Credit Counseling, Financial Coaching, and Client Outcomes: An Examination of Program Impacts and Implementation Dynamics

Dissertation

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Abstract

Consumers in the United States are beset by a number of serious financial issues and concerns that are unlikely to disappear in the near future. When issues such as high levels of consumer debt, financial illiteracy, and suboptimal financial management skills are coupled with the vulnerability to economic fluctuations and persistently low savings levels observed in the U.S., individuals may be rendered less capable of weathering even modest income and expense shocks and may face substantial financial distress over the course of their lives. Consumer credit counseling agencies offer a means of addressing the harms and risks caused by these economic realities.

Given the reach of counseling initiatives, which serve millions of people a year, there is a distinct need for rigorous assessments of credit counseling’s potential impact on client outcomes. Understanding the impact of these services helps validate credit counseling’s potential as a lever for policymakers to employ in addressing the consumer financial issues associated with both economic shocks and longer-term trends in consumer behaviors.

This dissertation focuses on two interventions housed within consumer credit counseling agencies: A credit counseling program and a financial coaching program. After outlining a conceptual framework through which the potential impacts of credit counseling may be understood, this dissertation empirically explores a nationwide credit counseling initiative and outlines a profile of counseling clients. To measure the impacts of this credit counseling program relative to the counterfactual, this dissertation estimates a series of differences-in-differences models to track outcomes for over 6,000 counseling clients relative to a matched non-counseled
comparison group. The key finding of this analysis is that counseling clients reduce both revolving debt and total debt relative to the comparison group and these reductions hold when controlling for debt write-offs and debt management plan participation.

This dissertation then narrows its focus to examine the impact that frontline implementation dynamics have on the outcome of an experimental financial coaching program. The analysis first demonstrates that both program outputs and target group outcomes vary by the frontline worker. It explores the sources of this variation and finds that these differences are associated with differing approaches to client engagement and different levels of worker engagement with the program itself. Specifically, the analysis finds that workers who are capable of successfully engaging clients are significantly more capable of driving program enrollment, while workers who are more engaged with the program’s change processes are significantly more capable of driving improved client outcomes.

These analyses show not only that credit counseling can drive improvements in client financial outcomes but that understanding how programs are delivered also matters in assessing outcomes. In doing so, this dissertation contributes to the broad general literature on consumer financial policies and programs and to the limited literatures on credit counseling and financial coaching, as well as both the theoretically- and empirically-oriented literatures on social service implementation in the fields of public policy and management. Further, it contributes to the emerging research on the use of behavioral economics to understand and address issues in public policy.
Dedication

This dissertation is dedicated to Genevieve, who makes the impossible seem inevitable.
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My loved ones.
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# Table of Contents

Abstract .................................................................................................................................. ii

Dedication ............................................................................................................................... iv

Acknowledgements ................................................................................................................... v

Vita ........................................................................................................................................... vi

List of Tables .......................................................................................................................... xii

List of Figures ......................................................................................................................... xv

Chapter 1: A Conceptual Framework for Credit Counseling Interventions ......................... 1

    Introduction to the Dissertation ....................................................................................... 1

    Structure of the Dissertation .......................................................................................... 7

Industry Background ............................................................................................................. 9

A Framework for Credit Counseling Initiatives .................................................................. 11

    The Target Population ................................................................................................... 12

    Credit Counseling Mechanisms, Client Behaviors, and Client Outcomes .................... 17

    Organizational and Frontline Influences on Credit Counseling Outcomes ...................... 23

    The Framework Summarized ........................................................................................... 29

Discussion ............................................................................................................................... 31
Chapter 2: Who Seeks Out Credit Counseling Services? ................................................................. 33

Introduction ............................................................................................................................................. 33

What We Know about Credit Counseling Clients .................................................................................. 37

Data and Method ......................................................................................................................................... 42

Results ......................................................................................................................................................... 46

Who Seeks Out Credit Counseling Services? .......................................................................................... 46

What are Counseling Clients’ Financial Behaviors at the Time of Credit Counseling? ........52

What Changes Do Clients Report After Credit Counseling? ................................................................. 60

How Do Credit Counseling Client Indicators Evolve from Pre- to Post-Counseling? ............ 64

Discussion .................................................................................................................................................. 72

Chapter 3: Credit Counseling’s Impact on Client Outcomes: Evidence from the Sharpen Your
Financial Focus Program .......................................................................................................................... 78

Introduction ................................................................................................................................................ 78

Literature Review ........................................................................................................................................ 81

The Credit Counseling Research Literature ......................................................................................... 81

Evidence from Related Programs ........................................................................................................... 85

The Impact of Income and Expense Shocks on Client Behavior ......................................................... 88

Theoretical Framework and Hypotheses ................................................................................................. 89

Program Description .................................................................................................................................. 92

Data and Methods ....................................................................................................................................... 93

Sample ...................................................................................................................................................... 93
Theoretical Framework and Hypotheses ................................................................................. 158

Data ...................................................................................................................................... 161

Research Context and Sample ............................................................................................... 161

Program Context .................................................................................................................... 163

Data Collection and Summary Statistics ............................................................................... 165

Method ................................................................................................................................. 171

Quantitative Analysis ............................................................................................................. 171

Qualitative Analysis .............................................................................................................. 173

Results ................................................................................................................................. 176

Contact Approaches and Frontline Workers ......................................................................... 179

Coaching Approaches and Frontline Workers ....................................................................... 183

Client Evaluations of Coaches ............................................................................................. 190

Implementation Approaches and Outcomes ........................................................................... 192

Discussion .......................................................................................................................... 197

Limitations ........................................................................................................................... 201

Implications and Future Research ......................................................................................... 202

Chapter 5: Conclusion ......................................................................................................... 204

Key Findings ......................................................................................................................... 206

Limitations ........................................................................................................................... 210

Future Research ................................................................................................................... 212

References ............................................................................................................................ 214
Appendix A: The Three-Month Post Counseling Survey ......................................................... 225
Appendix B: Sample Comparisons: MMCU and Client Survey ........................................... 228
Appendix C: Client Characteristics by Agency Evaluation Participation .............................. 230
Appendix D: Credit Evaluation Base Size Diagram ............................................................. 232
Appendix E: Comparing Matched and Unmatched Credit Counseling Clients ................... 233
Appendix F: Full Regression Output for Selected Models .................................................... 237
Appendix G: Excerpt from the Financial Coaching Training Manual ................................. 243
List of Tables

Table 1.1: Supplemental Services Provided by Selected Credit Counseling Agencies .......... 25
Table 2.1: Sharpen Client Demographics Compared to the U.S. Population ..................... 47
Table 2.2: Household Financials .................................................................................... 49
Table 2.3: Reason for Seeking Credit Counseling .......................................................... 50
Table 2.4: Household Financials by DMP Status ............................................................. 52
Table 2.5: Financial Confidence ..................................................................................... 53
Table 2.6: Budgeting Behaviors and Financial Strain ..................................................... 54
Table 2.7: Client Account Use ....................................................................................... 55
Table 2.8: Client Savings Behaviors .............................................................................. 56
Table 2.9: Household Borrowing Behaviors ................................................................... 57
Table 2.10: Housing Characteristics .............................................................................. 59
Table 2.11: Retirement Savings Behaviors ..................................................................... 60
Table 2.12: Self-Reported Changes in Financial Behaviors .......................................... 62
Table 2.13: Self-Reported Changes in Financial Conditions .......................................... 64
Table 2.14: Baseline Credit Characteristics ................................................................... 66
Table 2.15: Change in Debt Levels Over the Evaluation Period ..................................... 69
Table 3.1: Reason for Seeking Counseling ..................................................................... 94
Table 3.2: Client Demographic and Financial Characteristics ....................................... 95
Table 3.3: Summary Statistics for Treatment and Comparison Groups in Coarsened Exact
  Matching Analysis ........................................................................................................ 100
Table 3.4: Differences-in-Differences Analysis - Client Outcomes on Key Debt Indicators..... 109
Table 3.5: Differences-in-Differences Analysis - Client Outcomes on Key Credit Indicators.... 114
Table 3.6: Differences-in-Differences Analysis - Client Outcomes on Key Debt Indicators (For Those with Debt at Baseline)........................................................................................................ 117
Table 3.7: Differences-in-Differences Analysis - Client Outcomes on Key Credit Indicators (50th Credit Percentile at Baseline)........................................................................................................ 119
Table 3.8: Differences-in-Differences Analysis - Client Outcomes on Key Credit Indicators (25th Credit Percentile at Baseline)........................................................................................................ 121
Table 3.9: Differences-in-Differences Analysis - Credit Outcomes for Individuals Matched by Presence of Credit Shock .................................................................................................................. 124
Table 3.10: Differences-in-Differences Analysis - Client Outcomes Controlling for Debt Write-Offs ........................................................................................................................................ 126
Table 3.11: Differences-in-Differences Analysis - Debt Outcomes for Samples Split by Client DMP Recommendation........................................................................................................................................ 128
Table 3.12: Differences-in-Differences Analysis - Credit Outcomes by DMP Status............... 129
Table 3.13: Results Excluding Extreme Changes in Outcome Measures.................................. 130
Table 3.14: Debt Results Excluding Large Baseline Values .................................................... 132
Table 4.1: Client Enrollments and Treatment Takeup by Quarter............................................ 163
Table 4.2: Coaching Program and Session Characteristics.......................................................... 167
Table 4.3: Summary Statistics for Selected Client Characteristics Prior to Treatment .......... 169
Table 4.4: Summary Statistics by Coach Assignment................................................................. 170
Table 4.5: Proportion of Contact Types Prior to Takeup............................................................ 180
Table 4.6: Average Number of Sessions per Client................................................................. 183
Table 4.7: Average Coaching Session Time (Minutes).............................................................. 184
Table 4.8: Average Financial Goals Per Session....................................................................... 185
Table 4.9: Session Note Detail (Word Count per Session) ................................................................. 188
Table 4.10: Summary of Findings ..................................................................................................... 193
Table 4.11: Implementation Approach and Program Outcomes ....................................................... 196
Table C.1: Client Characteristics by Agency Participation in the Long-Term Credit Analysis .. 231
Table E.1: Credit Characteristics for Matched and Unmatched Counseling Clients ................. 234
Table E.2: Change in Credit Indicators Over the Evaluation Period For Unmatched Counseling
Clients ........................................................................................................................................... 236
Table F.1: Differences-in-Differences Analysis - Client Outcomes on Key Debt Indicators...... 239
Table F.2: Differences-in-Differences Analysis - Client Outcomes on Key Credit Indicators ... 240
Table F.3: Differences-in-Differences Analysis - Client Outcomes on Key Credit Indicators (50th
Credit Percentile at Baseline) .......................................................................................................... 241
Table F.4: Differences-in-Differences Analysis - Client Outcomes on Key Credit Indicators (25th
Credit Percentile at Baseline) .......................................................................................................... 242
List of Figures

Figure 1.1: The Theory of Planned Behavior Applied to Financial Behaviors ............................. 16
Figure 1.2: A Framework for Consumer Credit Counseling Initiatives ......................................... 30
Figure 2.1: U.S. Savings Rate and Consumer Credit Availability .............................................. 37
Figure 2.2: U.S. Foreclosures and Bankruptcy ............................................................................ 38
Figure 2.3: Change in Credit Score Over the Evaluation Period .................................................. 67
Figure 2.4: Distribution of Credit Score Changes Over the Evaluation Period ......................... 68
Figure 2.5: Distribution of the Change in Open Revolving Debt Over the Evaluation Period ...... 71
Figure 2.6: Change in Payments 60 Days Past Due Over the Evaluation Period ...................... 72
Figure 3.1: Total Debt Over the Evaluation Period ..................................................................... 108
Figure 3.2: Revolving Debt Over the Evaluation Period .............................................................. 108
Figure 3.3: Credit Scores Over the Evaluation Period ................................................................. 111
Figure 3.4: Sixty Day Payment Delinquencies Over the Evaluation Period ............................... 112
Figure 3.5: Revolving Debt Over the Evaluation Period (For Those with Debt at Baseline) ...... 115
Figure 3.6: Available Open Credit Ratios Over the Evaluation Period (For Those with Credit or Debt at Baseline) ......................................................................................... 116
Figure 3.7: Credit Scores Over the Evaluation Period (Bottom 50th Credit Percentile) .......... 118
Figure 3.8: Credit Scores Over the Evaluation Period (Bottom 25th Credit Percentile) .......... 120
Figure 3.9: Credit Scores Over the Evaluation Period (For Those Undergoing Credit Shocks in the First or Second Post-Counseling Period) ................................................................................. 123
Figure 4.1: Mortgage Delinquency by Coach ............................................................................ 177
Figure 4.2: Client Takeup Rates by Coach ................................................................. 178
Figure 4.3: Eliciting Client Responses ................................................................. 182
Figure 4.4: Clients with Personal Comments Registered by Coach ................. 189
Figure 4.5: Client Responses to Coaching (% “Strongly Agree”) ...................... 191
Figure D.1: Guide to Base Sizes at Different Stages of the Sharpen Evaluation .... 232
Introduction to the Dissertation

The issues surrounding low-income or financially vulnerable households are almost permanent fixtures on the United States policy agenda. Whether it is through the lens of the economic downturn and the housing collapse during the Great Recession (Willis, 2008), the perceived failure of welfare policies to achieve their goals decades after their implementation (Sherraden, 1991), the erosion of the real minimum wage in a time of stagnant incomes (Gordon & Dew-Becker, 2008), or many other concerns, the vulnerabilities, responsibilities, and economic realities of low-income households are perpetually being debated. Critical to this debate is the role that policies and programs can play in changing behaviors and outcomes for the financially vulnerable.

