter interactions is suppressed.

Source: Credit Attributes Data

\* p<0.1; \*\* p<0.05; \*\*\* p<0.01

Dasenne)			
Model (Standard Errors			
in Parentheses)	1	2	3
	Total Revolving	Credit	Payments 60 Days Delinquent (Past 6
Dependent Variable	Debt	Score	Months)
<b>Counseling Client</b>	-526.09	7.49***	-0.17
	(355.70)	(2.57)	(0.10)
Constant	3,631.72***	487.04***	1.48***
	(130.24)	(0.74)	(0.04)
R-squared	0.04	0.16	0.05
Observations			
(Individuals*Quarters)	18,095	17,906	18,095
Unique Individuals	2,585	2,558	2,585

# Table 8: Differences-in-Differences Analysis - Credit Indicators (25th Credit Percentile at Baseline)

This table presents the results for a fixed effects panel regression with standard errors clustered by observation. The Counseling Client indicator measures the difference in outcomes for counseling clients relative to a matched non-counseled comparison group. Output for the quarter indicators and counseling/quarter interactions is suppressed.

Source: Credit Attributes Data

\* p<0.1; \*\* p<0.05; \*\*\* p<0.01

Model (Standard Errors in Parentheses)	1
Dependent Variable	Credit Score
Counseling Client	5.85
	(5.53)
Constant	594.56***
	(1.76)
R-squared	0.18
Observations (Individuals*Quarters)	4,438
Unique Observations	634

 Table 9: Differences-in-Differences Analysis - Credit Outcomes for Individuals Matched

 by Presence of Credit Shock

This table presents the results for a fixed effects panel regression with standard errors clustered by observation. The Counseling Client indicator measures the difference in outcomes for counseling clients relative to a matched non-counseled comparison group. Output for the quarter indicators and counseling/quarter interactions is suppressed.

*Source: Credit Attributes Data* \* p<0.1; \*\* p<0.05; \*\*\* p<0.01

Table 10. Differences-in-Diff	erences Analysis -	Controlling for De	ot write-Ons	
Model (Standard Errors in				
Parentheses)	1	2	3	4
		Total Revolving		
	Total Revolving	Debt (Had Debt		Total Debt (Had Debt at
Dependent Variable	Debt	at Baseline)	Total Debt	Baseline)
<b>Counseling Client</b>	-1,988.54***	-2,659.47***	-6,604.27***	-7,614.55***
	(322.99)	(424.72)	(1,305.71)	(1,410.92)
Bankruptcy Post-Baseline <sup>†</sup>	-13,972.72***	-16,966.38***	-58,237.28***	-60,858.06***
	(1,002.68)	(1,183.58)	(3,859.80)	(3,998.96)
Charge-Offs Post-Baseline <sup>†</sup>	-5,778.28***	-6,563.97***	-9,852.71***	-9,801.84***
	(312.75)	(375.06)	(841.14)	(877.36)
Foreclosures Post-Baseline <sup>†</sup>			-64,529.61***	-64,555.67***
			(11,665.13)	(11,739.10)
Constant	16,532.97***	22,051.75***	82,582.95***	90,989.41***
	(98.36)	(128.86)	(397.55)	(429.51)
R-squared	0.08	0.10	0.04	0.05
Observations				
(Individuals*Quarters)	84,693	63,105	84,693	77,217
Unique Individuals	12,099	9,015	12,099	11,031

#### Table 10: Differences-in-Differences Analysis - Controlling for Debt Write-Offs

This table presents the results for a fixed effects panel regression with standard errors clustered by observation. The Counseling Client indicator measures the difference in outcomes for counseling clients relative to a matched comparison group. Output for the quarter indicators and counseling/quarter interactions is suppressed.

Source: Credit Attributes Data

\* p<0.1; \*\* p<0.05; \*\*\* p<0.01

†Coded as '0' or '1' in each quarter. Once variable is coded as 1, it remains coded as 1 for all subsequent quarters.

Model (Standard Errors in				
Parentheses)	1	2	3	4
Dependent Variable		Total Rev	olving Debt	
Counseling Client (DMP				
<b>Recommendation</b> )	-3,340.09***		-2,095.31***	
	(366.44)		(350.46)	-1,990.46***
Counseling Client (No DMP Recommendation)		-4,129.67***		(282.41)
		(6/4.14)		
Bankruptcy Post-Baseline <sup>†</sup>			-12,061.03***	-10,320.43***
			(1,187.47)	(1,158.27)
Charge-Offs Post-Baseline <sup><math>\dagger</math></sup>			-5,244.10***	-5,007.81***
			(387.07)	(304.34)
Constant	17,563.18***	14,818.66***	17,563.18***	14,049.70***
	(98.46)	(212.04)	(96.95)	(988.24)
R-squared	0.05	0.03	0.09	0.35
Observations				
(Individuals*Quarters)	54,089	33,145	54,089	33,145
Unique Individuals $\ddagger$	7,727	4,735	7,727	4,735

# Table 11: Differences-in-Differences Analysis - Debt Outcomes for Samples Split by Client DMP Recommendation

This table presents the results for a fixed effects panel regression with standard errors clustered by observation. The Counseling Client indicator measures the difference in outcomes for counseling clients relative to a matched non-counseled comparison group. Output for the quarter indicators and counseling/quarter interactions is suppressed.

#### Source: Credit Attributes Data

\* p<0.1; \*\* p<0.05; \*\*\* p<0.01

†Coded as '0' or '1' in each quarter. Once variable is coded as 1, it remains coded as 1 for all subsequent quarters.

#### **Appendix A: Analysis Sample Construction**



	Participating Agencies	Non-Participating Agencies	Significance*
	Mean	Mean	
Age (Years)	42.4	44.3	***
Male (%)	34%	33%	**
Marital Status			
Married or Living with a Partner (%)	43%	40%	***
Single (%)	36%	34%	***
Race			
Black (%)	19%	22%	***
White (%)	69%	65%	***
Education			
Four-Year College Degree (%)	26%	33%	***
High School Graduate or GED (%)	32%	37%	***
Financials			
Average Monthly Income (\$)	3,420	3,394	
Monthly Housing Expenses (\$)	1,162	1,010	***
Debt-Related Expenses (\$)	1,132	1,527	***
Tangible Assets (\$)	81,774	72,079	***
Savings (\$)	940	1,402	***
Liabilities (\$)	79,770	67,953	***
Total Clients	18.829	24,243	

### Appendix B: Comparison of Clients from Participating and Non-Participating Agencies

Source: NFCC Administrative Data

\*Significance for continuous variables is measured by t-tests, significance for dichotomous variables is measured by chi-squared tests