In this sphere there are a number of research streams focusing on, for example, financial education, financial coaching, Individual Development Accounts (IDAs), or emergency savings programs; but in these streams and others, research is either limited or conclusions about program efficacy are mixed. Credit counseling interventions, the central focus of this dissertation, suffer from similar limitations in demonstrating their effectiveness. The paucity of this literature is somewhat surprising given the credit counseling industry’s history, scope, and focus. Credit counseling agencies have existed for over 50 years and nonprofit credit counseling agencies alone provided services to between 1.5 and two million clients in 2013 and 2014; at the height of the

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1 A review of financial education and financial coaching literature can be found in Chapter Three of this dissertation.
recession these agencies serviced around four million clients in total (NFCC.org, 2015; Keating, 2012).  

The central focus of consumer credit counseling agencies is providing (1) financial education, (2) individualized counseling on financial and budgetary issues facing clients, and (3) debt management. Each of these services, which are available to anyone interested in them, has distinct policy relevance in the United States. Financial education programs are touted as a means to offset the relatively low levels of financial literacy in this country and many states have integrated some degree of financial education into general education curricula (Bernheim, Garrett, & Maki, 2001; Lusardi & Mitchell, 2014). Further, overconsumption relative to one’s income has been identified as a source of many social ills from general unhappiness to under-saving to taking on increasing levels of consumer debt (Laibson, 1997; Schor, 1999).

Individualized financial and budgetary counseling like that offered by credit counseling agencies can address issues of overconsumption by potentially identifying and helping to eliminate areas of excessive or unnecessary spending. Both financial education and individual financial management skills have emerged as issues of national concern, as the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 created the Consumer Financial Protection Bureau (CFPB) that, along with the Office of Financial Education housed within it, is charged with studying methods and developing programs to improve financial literacy and enhance the financial management skills of consumers (Dodd-Frank Wall Street Reform and Consumer Protection Act, 2010; Hastings, Madrian, & Skimmyhorn, 2013).

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2 These numbers have historically been higher when including clients served at any credit counseling agencies, rather than just nonprofit agencies. In 2003, for example, it was estimated that around nine million total clients sought credit counseling in any agency (Loonin & Plunkett, 2003).

3 While the exact number of debt management plans administered over this period is not available, based on correspondence with the National Foundation for Credit Counseling it is estimated that about a quarter of all financial reviews in NFCC-accredited counseling agencies result in debt management plans.
Finally, the level of debt held by individuals, be it consumer debt, student debt, or mortgage debt, is often raised as an area of substantial economic concern by politicians, policy makers, and researchers; with trillions of dollars in outstanding consumer debt (and almost a trillion in unsecured revolving debt) and the level of student loan debt tripling in the last decade to over a trillion dollars, this concern about the debt held by Americans is understandable (Bricker, Brown, Hannon, & Pence, 2015; Federal Reserve, 2016). Credit counseling agencies have the potential to address these issues through one of their central program offerings: The debt management plan (DMP), which consolidates unsecured debt payments and provides more favorable repayment terms for indebted clients (Hunt, 2005). Many credit counseling agencies also offer homeownership counseling for new and/or struggling homeowners and bankruptcy counseling for extremely distressed clients and are beginning to develop programs to address the needs of student loan holders (National Foundation for Credit Counseling, 2015a; Wilshusen, 2011).

Agencies can also pursue a variety of other supplemental interventions to help improve client outcomes or target specific populations. These interventions can include financial coaching (which involves working with clients to develop goals and action plans and then routinely following-up to help the client achieve those goals), small loans to help clients build their credit, programs to help build savings, and reminder systems to help keep clients on track with their payments. Approximately one-third of nonprofit consumer credit counseling agencies also provide social services beyond credit counseling (National Foundation for Credit Counseling, 2015b). Lutheran Social Services of Minnesota, for example, offers credit counseling as one of a large array of services, including employment services, foster care, and support for refugees, seniors, veterans, and homeless youth.

Beyond the policy relevance of credit counseling services, the credit counseling industry itself has been the target of regulatory scrutiny. Due to the emergence of credit counseling
agencies (and those offering related services) operating on a for-profit business model and sometimes engaging in deceptive practices or imposing high fees on clients (Loonin & Plunkett, 2003), the industry now faces an array of regulatory requirements that, among other things, require agencies to meet accreditation standards; disclose service details, risks, and benefits to clients; impose limits on the fees charged by agencies; and circumscribe the structure of certain services, particularly debt management plans⁴ (Wilshusen, 2011). Additionally, the regulation of the credit counseling industry was centralized within the CFPB relatively recently with the passage of the Dodd-Frank Act of 2010 (Wilshusen, 2011), which may result in increased regulatory scrutiny and contribute to the already complex regulatory landscape facing these agencies (Samuelson & Stiller, 2012).

The lack of research underpinning the services offered by credit counseling agencies and the heightened regulatory environment surrounding these agencies are not unrelated points. The credit counseling industry came under scrutiny because of a perception that these agencies were exploiting already-vulnerable consumers and not providing benefits commensurate with the fees they charged or the promises they made. Given the potential for these services to address financial issues of serious relevance to both individual clients and the American economy generally, there is an important role for research to play in determining the degree to which credit counseling services can address these issues and impact client welfare.

It is in this space that this dissertation operates. By empirically examining the client impacts of a nationwide credit counseling program and the frontline implementation dynamics within a credit counseling agency, it seeks to answer both the broad question regarding credit counseling’s potential impact on its clients and a narrower question about how dynamics within these agencies can influence program success. This research also takes the initial steps in

⁴ See, for example, the Uniform Debt-Management Services Act, which has currently been adopted by seven states (udmsa.org, 2013).
developing a conceptual framework through which the relationship between credit counseling services and client outcomes can be understood and explores the demographic, financial, and behavioral profile of credit counseling clients. In doing so, this dissertation contributes to the broad general literature on consumer financial policies and programs and to the limited literatures on credit counseling and financial coaching, as well as both the theoretically- and empirically-oriented literatures on social service implementation in the fields of public policy and management.

Additionally, the research in this dissertation has broader relevance to the emerging stream of research combining behavioral economics with public policy issues (Shafir, 2013). Behavioral economics, or the application of psychological models of individual behavior to economic concerns to understand how individual biases govern behavior, has been growing in prominence and its approaches and findings are increasingly being leveraged by policymakers (Thaler, 2015). The research in behavioral economics has made contributions in a number of finance-related policy areas, including individuals under-saving for retirement (Madrian & Shea, 2001; Thaler & Benartzi, 2004), the psychological impacts of poverty (Mullainathan & Shafir, 2013; Shah, Mullainathan, & Shafir, 2012), and credit card payment behaviors (Credit Card Accountability Responsibility and Disclosure Act of 2009, 2009; Soll, Keeney, & Larrick, 2013).

Outside of the context of financial behaviors there is also a growing body of work applying behavioral economics approaches to policy-relevant issues. In the field of social policy, for example, implicit biases have been found to govern employment decisions for typically underrepresented or disenfranchised target populations, particularly women and minorities (Krieger & Fiske, 2006; Pager, 2003). In health policy, questions of individual inattention and biases from environmental cues have driven debates around calorie labeling (Elbel, Kersh, Brescoll, & Dixon, 2009) and developing healthy eating heuristics (Wansink, Just, & Payne, 2009). In education, behavioral techniques have been used to reduce the impact of stereotypes on
individual educational achievement and have demonstrated long-lasting impacts (Cohen, Garcia, Purdie-Vaughns, Apfel, & Brzustoski, 2009).

At the core of much of the research on behavioral economics and its relation to public policy is the question of biases and how they impact individual and social welfare. These biases, broadly speaking, may stem from inattention, a preference for the status quo, discounted time preferences, problems with self-regulation, weighting losses more than gains, or a number of other sources. While not explicitly structured as an application of behavioral economics issues to consumer financial behaviors and policy, the credit counseling services that are the focus of this dissertation either currently employ techniques relevant to the study of behavioral economics and public policy, or have the potential to capitalize on an understanding of behavioral economics when optimizing the services offered by these programs. The mechanisms embedded in these services are detailed in the remainder of this chapter, but in summary they involve raising awareness of harmful behaviors, helping clients in developing goals and plans, monitoring client behavior, and altering the financial conditions of the client. Through these mechanisms, credit counseling programs provide a number of behaviorally-oriented interventions that have demonstrated potential in other behavioral economics-oriented research. This research includes work on overcoming issues related to the planning fallacy (Buehler, Griffin, & Peetz, 2010), the development of goal intentions and implementation intentions (Gollwitzer, 1999; Loibl & Scharff, 2010), the use of commitment devices and accountability to govern behaviors (Lerner & Tetlock, 1999), the use of monitoring and reminders to help individuals maintain health financial behaviors (Ashraf, Karlan, & Yin, 2006; Collins, Moulton, Samak, & Loibl, 2013; Oaten & Cheng, 2007), and how the structuring of debt payments can influence individual payment behaviors (Amar, Ariely, Ayal, Cryder, & Rick, 2011; Gal & McShane, 2012).

From this perspective the work in this dissertation not only contributes to the narrower fields of consumer financial policy, credit counseling initiatives, and policy and program
implementation, but also contributes to the broader and growing discourse on the use of behaviorally-oriented interventions to overcome individual behavioral biases and their associated problems to address issues of public policy.

**Structure of the Dissertation**

The first chapter of this dissertation provides a brief background on credit counseling programs and develops a conceptual framework to understand the change mechanisms underlying credit counseling programs, how these mechanisms may translate to behavioral changes in the target population, and how these behavioral changes translate to changes in outcomes. This chapter also explores dynamics at different levels of credit counseling’s implementation system, particularly at the organizational and frontlines levels, and describes how these dynamics may impact the success of the program in driving changes in the target population.

The second chapter uses several datasets to create a detailed profile of over 40,000 participants in a nationwide credit counseling initiative, investigating the demographic characteristics and self-reported financial behaviors of clients at the time of credit counseling and exploring the dynamics of these clients’ credit profiles both before and after they receive credit counseling. This chapter also compares aspects of credit counseling clients’ profiles to those of the general U.S. population using data from the Census and the Survey of Consumer Finances. This analysis finds that credit counseling clients typically seek credit counseling because they are facing some unforeseen income or expense shock such as job loss or an increase in medical expenses. Client credit outcomes reflect this shock: Clients experience a spike in payment delinquencies and a drop in their credit score; these metrics take about a year to recover. This analysis also finds that 71 percent of clients in the credit counseling program report paying the minimum or less on their last credit card payment, while fewer than a fifth of clients report having automatic savings deposits and almost half of clients report never setting money aside for savings. After credit counseling, clients see reductions in a variety of debt indicators, and over
two-thirds report that they are better managing money, paying their debt more consistently, setting financial goals, and seeing improvements in their overall confidence.

The third chapter of this dissertation presents an impact analysis of the national credit counseling initiative explored in Chapter Two. Using individual-level data on a random sample of general consumer credit profiles, this analysis generates a matched comparison group for over 6,000 credit counseling clients through Coarsened Exact Matching and estimates a series of differences-in-differences models to trace the evolution of credit outcomes for the credit counseling group relative to the matched comparison group. The key finding of this analysis is that credit counseling clients have reductions in both revolving debt and total debt relative to the matched comparison group and these reductions hold when controlling for client bankruptcies, foreclosures, debt charge-offs, and participation in debt management plans. This analysis also finds that clients with weaker credit profiles prior to credit counseling exhibit improvements in payment delinquency metrics and credit scores relative to the comparison group.

The fourth chapter of this dissertation moves from the broad assessment of credit counseling’s impact to an examination of program dynamics within a single credit counseling agency. Specifically, this chapter explores the impact that frontline implementation dynamics have on the outcome of an experimental financial coaching program implemented by the credit counseling agency. The analysis first demonstrates that both program outputs and target group outcomes vary by the worker implementing the program. It then explores the sources of this variation and finds that these differences in outputs and outcomes are associated with differing approaches to client engagement as well as with different levels of worker engagement with the change processes embedded in the program itself. Specifically, the analysis finds that workers who can successfully engage clients are significantly more capable of driving program take-up rates and promoting the program. Similarly, workers who are more engaged with the program’s change processes can significantly factors in drive improvements in client outcomes. This
analysis also finds that an ability to engage clients is not sufficient to drive program outcomes; the competencies required to drive program take-up and program outcomes are separate but not incommensurate.

The final chapter provides a brief conclusion to this research, outlining the dissertation’s contributions, key findings, limitations, and future avenues for research. This conclusion is followed by several appendixes providing additional context around the studies in this work.

**Industry Background**

Consumer credit counseling began in the 1950s, offering services to those clients experiencing financial distress, who desired to improve their overall credit profiles, or who were in the process of making important financial decisions. These programs are available to anyone and agencies generally operate through a mix of funding sources. They receive direct funding from client service fees (such as the fee associated with the administration of a debt management plan) and “fair-share” payments from creditors, which involve creditors remitting to the agency a percentage of the funds they receive from clients on a debt management plan. Beyond these direct funding services, agencies are also funded through grants from creditors, other nonprofit agencies (such as the United Way), and government agencies. Indeed, a review of the revenue sources for agencies involved in the impact analysis covered in Chapter Three of this dissertation found that 11 out of the 13 participating agencies reported receiving government grants for their services, indicating substantial public interest in the services provided by these agencies.

Nonprofit credit counseling agencies generally focus their services in three different areas: Education, counseling, and debt management (Loonin & Plunkett, 2003; Samuelson & Stiller, 2012). Educational programming informs consumers about core financial issues such as

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5 Chapter Two of this dissertation explores the demographic, behavioral, and financial characteristics of credit counseling clients.

6 Based on a review of IRS 990 reporting forms for the most recent available year, which was either 2013 or 2014.
general money management or credit usage and may also provide 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). The counseling aspect of these
agencies helps consumers better understand their financial situation, in part by looking at the
inflows and outflows of money to a household and helping them make informed decisions (such
as reducing expenses, liquidating assets, or closing existing credit accounts) about their spending
habits and how they might impact their financial health or short and long-term goals.

Debt management is the final major element of credit counseling services, primarily
involving the administration of the debt management plan. 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, based on the
resources accessible to that household. In exchange, the client commits to make a monthly debt
payment to the credit counseling agency (plus an administrative fee) and live within the budget
they established with the agency’s help (Samuelson & Stiller, 2012). In certain cases creditors
may also agree to re-age accounts under a DMP contingent on their successfully making
payments as part of the DMP, in essence treating any delinquent debt payments from the client as
being current (Hunt, 2005).

Nonprofit 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 credit counseling
services, while high unemployment or economic uncertainty leads to increased demand for these
services. Though demand for credit counseling services has remained high in an era of increasing
consumer debt there have been a number of developments that have presented threats to industry,
particularly among nonprofit credit counseling agencies. These include heightened competition as
the number of credit counseling agencies increased to serve the needs of an increasingly indebted society, reductions in the payments made by creditors to credit counseling agencies for administering DMPs, and the sharp fluctuations in demand for credit counseling services due to the Great Recession and subsequent recovery (Hunt, 2005; Keating, 2013; Loonin & Plunkett, 2003).

Additionally, the industry has struggled with the emergence of credit counseling agencies engaging in predatory or deceitful practices. While many agencies operate in good faith, employing a social services model that allows them to offer a wide variety of potentially beneficial services at low costs, the credit counseling industry is also populated by firms operating in a less reputable fashion. These firms will often push DMPs on clients regardless of their appropriateness and will often charge high (and sometimes hidden) fees to clients for the administration of these DMPs (Federal Trade Commission, 2012; Loonin & Plunkett, 2003). Debt settlement agencies, which attempt to reduce the overall debt balance for indebted clients and target a similar population as credit counseling agencies, also provide a source of competition for credit counseling agencies and have similarly been implicated for engaging in predatory practices (Samuelson & Stiller, 2012). The presence of these firms, which often aggressively advertise to consumers, cast a pall over the industry as a whole because it is difficult for consumers to distinguish between reputable and non-reputable firms and have resulted in increased regulatory scrutiny of the credit counseling industry.

A Framework for Credit Counseling Initiatives

Before undertaking the empirical analyses in Chapters Two through Four of this dissertation, it is important to both provide some context around credit counseling initiatives and specify the mechanisms by which credit counseling initiatives are expected to drive change in their target populations. Collins (2010) notes that there has been relatively little theoretical work done in the field of financial counseling (which includes credit counseling programs) and while
there does exist research that descriptively outlines the credit counseling industry (Hunt, 2005; Loonin & Plunkett, 2003; Samuelson & Stiller, 2012) and research that incorporates some theory into understanding trends in the credit counseling industry (Wilshusen, 2011), there does not yet exist any work developing a concrete conceptual lens through which one can understand the field of credit counseling. This chapter takes a step in that direction.

First, this chapter discusses the nature of the target population in credit counseling programs and how theory can contribute to understanding this target population. Then the tools embedded within credit counseling initiatives are discussed and these tools are linked to mechanisms for driving changes in client behaviors and outcomes. This discussion also details how the specific conditions of credit counseling’s target population may modify the link between credit counseling’s mechanisms and client outcomes and explores how different levels of the implementation system influence both service outputs and client outcomes. The relationship between the target population, credit counseling mechanisms, and client outcomes are summarized in Figure 1.2 below, and each of the subsequent sections make explicit reference to different aspects of this illustrated framework.

*The Target Population*

While a subset of clients may seek credit counseling for reasons outside of financial hardship, such as addressing deficits in financial knowledge or receiving general advice on budgeting practices, the target population for credit counseling initiatives is frequently a financially-distressed individual. This distress can take a variety of forms and there are two prominent financial motivations for those seeking credit counseling, illustrated in the “Financial Characteristics” box of Figure 1.2. The first is that clients are often driven to seek out these services due to some unforeseen event like the loss of a job or a medical issue that leads to

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7 Chapter Two of this dissertation provides an in-depth look at the characteristics of participants in counseling programs and summarizes the little available literature on the characteristics of these clients. As such, this description will be relatively brief.
unmanageable costs and the second is that clients take on unsustainably high levels of debt out of a desire to consume beyond their income levels (Wang, 2010). The relationship between job loss and seeking credit counseling helps explain the spike in demand for credit counseling services during the Great Recession (Bunting & Salandro, 2009; Keating, 2012), while the relationship between high credit usage and credit counseling demand explains the growth the credit counseling industry during a period of rapid increases in instantaneous credit access (Laibson, 1997; Loonin & Plunkett, 2003).

These income or expense shocks also have behavioral implications. Research has shown that individuals undergoing income shocks become more present-biased are may be more willing to pursue short-term and high-cost solutions to their financial problems, such as payday loans (Haushofer, Schunk, & Fehr, 2013; Mullainathan & Shafir, 2013). These shocks may also cause individuals to focus much more on financial decisions, which drain cognitive resources and may lead to an increased propensity to make poor financial decisions (Muraven & Baumeister, 2000; Spears, 2011). However, these shocks can also lead to individuals focusing more on their financial issues (Shah et al., 2012) and may make individuals more receptive to interventions like credit counseling.

The financial characteristics of the target population can also impact the type of services provided by the agency, as illustrated in the “Service Outputs” box of Figure 1.2. Debt management plan enrollment is contingent on the financial state of a client. If a counselor determines that a client has an income sufficient to pay down their debts without enrollment in a DMP, they will not be recommended for one and receive only the financial education and budget counseling components of the program. Similarly, if a client either lacks an income source or lacks sufficient income to pay down their debts even with a DMP, they also may not be enrolled (Loonin & Plunkett, 2003). If a client does meet these criteria (i.e. if they satisfy the debt and
income requirements), they receive all components of the program including the educational, counseling, and debt management components.

The target population may also be driven to take-up credit counseling due to demographic or individual characteristics (the “Non-Financial Characteristics” box in Figure 1.2). While the antecedents of take-up in credit counseling programs have not been extensively explored, research has shown that clients tend to be white, female, and relatively well-educated, and also have high expenses for their income levels and experience difficulties paying their bills on time (Bagwell, 2000; Collins & O’Rourke, 2010; Disney & Gathergood, 2009; Chapter 2 of this dissertation). Counseling clients also tend to have lower levels of financial literacy than the general population (Disney, Gathergood, & Weber, 2015) and clients may have self-control issues, which can lead to high levels of indebtedness, lower savings, increased risks of income shocks, and the non-payment of debts (Baumeister, 2002; Gathergood, 2012; Oaten & Cheng, 2007). Generally speaking, individual motivation may also drive take-up in credit counseling programs. Inasmuch as individuals differ in their willingness to seek credit counseling services (or vary in the thresholds at which they are willing to seek help), these latent characteristics also drive take-up in these programs and influence the makeup of the target population.

The characteristics of the target population may have direct effects on both behavioral changes and outcomes as well. Clients with higher levels of motivation to seek financial help, for example, may also be more motivated to pay down their debts, avoid payment delinquencies, reduce expenses, or start a household budget irrespective of their receipt of credit counseling; a classic case of the selection effect and a reason why using comparison groups in evaluations of these services is important. Alternately, clients who have higher educational attainment, income levels, or job security may experience less income volatility and less financial distress, resulting in higher savings or fewer payment delinquencies. Though the receipt of credit counseling may still drive other changes in these clients, any assessment of credit counseling’s impact needs to
disentangle the direct effects of client characteristics on behaviors and outcomes from the effects of receiving credit counseling.

The links between individual motivations and characteristics to both credit counseling take-up and program impacts are fertile ground for the incorporation of theory, particularly existing theories of behavior and behavioral change. The Theory of Planned Behavior (Ajzen, 1991), for example, views behaviors largely as a function of the intention to perform those behaviors, while intention itself is a function of the attitude towards the behavior (i.e. viewing the behavior favorably or unfavorably), the subjective norms surrounding the behavior (i.e. the social pressure to perform the behavior), and the perceived control an individual has over her behavior. Intentions to perform behaviors are strong predictors of actual behaviors (see also: Brandstätter, Lengfelder, & Gollwitzer, 2001; Gollwitzer, 1999) and individual variation in attitudes, normative influence, and perceived control can lead to variation in the intention to perform behaviors and thus to variation in the behaviors themselves.

The Theory of Planned Behavior has been used in a prior study linking these factors to the completion of a debt management program (Xiao & Wu, 2008), which found that attitudes and perceived behavioral control (though not subjective norms) are associated with the intention to complete DMPs and, thus, to actually completing DMPs. Figure 1.1 similarly illustrates how the Theory of Planned Behavior may lead to individual variation in financial behaviors more generally. This theory may also be used to predict individual take-up in credit counseling programs, as attitudes, norms, and beliefs about control all may govern an individual’s intention to seek external help (the behavior of interest) in resolving debt issues.
Figure 1.1: The Theory of Planned Behavior Applied to Financial Behaviors

Theory can also guide understanding of how behavioral changes may vary within the target population. The Transtheoretical Model of Behavioral Change (Prochaska, DiClemente, & Norcross, 1992) specifies that individuals may inhabit a variety of behavioral stages before undertaking (and maintaining) concrete behavioral changes. These stages include (1) precontemplation, in which an individual has no intention to change their behavior; (2) contemplation, in which an individual is aware of a problem and is thinking about changing their behavior; (3) preparation, in which an individual is preparing to take action in the near future; (4) action, in which an individual actively takes steps to change their behavior (or their environment); (5) maintenance, in which an individual works to prevent relapse. Variation in the stages inhabited by credit counseling clients may impact the degree to which credit counseling can improve client outcomes. For example, individuals in the preparation or action stages of behavioral change may draw additional benefits from interventions that raise awareness of problems or require explicit behavioral commitments from them, while individuals in the
maintenance stage may benefit from social support-oriented interventions such as coaching relationships (Prochaska et al., 1992)

While the relationship between the stages of change in the Transtheoretical Model and their relationship to outcomes has not been studied explicitly in a credit counseling context, research has shown that clients of a debt counseling agency inhabited each of the different stages and concluded that effective counseling interventions should provide tailored services to clients based on the stage they inhabited (Xiao et al., 2004).

**Credit Counseling Mechanisms, Client Behaviors, and Client Outcomes**

The essential logic underlying credit counseling’s potential to change target group behaviors and outcomes is relatively clear. Credit counseling services are typically aimed at financially-distressed or over-indebted individuals (the target population) and seek to improve financial behaviors in clients particularly in terms of their credit management skills. These skills include being better able to make debt payments on time, managing expenses to avoid unsustainable debt burdens, paying down debts in a way that avoids high interest 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 that allow clients to access mortgages and other loan products at affordable rates. 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.

Understanding the *processes and specific mechanisms* driving these changes in target group behaviors is more complex. Credit counseling agencies, or at least the accredited nonprofit credit counseling agencies under study in this dissertation, operate on a multi-service model that seeks to drive client change in a number of ways. These agencies typically offer some combination of budget counseling, financial education, and programs aimed at reducing the burden of debt payments for clients. The mechanisms of client change for each of these core
offerings differ somewhat and are here referred to as “Information/Awareness,” “Planning/Intentions,” “Monitoring/Support,” and “Altered Conditions.”

The remainder of this section describes the mechanisms underlying the three core services offered by many credit counseling programs, how these mechanisms are modified by the conditions of the target population, and how the interaction of these mechanisms and the target population may translate into changes in behaviors and subsequently to changes in outcomes. As such, this section elaborates on the “Counseling Mechanisms,” “Potential Behavioral Changes,” and “Potential Outcomes” boxes in Figure 1.2.

Importantly, the link between these mechanisms and outcomes should not be taken for granted; the research in these areas is either too sparse or too conflicted to make any categorical assessments of the ability for these mechanisms to drive outcomes. Instead, these mechanisms should be understood as potential drivers of outcomes and these outcomes should be understood as potential dependent variables in analyses of credit counseling programs.

Financial Education

In providing financial education, credit counseling agencies address the overall lack of consumer financial literacy among the general population, which has been tied to suboptimal behaviors such as paying higher fees on financial transactions, using high-cost financial services like payday lenders, and taking on too much credit card debt (and not paying this debt down quickly) due to unfamiliarity with concepts like compound interest, inflation, stock market participation, or the management of complex financial instruments (Lusardi & Mitchell, 2014). The provision of financial education and increases in financial education have also been tied positive financial behaviors such as increased savings rates (Bernheim, Garrett, & Maki, 2001; Lusardi & Mitchell, 2007), which can help offset short-term emergencies like job loss or healthcare costs, or facilitate large investments like home purchases. By virtue of providing this financial information, financial education services may also help clients develop financial goals
by distinguishing between optimal and sub-optimal financial behaviors; clients may for example set a goal to pay off a payday loan quickly once they understand the true costs of the service. In the case of targeted education, this service may also provide guidance on specific financial decisions such as saving for retirement or college. As such, the provision of financial education influences outcomes through the mechanisms of “Information/Awareness” and “Planning/Intentions.”

The conditions of the target population may influence the impact that the financial education component of credit counseling has on behaviors and outcomes. For example, if credit counseling clients have lower levels of financial literacy than the general population (which may be a partial explanation for their misuse of credit), then the provision of financial education can potentially yield disproportionately high returns for these clients (Bernheim & Garrett, 2003; Lusardi, 2003).

Additionally, clients seeking credit counseling services are likely at a point of relatively high financial distress either through the presence of income and expense shocks or through high levels of consumer debt (Collins, 2010; Elliehausen, Lundquist, & Staten, 2007; Chapter Two of this dissertation). This high level of distress may lead to credit counseling clients being more receptive to financial advice and education. Indeed, while a review of financial education programs’ efficacy revealed few impacts from experimentally-delivered education programs, it did find that “just-in-time” education that responds to an individual’s immediate financial needs has the potential to drive client improvements (Fernandes, Lynch Jr, & Netemeyer, 2014).

Thus, the change process embedded in financial education-oriented interventions comes from making clients aware of healthy and unhealthy financial behaviors and strategies at a point where they may be exceptionally receptive to this information. The educational aspect of credit

8 See Chapter Three for a brief review of the literature on the relationship between financial shocks and behaviors.
counseling, nominally, then leads to a number of improved financial behaviors, including the selection of lower-cost lenders and financial instruments, a propensity to take on less debt (and pay less in interest), and to pay down existing debts more quickly.

Budget Counseling

In providing budget counseling, counselors sit down with clients for in-depth sessions where they examine in detail all the inflows and outflows of money to a household and look for ways to increase income where possible or reduce expenses on non-essential purchases. As part of this process, counselors will often help clients develop an action plan for strengthening their financial circumstances (the “Planning/Intentions” mechanism). In cases where clients enroll in debt management plans, they make explicit commitments to follow these action plans. Similar to the change process embedded in financial education offerings, change from budget counseling sessions may be driven in part by increased awareness on the part of the client for their expenses. Perhaps they had forgotten about a monthly gym membership they were paying or had not fully appreciated how much money they were spending on dining out multiple times a week. This increased awareness potentially helps clients shift their behaviors to be more in-line with their financial goals. In behavioral terms, budget counseling can help overcome problems of inattention by focusing attention on key problem areas the client’s financial profile. Individual inattention has been tied to problematic financial behaviors elsewhere, notably in terms of building savings and retirement assets (Duflo & Saez, 2003), and helping clients focus on issues in their finances may help overcome this issue.

The action plan developed for clients may also 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 strain on their cognitive resources, limiting their willpower and preventing them from thinking about longer-term goals (Baumeister, Heatherton, & Tice, 1994; 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 that likely drove them to seek credit 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. This use of concrete plans to drive behaviors is also in-line with the work tying implementation intentions to goal attainment (Brandstätter et al., 2001; Gollwitzer, 1999). Finally, budget counseling may also drive changes in behaviors by providing a type of behavioral monitoring. Credit counseling clients, who commit to following their action plans to reduce expenses, may feel accountable to the counselor (the “Monitoring/Support” mechanism) if they do not stick to their action plans and this sense of accountability may lead to better adherence to the plan (Lerner & Tetlock, 1999).

Some credit counseling agencies will also follow up with clients at set intervals 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. These follow-ups (which may also take the form of explicit reminders of goals and obligations) can help overcome problems of self-regulation that can result in people delaying necessary tasks or underestimating the time required to complete them (Buehler et al., 2010) and an inability to maintain behaviors consistent with financial plans (Ashraf et al., 2006). Reminders of these types act as a type of commitment or accountability mechanism keeping client on tract to accomplish financial goals or maintain their existing financial obligations.

From this increased awareness of their expenses, the potential for reduced stress in financial planning and decision-making, and behavioral monitoring (i.e. the change processes embedded in the budget counseling service), several potential behavioral changes may emerge. Clients may reduce unnecessary expenses and, as a result, take on less debt or increase their savings levels. They also may develop a household budget they can follow with some regularity.

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9 Based on service descriptions from agencies provided as part of this dissertation research.
(versus the one-time budget analysis done as part of the credit counseling session). Budget counseling may also incorporate an action plan, which helps identify concrete steps clients can take to reach their shorter and longer-term financial goals and these action plans may shift client financial behaviors in such a way that makes these goals more attainable.

Debt Management Plans

For clients who enroll in debt management plans, the change process can also stem from multiple mechanisms. The first is from the direct financial benefits DMP enrollment may offer. Credit counseling agencies may negotiate with creditors to lower interest rates or waive fees for clients (the “Altered Conditions” mechanism), which makes an individual’s overall debt situation more sustainable and increases the likelihood of successful debt repayment (Bagwell, 2000). Agencies can also work with creditors to re-age client accounts and remove the record of a client’s payment delinquencies, contingent on successful completion of the DMP (Hunt, 2005). DMPs may also reduce client stress by acting as an intermediary between creditors and their clients (the “Monitoring/Support” mechanism), which eliminates the overall burden on clients by allowing them to only engage with one organization (the credit counseling agency) instead of multiple creditors; DMP enrollment also reduces debt collection calls that may contribute to client stress (Elliehausen et al., 2007).

There is also a behavioral component to the impact DMPs may have on clients. By consolidating multiple debt streams into one and altering the condition of the loans, 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, though the literature here is somewhat conflicted. From one perspective, debt consolidation offered by the DMP may lead to consumers acting more rationally by reducing their propensity to pay down low-balance accounts first regardless of the interest rate associated with that account (Amar et al., 2011). Yet
there is also research on debt settlement programs\textsuperscript{10} implying that consolidating multiple smaller payments into one larger payment may actually reduce the propensity for individuals to pay down their debt balance, as successfully paying off smaller accounts first (regardless of interest) may motivate individuals toward further progress in debt repayments (Gal & McShane, 2012).

Beyond enrollment criteria, DMPs may provide the most benefits to clients with short-term debt problems or clients with poor money management skills (Loonin & Plunkett, 2003); the former may benefit from the improved terms of their debt repayment requirements, while the latter may benefit from a more structured and simplified debt repayment regime. These benefits may manifest in outcomes such as fewer payment delinquencies or reductions in consumer debt. Clients who face structural financial problems such as a high level of income or expense volatility (i.e. an inability to hold a job for long periods of time) will likely see limited benefit from DMPs, as they will not be able to maintain their enrollment in these plans.

\textit{Organizational and Frontline Influences on Credit Counseling Outcomes}

It is important to note that the above discussion represents something of an ideal-type when it comes to credit counseling services, as it implicitly assumes homogeneity in the delivery of credit counseling services. However, variation in the nature of the credit counseling organizations and in the frontline workers within these organizations can lead to variation in both the services delivered to clients and the efficacy of the mechanisms embedded within those services. The relationship between the organizational and frontline factors and credit counseling services is illustrated in the “Organizational Factors” and “Frontline Factors” boxes in Figure 1.2.

The organizational differences among credit counseling agencies have been a subject of some controversy. While many consumer credit counseling services are multi-service agencies

\textsuperscript{10} Debt settlement programs differ from the credit counseling programs in that they typically involve an initial reduction in the debt principal negotiated by the settlement firm. Clients then make payments into a dedicated account and these funds are then disbursed to creditors by the debt settlement firm. In a sense, it can be seen as an intermediate option between credit counseling and bankruptcy (Gal & McShane, 2012).
that provide educational opportunities and in-depth budget counseling, others do not emphasize these services and instead operate as “DMP mills” and may recommend clients to enroll in DMPs even when enrollment may not be optimal (as enrolling clients in DMPs benefits these agencies financially; Bunting & Salandro, 2009; Loonin & Plunkett, 2003). Conversely, many agencies provide program offerings beyond these three core services and these variations in program offerings may shape client outcomes.

To illustrate this, Table 1.1 presents an array of supplemental services offered by agencies in addition to their core counseling services.\textsuperscript{11} Qualitatively speaking, the supplemental services offered by the selected agencies presented here exhibit noteworthy differences. Some agencies only specify that they supplement the core counseling service with quarterly emails or follow-ups. Other agencies offer email, phone, or text-based reminder services that can help clients avoid payment delinquencies or stay on track with their financial goals even after they have left the agency. Some agencies even offer credit builder loan programs, smartphone apps, or online tools to help improve clients’ financial behaviors or credit profiles over time.

\textsuperscript{11} Agencies identified these supplemental services when applying to participate in the credit analysis covered in Chapters Two and Three of this dissertation.
<table>
<thead>
<tr>
<th>Agency</th>
<th>Supplemental Service Descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Offered text-based payment reminders after counseling</td>
</tr>
<tr>
<td>2</td>
<td>Provided a mobile app to manage and track their DMP status; also introduced to additional online services including a financial health test and financial health optimizer</td>
</tr>
<tr>
<td>3</td>
<td>Offered follow-up coaching sessions, with additional resources offered to un- or underbanked households</td>
</tr>
<tr>
<td></td>
<td>Provided follow-up email 6 months after contact/coaching to assess their progress and offer additional coaching via phone, email, or in-person</td>
</tr>
<tr>
<td>4</td>
<td>Used online tools (mint.com, for example) to supplement financial coaching initiatives</td>
</tr>
<tr>
<td></td>
<td>Coordinated with other local organizations to link clients with other targeted services post-counseling, such as job training and placement, tax preparation, and access to Individual Development Accounts</td>
</tr>
<tr>
<td>5</td>
<td>Provided follow-up email reminders about the benefits clients receive through the counseling program (including access to free copies of their credit score)</td>
</tr>
<tr>
<td>6</td>
<td>Offered text-based payment and goal reminders after counseling</td>
</tr>
<tr>
<td></td>
<td>Offered a supplemental financial education program on a variety of financial topics (such as credit, homeownership, and identity theft)</td>
</tr>
<tr>
<td>7</td>
<td>Provided access to online system monitoring their payment performance</td>
</tr>
<tr>
<td>8</td>
<td>Provided email or phone-based payment reminders, as well as follow-ups reminding clients of their goals and implementation intentions</td>
</tr>
<tr>
<td>9</td>
<td>Offered targeted coaching follow-ups based on client outcomes (going through bankruptcy, entered a debt management plan, etc) and stated goals</td>
</tr>
<tr>
<td>10</td>
<td>Offered access to a credit builder program, which evaluates a client's credit report and formulate an action plan to improve credit</td>
</tr>
<tr>
<td></td>
<td>Offered a loan program to assist in building credit</td>
</tr>
<tr>
<td>11</td>
<td>Provided email or phone-based payment reminders, as well as follow-ups reminding clients of their goals and implementation intentions</td>
</tr>
<tr>
<td>12</td>
<td>Provided an array of targeted follow-ups are given to clients at set intervals</td>
</tr>
<tr>
<td>13</td>
<td>Sent quarterly email to clients on how to improve their finances</td>
</tr>
</tbody>
</table>

Note: This table presents an array of supplemental services offered by agencies in addition to their core credit counseling program. Each agency is anonymized and identified by a number 1 to 13, and each row represents an individual supplemental service offered by that agency.

Table 1.1: Supplemental Services Provided by Selected Credit Counseling Agencies

While variations in the programs offered by credit counseling agencies lead to differing levels of service outputs and may lead to variations in client outcomes, it is also possible that the structure of credit counseling organizations themselves have an impact. For example, multi-
service agencies may be able to take a more holistic approach to their credit counseling services, identifying the need for job training, low-cost healthcare, rehabilitation, or housing assistance, and linking clients directly to those services within the organization. Indeed, a review of client data provided by the NFCC reveals that credit counseling agencies are willing to refer clients to social services, though this happens infrequently. If agencies are more willing to refer clients to additional services when those services are provided “in-house,” then a credit counseling program administered by these multi-service agencies has the potential to provide more holistic support for distressed clients; this may impact long-term client outcomes if clients benefit from these additional services. On the other hand, it is also possible that agencies purely focused on providing credit counseling services have more expertise and capacity to implement new credit counseling innovations, as that is their central mission. These agencies may also have better or more extensive contacts with creditors allowing them to get more favorable terms for clients enrolling in DMPs. Further, these agencies may be better able to provide extensive training and credit counseling-specific resources to their workers, which may improve client outcomes.

Additionally, the ways in which the program is delivered by agencies may also be important in properly framing credit counseling’s impact on outcomes. One of the central sources of variation in program delivery is the way in which agencies offer the service of credit counseling to clients. As credit counseling agencies proliferated in the late 1980s and 1990s, a chief concern was that many newer agencies were moving away from traditional in-person counseling within credit counseling offices and toward lower-cost modes of delivery like phone or online credit counseling (Loonin & Plunkett, 2003). While one study (Barron & Staten, 2011) found no substantial relationship between the mode of credit counseling and outcomes, it remains

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12 Based on data provided by the National Foundation for Credit Counseling for 43,072 participants who enrolled in the Sharpen Your Financial Focus counseling program between September, 2013 and March, 2015. These data showed that agencies provided 739 referrals to social services over this period, representing two percent of program clients.
a possibility that this factor may impact outcomes. Modes of delivery may also impact other elements central to program success, as more convenient methods of service delivery such as online or phone-based counseling may be more accessible or more appealing to credit counseling’s potential beneficiaries. This may be particularly true as financially-distressed individuals may have less capacity to travel to a physical credit counseling office.

The frontlines of credit counseling programs (where counselors and clients interact) are embedded within the credit counseling organization, but the dynamics at the frontlines of these programs may also shape the impact of credit counseling services. Very little work has been done regarding frontline dynamics in credit counseling agencies and in consumer financial programs generally, but Chapter Four of this dissertation explores how frontline dynamics can impact the success of these programs, specifically by exploring the implementation of a financial coaching program administered by a credit counseling agency. This analysis finds that workers’ ability to engage clients and get them interested in a program can drive program take-up while workers who are committed to the change processes embedded in these programs have clients who demonstrate improved outcomes. Though not directly relevant for core counseling services (which do not rely on client take-up in the same sense, as clients seek out credit counseling services themselves), frontline workers who can engage clients may be able to encourage take-up of supplemental services offered by the agencies. More generally, research demonstrates the importance of relationship-building skills at the frontlines in driving program success (Lurie, 2006; Maynard-Moody & Musheno, 2003; Radey, 2008; Thompson, VanNess, & O’Brien, 2001). As finances tend to be relatively personal issues and individuals going through financial distress are likely in a uniquely vulnerable state with regard to this personal issue, relationship-building skills at the frontlines may yield dividends in improving client behaviors and driving client outcomes.
Another potential factor at the frontlines of credit counseling programs is the practical issue of training, funding, and capacity for the frontline workers, which themselves are functions of constraints and decisions taking place at the organizational level in credit counseling agencies. Loonin and Plunkett (2003) examined the finances of 40 credit counseling agencies and found that nonprofit consumer credit counseling agencies were facing financial troubles; fifty percent of NFCC agencies reported more expenses than revenue and an additional thirty percent were on the verge of running deficits.\(^{13}\) There is a substantial literature on the role that training, funding, and capacity play in successful program implementation (e.g. Brodkin, 1997; Hasenfeld, 2010; May & Winter, 2009). Inasmuch as precarious funding levels may impact the resources available to counselors, the training provided to them, or the ability to hire more counselors to meet increases in demand, this could lead to issues in the implementing credit counseling programs optimally.

Each of these factors may influence the efficacy of certain mechanisms embedded in credit counseling services. The ability of frontline workers to engage clients, get them invested in the program, and build relationships with them may particularly impact the “Planning/Intentions” and “Monitoring/Support” mechanisms, as clients who feel trust or identification with their counselor may be more likely to follow through on their behavioral commitments and respond more favorably to the behavioral monitoring and follow-ups provided by certain agencies (particularly those that check on clients after credit counseling or offer financial coaching services). Frontline workers’ ability to engage clients may also impact the efficacy of the financial education they are provided; the efficacy of educational services may also be contingent on the training and expertise of the counselor. However, frontline worker characteristics are not anticipated to impact the efficacy of debt management programs, as the mechanisms underlying

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\(^{13}\) While this analysis is over a decade old and the financial stability of these agencies may have changed in the intervening years, inadequate funding is almost certainly still a potential risk in many nonprofit counseling agencies.
DMPs (which involve the consolidation of payments, improved interest rates, and the elimination of collection calls) are not subject to frontline worker discretion.\footnote{Though it may still be possible that frontline worker characteristics may impact the efficacy of DMPs. For example, a poorly-trained or poorly-qualified counselor may fail to remit payments to creditors on time, resulting in the further degradation of the client’s financial circumstances.}

\textit{The Framework Summarized}

Figure 1.2 presents an illustration of the framework described above. Demographic characteristics, differences in individual motivation, and an individual’s specific financial and credit characteristics drive the decision to take-up credit counseling. Once they enter the credit counseling program, clients within accredited nonprofit credit counseling agencies receive financial education and budget counseling and may be recommended for a DMP contingent on their specific financial situation. The decision to enroll clients in a DMP is governed in part by the characteristics of the credit counseling organization, which also determine the array of supplemental services offered to clients. Each of these program services have specific mechanisms embedded within them that may be linked to a variety of behavioral changes on the part of the client, while the degree to which clients change their behaviors is contingent on their demographic, motivational, and financial characteristics. The efficacy of these mechanisms in driving client behaviors is governed in part by the frontline worker delivering these services to clients and the behaviors of that frontline worker are governed in part by the organization in which they work. Finally, these behavioral changes are linked with short- and long-term changes in client outcomes including cognitive benefits, such as experiencing less financial stress and increasing financial knowledge, and tangible benefits such as lower consumer debt, higher savings, and higher credit scores. These outcomes are also governed in part by individual characteristics; the ability for changes in behaviors to translate into changes in outcomes may be influenced by factors like income levels and volatility, or vulnerability to fluctuations in the economy.
Figure 1.2: A Framework for Consumer Credit Counseling Initiatives
Discussion

This chapter takes a step toward providing a framework in which the link between credit counseling’s target population, its central program mechanisms, and the potential behavioral changes and client outcomes can be understood. It has also provided a brief discussion on how factors in credit counseling organizations and at the frontlines of credit counseling delivery can impact these outcomes.

While the development of a framework is important, it is worth noting that many of the links outlined here remain hypothetical. There simply is not enough research yet done on credit counseling generally, let alone on its specific mechanisms, to empirically link these mechanisms to specific behavioral changes and financial outcomes. Even financial education, one of the most well-studied financial interventions yet developed, cannot be categorically linked to improvements in given outcomes. Further, the combined bundle of these mechanisms delivered as part of credit counseling’s core services have not yet been convincingly linked to many of these outcomes, as only a small handful of studies have investigated the impact of credit counseling.

This remainder of this dissertation takes steps to address this empirical gap and this conceptual chapter has laid the groundwork for the empirical analyses to follow. Each of the remaining chapters covers a different aspect of the framework presented in this chapter. Chapter Two explores the financial and non-financial characteristics of the target population and the motivations of clients seeking credit counseling. Chapter Three presents an impact analysis of the full bundle of service outputs in credit counseling programs on client outcomes, and this analysis also controls for organizational factors in supplemental models. Chapter Four investigates the frontlines of program implementation in a credit counseling agency and specifically explores the relationship between worker engagement and measures of program success.
What this dissertation does not do is investigate the role that individual services and mechanisms have on changes in behaviors and outcomes. Future research should seek to test the relative ability of these different mechanisms to drive outcomes by varying their delivery in an experimental context. While credit counseling services themselves likely cannot be delivered in a randomized and controlled setting, additional programming offered to clients within these agencies and augmentations of existing practices can be delivered experimentally. The insights from future experimental analyses will help to strengthen or modify the framework presented here.
Chapter 2: Who Seeks Out Credit Counseling Services?

Introduction

Before engaging in the impact analysis of the credit counseling program in Chapter Three of this dissertation, it is important to develop a profile of a typical credit counseling client. In the research literature on credit counseling, clients are portrayed as generally being financially-distressed (Elliehausen et al., 2007; Hunt, 2005; Loonin & Plunkett, 2003; Wilshusen, 2011) or over-indebted (Disney & Gathergood, 2009), but relatively little attention is paid to the specific financial, behavioral, and motivational characteristics of these individuals. Also relatively unexplored is how these characteristics compare to the general U.S. population. Despite this lack of focus on the nature of these programs’ target population, understanding who among the public is receiving credit counseling services and the circumstances in which they seek those services is important for policymakers and practitioners, particularly as the economic circumstances necessitating credit counseling services are unlikely to disappear in the near future. As discussed in the introduction to the first chapter, consumer credit usage continues to increase and the almost of revolving debt held in the U.S. is almost a trillion dollars (Federal Reserve, 2016), individuals remain vulnerable to fluctuating economic circumstances that can lead to extreme financial distress for wide swaths of the population, and savings rates and savings levels have been persistently low for years, rendering individuals less capable of weathering the shocks associated with economic fluctuations. Credit counseling services offer a potential means of offsetting the harms caused by these economic realities. Examining the profile of clients who voluntarily seek these services facilitates greater understanding of who can benefit from these

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15 Credit usage and savings levels are explored in the next section using data from the Federal Reserve.
services and reinforces credit counseling’s potential as a lever for policymakers to employ in addressing consumer financial issues associated with both economic shocks and longer-term trends in consumer behaviors. Another key point of this chapter is understanding how the financial reality of credit counseling clients may impact the design and evaluation of credit counseling (and related) programs. Analyses of these programs have typically relied on self-reported data (Bagwell, 2000; Kim, Garman, & Sorhaindo, 2003) or more objective data drawn from credit reporting bureaus (Barron & Staten, 2011; Elliehausen et al., 2007). These empirical analyses also typically employ timeframes that fail to capture client credit dynamics at the time they are seeking credit counseling, instead focusing on client outcomes over the long-term (a year or more after credit counseling). From both a practical and theoretical perspective, this approach is reasonable. Both credit and survey data can be difficult and expensive to collect over a large number of periods and many outcomes of interest for credit counseling clients take time to manifest. For example, the risk-scoring products used by credit reporting agencies (e.g. the FICO credit score) are common measures of financial well-being in studies of credit counseling programs and related financial interventions. Yet one issue with using credit scores as an outcome is that credit scores are lagging indicators of financial behaviors; a payment delinquency made several years back may depress an individual’s credit score even in the absence of any subsequent delinquencies. Given the lagged nature of credit scores, evaluating client outcomes on a longer time-frame makes sense. Using this longer time horizon may also allow behavioral impacts of financial interventions to manifest. If a program emphasizes paying more than the minimum on a credit card to avoid accruing interest on credit accounts, for example, it may take a client time to make the requisite changes to consumption patterns in order to make those higher payments and more time still for that accelerated payment schedule to make a substantial difference in overall debt levels.
While this long-term focus allows for behavioral and financial changes to manifest, understanding the financial realities of these clients at the time of credit counseling, as well as their shorter and longer-term credit outcomes is also of interest. In particular, analyzing the credit trends for clients at the time of credit counseling, along with their financial behaviors and individual motivations to seek credit counseling can help inform the dynamics seen in credit counseling studies with longer timeframes. Further, understanding who seeks credit counseling and their specific circumstances can help inform both future research in this field as well as future program development to address the needs of these clients.

To that end, the research in this chapter seeks to answer the following questions:

1. What are the demographic and financial characteristics of those seeking credit counseling services?
2. How do the characteristics of credit counseling clients differ from the general U.S. population?
3. Why do clients report seeking credit counseling services?
4. What financial behaviors do clients display at the time of credit counseling?
5. How do clients’ credit indicators evolve after credit counseling?
6. What behavioral changes do credit counseling clients report shortly after counseling?

In order to address these questions, this chapter uses four separate datasets to create a detailed profile of participants in the Sharpen Your Financial Focus credit counseling initiative. These datasets allow for the exploration of client demographic characteristics, asset and debt indicators, self-reported financial behaviors, and self-reported indicators of financial well-being, as well as how key credit indicators evolve for these clients from the period prior to credit counseling to a year and a half after credit counseling. This chapter also leverages data from large, national surveys to compare credit counseling clients to the general U.S. population across
many of these indicators. Finally, this chapter presents data on how clients report faring three months after receiving credit counseling and explores how these results vary for certain subgroups. In this, it supplements other research that features self-reports from credit counseling clients (Bagwell, 2000; Kim et al., 2003).

While the analyses featured in this chapter are descriptive and not intended to make a causal argument about the relationship between credit counseling and client characteristics or outcomes, this research contributes to the understanding of an under-studied population. Among the key findings from this analysis are that credit counseling clients typically seek credit counseling because they are facing some unforeseen income or expense shock, either from the loss of a job, reduction in income, or an increase in expenses (most typically medical expenses). The ramifications of this shock are demonstrated in the credit outcomes for these clients: On average clients experience a spike in payment delinquencies and a concurrent drop in their credit score, though both of these metrics recover about a year after credit counseling. Credit counseling clients also have relatively low incomes and report extremely low levels of liquid savings at the time of counseling. Additionally, 71 percent of clients in the Sharpen credit counseling program report paying the minimum or less on their last credit payment, while fewer than a fifth of clients report having automatic savings deposits and almost half of clients report never setting money aside for savings. In terms of income, savings, and borrowing indicators, credit counseling clients appear to be in a much more precarious state than the general U.S. population. After credit counseling, clients see reductions in a variety of debt indicators, and over two-thirds report that they are better managing money, paying their debt more consistently, setting financial goals, and seeing improvements in their overall confidence.

This chapter first describes the existing research on the characteristics of credit counseling clients, then reviews the four data sources used to create a detailed profile of these
clients, then presents the results from these data sources, and finally provides a discussion of these results and the implications for future research and program design.

What We Know about Credit Counseling Clients

The United States has experienced a long period of expanding credit availability coupled with declining savings rates, as illustrated in Figure 2.1. Decades of access to instantaneous credit and the increased ease of borrowing against illiquid assets has increased the propensity to consume income; a phenomenon that has been directly linked to the anemic savings rates among U.S. consumers (Laibson, 1997). It is not simply savings rates that are anemic but also savings levels; many households have a buffer stock of liquid savings below their desired levels and the lack of emergency savings is particularly pronounced for lower-income households (Collins, 2015; Kennickell & Lusardi, 2004). This high level of indebtedness coupled with low savings has led to many households being burdened with high debt payments and little financial slack to weather even modest income or expense fluctuations.

Source: Federal Reserve Economic Data

Figure 2.1: U.S. Savings Rate and Consumer Credit Availability
Beyond these long term trends in credit usage and declining savings, consumers are also vulnerable to short-term fluctuations in the economy. Figure 2.2 traces the number of bankruptcies and foreclosures in the United States over the last decade\textsuperscript{16} to illustrate the impact that this volatility has on consumer financial distress, showing that both these metrics of extreme distress essentially tripled due to the Great Recession and only returned to their pre-recession levels around five years after their peak.

![Figure 2.2: U.S. Foreclosures and Bankruptcy](image)

\textit{Source: Federal Reserve Bank of New York Quarterly Report on Debt and Credit}

It is in this market context that credit counseling operates. Credit counseling programs target individuals who are, almost by definition, financially distressed and this distress can take many forms in an environment of relatively easy credit access and low savings rates. Consumers

\textsuperscript{16} This time period was chosen to capture the period after the Bankruptcy Abuse and Consumer Protection Act of 2005, which led to a substantial decrease in bankruptcy declarations due to more stringent eligibility requirements associated with filing Chapter 7 bankruptcy.
may use credit to pursue status symbols (such as nicer homes, cars, or clothes than their incomes might otherwise warrant) and find themselves in an unsustainable debt position from overconsumption due to self-control problems (Gathergood, 2012) and/or from poor understanding of their credit products (Peñaloza & Barnhart, 2011). Alternately, consumers with few liquid assets may take on debt in response to a crisis like a health emergency and find themselves unable to eliminate that debt quickly (Babiarz, Widdows, & Yilmazer, 2013). Taking on high-interest debt (such as payday loans) in response to short-term crises or needs has been shown to negatively impact an individual’s welfare, particularly for those already in a state of financial vulnerability (Carrell & Zinman, 2014). Distress may also stem from a hybrid of these circumstances, in which the loss of income can make existing debt levels unsustainable and drive consumers to seek relief.

While it is relatively simple to conceptualize any number of scenarios that can lead an individual into financial distress and thus to seek relief from credit counseling or related programs, there has been relatively little research empirically examining these clients, their behaviors, and their motivations. There is of course a general literature on the take-up of social programs in both the public and nonprofit spheres, which finds that factors like eligibility requirements and administrative burden, financial and transaction costs, the stigma associated with service use, geographical and practical accessibility (e.g. the hours of operation for a social service agency), and the sense that an agency represents the local community can all influence individual take-up of services (Currie, 2004; Herd, Deleire, Harvey, & Moynihan, 2013; Kissane, 2010, 2013; Moffitt, 1983; Riphahn, 2001; Russell, Moulton, & Greenbaum, 2014). There has also been research into the factors associated with the take-up of financial advice generally, finding that financial advice is pursued at higher rates by older individuals, households with higher assets, and relatively financially sophisticated individuals (Bluethgen, Gintschel, Hackethal, & Müller, 2008; Hackethal, Haliassos, & Jappelli, 2012). This research, however,
centered on investment advice rather than guidance on debt or credit issues typically faced by
distressed households. By contrast, Collins (2010) used survey data to assess the antecedents of
pursuing several types of financial advice including advice relating to debt issues and found that
difficulty paying bills, having a large drop in income in the past year, and income levels are
positively associated with using a financial advisor for debt concerns. In research on the use of
credit counseling programs specifically, Disney, Gathergood, and Weber (2015) found that the
presence of income, employment, or health shocks were associated with seeking credit
counseling, and that individuals with lower levels of financial literacy were more likely to seek
out counseling services.

With regard to credit counseling programs specifically, Bagwell (2000) found that the
typical credit counseling client is a white female with some post-high school education and
relatively limited income, Elliehausen, Lundquist, and Staten (2007) showed that, prior to
entering credit counseling, the average client had relatively high debt levels and a history of
payment delinquencies. Yet the intent of these studies was not necessarily to examine the
characteristics, motivations, and financial realities of credit counseling clients but rather to track
credit counseling’s impact on these clients over time. Indeed, most analyses of credit counseling
do not focus on the relatively unique state of credit counseling clients and instead focus on the
impact of credit counseling (e.g. Bagwell, 2000; Elliehausen et al., 2007; Kim et al., 2003) or on
the structure of the credit counseling industry itself (Bunting & Salandro, 2009; Hunt, 2005;
Loonin & Plunkett, 2003; Wilshusen, 2011). Other research has examined the motivations of
credit counseling clients and found they prioritize debt repayments and managing their expenses
over building savings (Xiao, Sorhaindo, & Garman, 2006).

The one detailed analysis of credit counseling clients comes from Disney and Gathergood
(2009). Using data on British credit counseling clients for the years 2004 to 2008, they found that
the typical counseling client was unmarried, had a relatively low income, worked in either low- or
semi-skilled occupations, had almost no financial assets, and held high levels of unsecured debt. This analysis also found that 71 percent of credit counseling clients are recommended into DMPs, and 67 percent of clients entering DMPs remained in them over the study period.

While the Disney and Gathergood (2009) work outlined the basic demographic and financial characteristics of credit counseling clients, the behavioral and motivational characteristics of clients seeking credit counseling have not been thoroughly studied, though there has been qualitative research on this subject. In a series of in-depth interviews with credit counseling clients and counselors, Wang (2010) provided a detailed profile of credit counseling clients, presenting two narratives underpinning clients’ decisions 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 that 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.

This relative lack of knowledge on the makeup and behaviors of credit counseling clients is troubling for both researchers and practitioners in the field of credit counseling as well as those in related program areas. While there is some general quantitative evidence on what drives clients to seek debt-related advice (i.e. having trouble with their bills or having a large drop in income) and detailed qualitative evidence on their motivations, little has been done exploring the behaviors and financial realities of this population in detail. Absent this information, practitioners may lack needed context to design new programs (or augment existing ones) tailored to the
unique needs of this population and researchers may fail to incorporate the unique characteristics of these financially-distressed individuals into evaluations of credit counseling and related programs.

Data and Method

This chapter focuses on the characteristics of clients participating in the Sharpen Your Financial Focus (Sharpen) initiative from September 2013 through March 2015. The Sharpen program has a high degree of similarity to traditional credit counseling programs, and a detailed description of the Sharpen program follows in the next chapter. Data are drawn from four primary sources and two secondary sources. First, administrative data on all clients counseled under the initiative are collected by individual member agencies through a centralized database maintained by the National Foundation for Credit Counseling (NFCC). Administrative data are collected by member agencies when clients begin the credit counseling process and are subsequently shared with the NFCC. The administrative data collected on Sharpen clients include basic demographic and household information, financial characteristics, and broad details of the types of interventions each client received. Administrative data are available for 43,072 clients, though some observations are missing in these data either because clients refused to provide the information or because the information was missing. These cases account for around five percent of observations for every indicator under study except the racial indicator, for which fifteen percent of clients have no available data.

Second, self-assessment data are obtained from clients participating in the online financial stress test (known as the MyMoneyCheckUp program, or MMCU®). The MyMoneyCheckUp (MMCU) instrument can be conceived of as a type of survey that provides rapid feedback to the participant so they can see their financial strengths and weaknesses. While most clients completed the MMCU, due to data limitations only a subset of these can be linked
(around 40 percent) to the administrative data to confirm they are Sharpen clients. Only results for clients who completed the MMCU are presented, a total of 16,227 clients. Broadly speaking, the MMCU instrument can be separated into six categories capturing the financial experiences of households: Financial confidence, budgeting, saving, borrowing, housing, and retirement. Each of these core areas of the instrument will be addressed in turn by presenting selected questions from each category.

Third, self-reported data on client perceptions are collected through a follow-up survey of Sharpen participants, which was conducted on a rolling basis by the NFCC three months after a client completed the program. The brief email survey includes questions about changes in a household’s financial situation and financial behaviors. Over the period studied in this chapter, 777 Sharpen participants had responded to the survey.

One potential issue with the MMCU and post-counseling survey is that the clients for whom there are no data (either through non-response in the survey or an inability to link MMCU responses to administrative data) may differ significantly and systematically from clients for whom there are data. This is particularly true for the post-counseling survey, as the response rate for this survey was just under two percent. Appendix B compares clients based on the availability of self-reported data for both of these sources and finds that clients do not differ much based on MMCU data availability (clients with linked MMCU data are slightly less likely to be black, have slightly higher savings, and slightly lower liabilities than those who could not be linked with their MMCU data). Clients who completed the post-counseling survey, however, are more likely to be white, less likely to be male, and are slightly older, more educated, and have more savings and assets than non-completers. While the differences between survey completers and non-completers

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17 Non-Sharpen clients could also use the MyMoneyCheckUp tool. To confirm that clients from the MMCU data were Sharpen clients, participants were linked from the MMCU data to the Sharpen portal via email address. As clients could give different email addresses in these two sources, only a subset of Sharpen clients participating in the MMCU could be linked.
are significant, they are not stark, and overall the two groups look reasonably similar, particularly in terms of their income and expenses.

The final primary data source covers credit attributes data for Sharpen clients, collected by the NFCC in partnership with Experian. Archival credit data are obtained quarterly, beginning in the month before the start of the Sharpen initiative (August, 2013), and are updated at three month intervals thereafter, through February, 2015. Credit attributes data are only obtained for clients from a subset of NFCC member agencies that applied to the NFCC to be included in this portion of the analysis. Thirteen agencies were selected based on successful implementation of the Sharpen initiative, as well as their capacity to submit additional data including documented permission from clients to obtain credit data. During the entire evaluation period, clients from the 13 member agencies comprised 44% of the total 43,072 clients enrolled.\(^\text{18}\)

Second, credit attributes data are only included in the evaluation for clients enrolling in the Sharpen initiative during the first quarter of the initiative, from September 1, 2013, through November 30, 2013.\(^\text{19}\) This allows the evaluation to include six quarters of credit data after the baseline quarter. Over this period, a total of 10,925 clients enrolled from participating agencies. Complete credit data could be linked to administrative data for 8,963 clients; the remaining 1,962 were unable to be located in Experian’s credit database with the client information provided by the agencies or did not have full data across all quarters of the evaluation. See Appendix D for a chart summarizing the base sizes at different points in this analysis.

\(^{18}\) Appendix C compares the administrative characteristics of clients from agencies participating in the credit analysis to clients from non-participating agencies. While demographics, average monthly income, and monthly housing expenses are similar between these client groups, clients in participating agencies had fewer debt-related expenses, more tangible assets, less in liquid savings, and more liabilities.

\(^{19}\) Credit data were also available for the baseline period of December, 2013 through February, 2014, which included an additional 1,662 clients. However, this baseline period only had five quarters of post-counseling data available. Analyses conducted on this expanded baseline revealed no substantial changes in baseline credit characteristics or long-term credit outcomes, so only the sample for whom full data were available is included here.
These data sources will be analyzed in a descriptive fashion as the intent of this chapter is to create a profile of credit counseling clients rather than draw any conclusions about the overall impact of credit counseling; the impact analysis of credit counseling is undertaken in Chapter Three of this dissertation. The administrative, MyMoneyCheckUp, and survey data are cross-sectional; administrative and MyMoneyCheckUp data are only measured at the time clients enter credit counseling, while the client survey is administered three months after credit counseling. Credit attributes data, however, are measured quarterly and client outcomes on key credit indicators are traced from the pre-counseling (or baseline) quarter to six quarters post-counseling.

For the survey, self-reported results will be explored for several different sub-groups of credit counseling clients. While not intended to draw a causal link between demographic characteristics and self-reported outcomes, the exploration of self-reported results by different demographics may give a sense of how different groups (here specified as being below the median client income, female, a minority, or being recommended for a DMP) behave after credit counseling. Significant differences in the probability of being in a given demographic group and exhibiting a given financial behavior are measured through chi-squared tests.

Secondary data from the American Community Survey and the Survey of Consumer Finances (SCF) are used to provide a means of comparison between credit counseling clients and the general United States population. The American Community Survey (ACS) is a yearly survey conducted by the United States Census Bureau that contacts more than 3.5 million households per year to create a representative sample of the U.S.; households contacted by the Census are required to complete the survey. The pooled results from the ACS for the five years from 2010 to 2014 are used in this chapter. The Survey of Consumer Finances is a triennial survey of U.S households conducted by the U.S. Federal Reserve that provides a detailed description of household finances. Potential respondents are selected randomly and weights are employed to
provide representative estimates for the full U.S. population. The survey data from the 2013 SCF, which includes 6,026 respondents, are used here.

Results

Who Seeks Out Credit Counseling Services?

This section develops a demographic and financial profile for credit counseling clients using administrative data collected on all participants in the Sharpen Your Financial Focus credit counseling program between September, 2013 and March, 2015. This section also explores the reasons clients seek credit counseling as well as the outcomes of those counseling sessions.

Demographic Characteristics

Table 2.1 presents the demographic and household characteristics for Sharpen clients and compares them to the general U.S. population as reported in the Census’ American Community Survey (with results averaged over the five-year period from 2010-2014). Clients in the Sharpen Your Financial Focus credit counseling program skew heavily female, as 64 percent of Sharpen clients are women (the general population is close to evenly distributed between the two genders). Two-thirds of participants are white while about one-fifth are black, which is somewhat different from the general population where nearly three-fourths of individuals are white. The median age of Sharpen clients is 42 while the median age of Americans in general is 37, a difference likely driven by the fact that counseling clients are almost universally adults. Thirty-five percent of participants are single, while 42 percent are married or living with a partner, and 20 percent are either separated or divorced; this pattern is roughly similar to that seen in the broader U.S. population.

Sharpen clients tend to be relatively well-educated compared to the general U.S. population, with almost two-thirds of clients reporting some education beyond high school (20 percent have a two-year degree or technical degree, 30 percent have a bachelor’s degree and an

20 The client characteristics in Table 2.1 were chosen for their comparability with Census data.
additional 11 percent have some sort of graduate degree). Only two percent of clients report not completing high school. By contrast, only 29 percent of the general U.S. population has a college degree or more.

<table>
<thead>
<tr>
<th></th>
<th>Sharpen Clients</th>
<th>U.S. Population</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Median Age</strong></td>
<td>42.0</td>
<td>37.4</td>
</tr>
<tr>
<td><strong>Race</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asian</td>
<td>2%</td>
<td>5%</td>
</tr>
<tr>
<td>Black</td>
<td>21%</td>
<td>13%</td>
</tr>
<tr>
<td>White</td>
<td>66%</td>
<td>74%</td>
</tr>
<tr>
<td>Other</td>
<td>11%</td>
<td>9%</td>
</tr>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>36%</td>
<td>49%</td>
</tr>
<tr>
<td>Female</td>
<td>64%</td>
<td>51%</td>
</tr>
<tr>
<td><strong>Marital Status</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Single</td>
<td>35%</td>
<td>33%</td>
</tr>
<tr>
<td>Married/Living with a Partner†</td>
<td>42%</td>
<td>48%</td>
</tr>
<tr>
<td>Separated/Divorced</td>
<td>20%</td>
<td>13%</td>
</tr>
<tr>
<td>Widowed</td>
<td>3%</td>
<td>6%</td>
</tr>
<tr>
<td><strong>Education</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less than High School</td>
<td>2%</td>
<td>14%</td>
</tr>
<tr>
<td>High School Degree</td>
<td>34%</td>
<td>28%</td>
</tr>
<tr>
<td>Some College</td>
<td>3%</td>
<td>29%</td>
</tr>
<tr>
<td>College Degree or Higher</td>
<td>61%</td>
<td>29%</td>
</tr>
</tbody>
</table>

n=43,072

Sources: NFCC Administrative Data; 2010-2014 American Community Survey

†Approximately five percent of clients did not have data available for certain indicators, because either they refused to answer or the indicator was missing. This number varies slightly depending on the indicator in question, though it is much higher for the racial indicator (around 15 percent).

‡The Census estimates do not include "Living with a Partner" in this metric.

Table 2.1: Sharpen Client Demographics Compared to the U.S. Population
The median Sharpen household size is 2, and the majority of Sharpen clients (58 percent) report having no children under the age of 18. Forty-one percent of households either own their home or are in the process of buying one, while 46 percent rent. An additional 13 percent have “other” homeownership status, which may include situations like clients living at home with their parents or other relatives.

Financial Characteristics

Table 2.2 outlines the financial characteristics of clients at the time of credit counseling. The median Sharpen client has around $2,800 in gross monthly household income, $10,000 in non-liquid assets such as housing equity, and zero dollars in savings, while the median level of monthly housing and debt-related expenses is around $910 and $1,000, respectively. By way of comparison, the median reported income in the Census’ American Community Survey\(^{21}\) is $4,457 (U.S. Census Bureau, 2014), indicating that households in this credit counseling program had a median income 37 percent lower than the median U.S. household. These income levels become particularly concerning when comparing income to the monthly housing and other debt-related expenses faced by clients. When these expenses are subtracted from the average monthly income of clients, they only have a median discretionary income of $720 (and a mean of $978) left over for any remaining expenses.

The low income levels may be due in part to the relatively high levels of reported unemployment among these clients. While agencies involved in this program did not begin to track employment characteristics until mid-way through the period of study, employment characteristics (and student status) are available for 5,075 of the 43,072 Sharpen clients in the data. Of these clients, 68 percent report being employed, a quarter report being unemployed, and seven percent report being underemployed. Fewer than one percent of Sharpen clients within this subsample are students.

\(^{21}\) Over the five-year period from 2010 to 2014.
### Sharpen Client Financials

<table>
<thead>
<tr>
<th></th>
<th>Average</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average monthly income</td>
<td>$3,406</td>
<td>$2,820</td>
</tr>
<tr>
<td>Monthly housing expenses</td>
<td>$1,080</td>
<td>$909</td>
</tr>
<tr>
<td>Monthly debt-related expenses</td>
<td>$1,345</td>
<td>$1,031</td>
</tr>
<tr>
<td>Tangible assets</td>
<td>$76,551</td>
<td>$10,000</td>
</tr>
<tr>
<td>Savings</td>
<td>$1,189</td>
<td>$0</td>
</tr>
</tbody>
</table>

\( n=43,072 \)

*Source: NFCC Administrative Data*

\(^\d\) Approximately five percent of clients did not have data available for certain indicators, because either they refused to answer or the indicator was missing. This number varies slightly depending on the indicator in question.

| Table 2.2: Household Financials |

The savings levels of Sharpen clients are of particular concern, as almost three-fourths of Sharpen clients report having no savings. This is substantially lower than the liquid savings in the Survey of Consumer Finances, which found that the median level of savings among U.S. households was $4,100 in 2013 (Bricker et al., 2014). However, what is unclear from these results is whether clients entering this program have persistently weak savings profiles or if they are using all their liquid savings before entering the program. Regardless of the reason for these low savings levels, when the lack of savings is paired with the fact that clients have little income left over each month after their debt and housing expenses are accounted for, it presents a portrait of a client with little room to weather even short-term fluctuations in income or expenses.

**Counseling Motivations and Program Outputs**

As shown in Table 2.3, a strong majority of clients (63 percent) report seeking credit counseling because they faced a reduction in income, much of which is driven by a change in a client’s employment situation. Almost 30 percent report seeking credit counseling because they face increased expenses due largely to medical expense increases or an increase in debt payments via increased interest rates. Thirty-one percent also report seeking credit counseling for some other reason, with the most prominent reason being that they had poor credit. Clients could
choose more than one option for why they sought credit counseling, and in total 75 percent of clients reported seeking credit counseling for either an income or expense-related issue. This reveals that, while exceptionally high debt levels alone may be driving many clients into credit counseling, a large proportion of clients are actually seeking these services because of some unforeseen or irregular shock to their finances.

<table>
<thead>
<tr>
<th>Reason For Seeking Counseling†</th>
<th>#</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reduced income</td>
<td>27,258</td>
<td>63%</td>
</tr>
<tr>
<td>Un/underemployment</td>
<td>14,548</td>
<td>34%</td>
</tr>
<tr>
<td>Domestic conflict</td>
<td>3,823</td>
<td>9%</td>
</tr>
<tr>
<td>Other</td>
<td>8,887</td>
<td>21%</td>
</tr>
<tr>
<td>Increased expenses</td>
<td>12,332</td>
<td>29%</td>
</tr>
<tr>
<td>Medical/Disability expenses</td>
<td>4,094</td>
<td>10%</td>
</tr>
<tr>
<td>Creditors increased interest rates</td>
<td>1,869</td>
<td>4%</td>
</tr>
<tr>
<td>Increased family size</td>
<td>1,350</td>
<td>3%</td>
</tr>
<tr>
<td>Costs of death in family</td>
<td>315</td>
<td>1%</td>
</tr>
<tr>
<td>Paying off gambling debt</td>
<td>88</td>
<td>0.2%</td>
</tr>
<tr>
<td>Addiction/substance abuse</td>
<td>176</td>
<td>0.4%</td>
</tr>
<tr>
<td>Other</td>
<td>4,440</td>
<td>10%</td>
</tr>
<tr>
<td>Other reasons</td>
<td>13,318</td>
<td>31%</td>
</tr>
<tr>
<td>Previous bad experience</td>
<td>646</td>
<td>1%</td>
</tr>
<tr>
<td>Bad credit</td>
<td>3,090</td>
<td>7%</td>
</tr>
<tr>
<td>Haven't established a credit history</td>
<td>299</td>
<td>1%</td>
</tr>
<tr>
<td>Credit problems of ex-spouse</td>
<td>250</td>
<td>1%</td>
</tr>
<tr>
<td>Identity theft/fraud</td>
<td>126</td>
<td>0.3%</td>
</tr>
<tr>
<td>Error in credit report</td>
<td>89</td>
<td>0.2%</td>
</tr>
<tr>
<td>Discrimination</td>
<td>12</td>
<td>0.0%</td>
</tr>
<tr>
<td>Other</td>
<td>8,806</td>
<td>20%</td>
</tr>
</tbody>
</table>

n=43,072

†Respondents could select multiple reasons for seeking counseling. Approximately five percent of clients did not have data available for certain indicators, because either they refused to answer or the indicator was missing. This number varies slightly depending on the indicator in question.

Source: NFCC Administrative Data

Table 2.3: Reason for Seeking Credit Counseling
Many clients also identified as having “other” reasons for seeking credit counseling in each of these buckets.\textsuperscript{22} When the “other” option is selected, specific reasons for seeking credit counseling can then be recorded. A review of these answers provides additional insight on credit counseling motivations. Though responses are not systematically coded, common themes in these answers are apparent. Many clients reporting decreased income seek credit counseling due to fluctuations in income from being self-employed or managing a struggling or failing business, the loss of child support payments, a death in the family, or the incarceration of an income earner. Clients reporting some other source of increased expenses often point to a need to help family members with expenses, legal expenses, divorce costs, a need to pay child support, student loan payments coming due, or general increases in uncontrollable living expenses (such as rent or utilities). Clients selecting general “other” reasons identified low credit scores, a desire to review their credit report, having accounts in collections, general money mismanagement issues, and concerns about buying a home for the first time.

Of all the clients completing the Sharpen program, almost half (41 percent) were recommended to enter into a debt management plan while 44 percent only received credit counseling services with no DMP. Nine percent of clients were referred to legal assistance, two percent were referred to social services, and four percent of Sharpen clients received “other” services.

\textsuperscript{22} Some of the over 20,000 “other” responses appear to have been categorized incorrectly by the counselors entering these data, yet these inconsistencies do not appear systematic and an analysis of the results excluding any “other” answers does not change the overall findings on client motivations. As such, the reported results here retain all observations on counseling motivations without any alterations.
Table 2.4: Household Financials by DMP Status

Table 2.4 explores client financial characteristics contingent on a client being recommended into a DMP. The median client recommended for a DMP has a higher monthly income and substantially higher assets but also has somewhat higher monthly expenses and substantially higher liabilities. This is a somewhat intuitive result, as clients will not be recommended for DMPs if a counselor determines that a client either lacks an income source or lacks sufficient income to pay down their debts even with a DMP (Loonin & Plunkett, 2003), but these results also indicate that clients recommended for DMPs typically face higher levels of debt and related expenses than those who only receive credit counseling services.

What are Counseling Clients’ Financial Behaviors at the Time of Credit Counseling?

This section presents selected results from the MyMoneyCheckUp (MMCU) instrument for 16,227 credit counseling clients, covering the areas of financial confidence, budgeting, saving, borrowing, housing and retirement.
Financial Confidence

In the MyMoneyCheckUp instrument, Sharpen clients were asked how confident they were in their ability to manage five different areas of their financial lives, with 1 being “Not at all Confident” and 4 being “Confident.” As shown in Table 2.5, Sharpen clients appear to be less confident in the areas of managing future expenses, retirement planning, and paying off loans. By contrast, Sharpen clients are somewhat confident in their day-to-day finances and fairly confident in making mortgage payments.

<table>
<thead>
<tr>
<th>How confident are you about…</th>
<th>Day to Day Finances</th>
<th>Managing Future Expenses</th>
<th>Retirement Planning</th>
<th>Making Mortgage Payments</th>
<th>Paying Off Loans</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not at all confident</td>
<td>10%</td>
<td>16%</td>
<td>27%</td>
<td>7%</td>
<td>20%</td>
</tr>
<tr>
<td>Not confident</td>
<td>18%</td>
<td>25%</td>
<td>27%</td>
<td>10%</td>
<td>23%</td>
</tr>
<tr>
<td>Somewhat confident</td>
<td>42%</td>
<td>35%</td>
<td>28%</td>
<td>23%</td>
<td>27%</td>
</tr>
<tr>
<td>Confident</td>
<td>30%</td>
<td>23%</td>
<td>18%</td>
<td>60%</td>
<td>29%</td>
</tr>
</tbody>
</table>

Mean Confidence: 2.9, 2.6, 2.4, 3.4, 2.7

Source: NFCC MyMoneyCheckUp Data

Table 2.5: Financial Confidence

Budgeting and Account Use

As shown in Table 2.6, budgeting behavior among Sharpen clients is relatively inconsistent, with only 37 percent reporting that they maintain a budget. Of those that have a budget, seven percent report never being able to stick to their budget, while 93 percent report being able to stick to their budget “at least some of the time.” Conversely, only 28 percent of respondents report being “rarely” or “never” short of money, with the other 72 percent reporting being short of money at least “often.” Clients reporting that they keep a budget appear to have
fewer issues managing their money, as 40 percent these clients report being “rarely” or “never” short of money compared to 20 percent for respondents who do not keep a budget.

<table>
<thead>
<tr>
<th>MyMoneyCheckUp Budgeting Indicators</th>
<th>Keep a Budget</th>
<th>Do Not Keep a Budget</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Budgeting Behavior</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>How frequently do you stick to your budget?</td>
<td>37%</td>
<td>63%</td>
</tr>
<tr>
<td>Most of the Time</td>
<td>60%</td>
<td>n/a</td>
</tr>
<tr>
<td>Some of the Time</td>
<td>33%</td>
<td>n/a</td>
</tr>
<tr>
<td>Never/I Don't Know</td>
<td>7%</td>
<td>n/a</td>
</tr>
<tr>
<td>How frequently are you short of money at the end of the month?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Never</td>
<td>12%</td>
<td>5%</td>
</tr>
<tr>
<td>Rarely</td>
<td>28%</td>
<td>15%</td>
</tr>
<tr>
<td>Often</td>
<td>38%</td>
<td>42%</td>
</tr>
<tr>
<td>Always</td>
<td>21%</td>
<td>37%</td>
</tr>
</tbody>
</table>

*n=16,227

Source: NFCC MyMoneyCheckUp Data

Table 2.6: Budgeting Behaviors and Financial Strain

Maintaining accounts with a financial institution and regularly making direct deposits is also a key factor in budgeting behaviors. As can be seen in Table 2.7, almost all clients are banked in some way, with only seven percent of respondents reporting that they have neither a checking nor a savings account. The vast majority (89 percent) have at least a checking account, while 53 percent have both a checking and a savings account. Further, over three-fourths of clients in the MMCU (77 percent) report having money from their paycheck directly deposited in a bank account. This table also reveals that 93 percent of clients have either a checking or a savings account, which is in-line with the 93 percent of U.S. households owning any transaction account in 2013²³ (Bricker et al., 2014).

²³ In the Survey of Consumer Finances summary data, account use includes checking and savings accounts as well as money market and call accounts.
Table 2.7: Client Account Use

<table>
<thead>
<tr>
<th>MyMoneyCheckUp Account Indicators</th>
<th>% Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Have checking account</td>
<td>89%</td>
</tr>
<tr>
<td>Have savings account</td>
<td>57%</td>
</tr>
<tr>
<td>Have both checking and savings</td>
<td>53%</td>
</tr>
<tr>
<td>Have neither checking nor savings</td>
<td>7%</td>
</tr>
</tbody>
</table>

n=16,227

Source: NFCC MyMoneyCheckUp Data

Savings

Table 2.8 covers client savings behaviors. Only 25 percent of clients report saving money regularly, which is unsurprising given the very low levels of liquid savings among this population. The reported rate of saving money among respondents is less than half of what it is in the general U.S. population, with 53 percent reporting saving money in 2013 (Federal Reserve, 2013). Seventeen percent of respondents report having funds automatically deposited from their paycheck into a savings account. Of those not making direct deposits, almost half report never saving any money, while only 14 percent of clients save money frequently. An additional 39 percent of clients save occasionally (e.g., with additional income in the form of a tax refund or wage bonus). A quarter of respondents report currently saving money and of these respondents 35 percent report saving less than they normally do over the past year while 30 percent report saving more than they normally do over the same period. In terms of the reasons clients have for savings, around two-thirds of clients report saving for both specific goals (such as a vacation or large purchase) and to develop an emergency fund.
<table>
<thead>
<tr>
<th>MyMoneyCheckup Saving Indicators</th>
<th>Response %</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Are you currently saving money?</strong></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>25%</td>
</tr>
<tr>
<td>No</td>
<td>75%</td>
</tr>
<tr>
<td><strong>Over the past year have you saved...†</strong></td>
<td></td>
</tr>
<tr>
<td>Less than usual</td>
<td>35%</td>
</tr>
<tr>
<td>About the same as usual</td>
<td>35%</td>
</tr>
<tr>
<td>More than usual</td>
<td>30%</td>
</tr>
<tr>
<td><strong>Are you currently saving money via automatic deductions?</strong></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>17%</td>
</tr>
<tr>
<td>No</td>
<td>83%</td>
</tr>
<tr>
<td><strong>Aside from automatic payments, I set money aside for savings...</strong></td>
<td></td>
</tr>
<tr>
<td>Never</td>
<td>48%</td>
</tr>
<tr>
<td>Once a year (tax time, bonuses, etc.)</td>
<td>10%</td>
</tr>
<tr>
<td>Not often (only if you have extra money)</td>
<td>29%</td>
</tr>
<tr>
<td>Frequently</td>
<td>14%</td>
</tr>
</tbody>
</table>

*n=16,227

Source: MyMoneyCheckUp Data

†Asked only for those who are currently saving money.

Table 2.8: Client Savings Behaviors

**Borrowing**

Counseling clients report holding both installment and revolving debt. Thirty-seven percent of clients have mortgage debt, 74 percent have credit card debt, 49 percent have a car loan, and 38 percent have a student loan. The percent with credit card debt is of particular interest, as only 38 percent of respondents to the 2013 Survey of Consumer Finances carried credit card debt (Bricker et al., 2014). Table 2.9 summarizes client responses to a variety of questions related to credit use. Two-thirds of clients report owning a credit card and of these clients, 20 percent of clients report using no credit cards regularly while 24 percent report using a single credit card regularly. The remaining 56 percent of clients report regularly using more than one credit card, with 21 percent reporting that they regularly use five or more credit cards.
There is some indication that clients are at risk of falling behind on their debt payments, as 30 percent report that they paid less than the minimum amount due on their last credit card (or paid a late fee with the minimum payment), while an additional 41 percent only report paying the minimum amount due. This leaves a minority of clients with credit cards who report that they are paying more than the minimum amount due.

<table>
<thead>
<tr>
<th>MyMoneyCheckup Borrowing Indicators</th>
<th>Response %</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Do you have a credit card?</strong></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>66%</td>
</tr>
<tr>
<td>No</td>
<td>34%</td>
</tr>
<tr>
<td><strong>About how many cards do you regularly use?</strong>†</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>20%</td>
</tr>
<tr>
<td>1</td>
<td>24%</td>
</tr>
<tr>
<td>2</td>
<td>16%</td>
</tr>
<tr>
<td>3</td>
<td>11%</td>
</tr>
<tr>
<td>4</td>
<td>7%</td>
</tr>
<tr>
<td>5+</td>
<td>21%</td>
</tr>
<tr>
<td><strong>What did you do the last time you got your credit card bill?</strong>†</td>
<td></td>
</tr>
<tr>
<td>Didn't pay anything</td>
<td>19%</td>
</tr>
<tr>
<td>Paid less than the minimum amount due</td>
<td>7%</td>
</tr>
<tr>
<td>Paid the minimum amount due plus a late fee</td>
<td>4%</td>
</tr>
<tr>
<td>Paid the minimum amount due</td>
<td>41%</td>
</tr>
<tr>
<td>Paid more than the minimum amount due</td>
<td>23%</td>
</tr>
<tr>
<td>Paid the entire balance in full</td>
<td>6%</td>
</tr>
<tr>
<td><strong>Have you received a call from a bill collector?</strong></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>39%</td>
</tr>
<tr>
<td>Yes, once</td>
<td>11%</td>
</tr>
<tr>
<td>Yes, more than once</td>
<td>50%</td>
</tr>
<tr>
<td><strong>Have you recently taken a payday loan?</strong></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>10%</td>
</tr>
<tr>
<td>No</td>
<td>90%</td>
</tr>
</tbody>
</table>

*n=16,227

Source: MyMoneyCheckUp Data

†Asked only for those with credit cards.

Table 2.9: Household Borrowing Behaviors
Sixty-one percent of MMCU respondents report receiving a call from a bill collector in the last three months, with half of respondents receiving multiple calls; a strong indicator of the degree of financial distress faced by these clients at the time of credit counseling. Ten percent of clients also report recently relying on payday loans. When this fact is taken in conjunction with the fact that a strong majority of clients have a tendency to pay the minimum amount (or less) on their credit card debt, this may be an indication that a large portion of Sharpen clients are exposed to substantial financial risk stemming from high interest rates on debt (particularly in the case of payday lenders) and long repayment periods.

**Housing**

Table 2.10 summarizes the responses to a variety of housing-related questions. A minority (42 percent) of respondents own their home, and a substantial portion (28 percent) of people who do not own their home are considering the purchase of a home at some point in the next year. By comparison, 65 percent of the general U.S. population reported owning their own home in 2013 (Federal Reserve, 2013). These potential homebuyers on average report being cautiously confident in their ability to make a down payment, qualifying for a mortgage, knowing how much they can afford on a mortgage, selecting the best mortgage, and saving for home repairs. Within these areas, they are most cautious regarding their potential to qualify for a mortgage.
Table 2.10: Housing Characteristics

Of the clients who have a mortgage, only 30 percent of respondents report that they pay their mortgage automatically out of their bank account. Most home-owning respondents also seem to feel fairly secure in their ability to pay their mortgage as only two percent report that they cannot afford their mortgage and an additional 17 percent report being behind on their payments, while 26 percent do not struggle at all with their mortgage payment.

Retirement

Fewer than half (43 percent) of respondents report having a retirement savings account, while 38 percent report actively saving for retirement, as shown in Table 2.11. Interestingly, this
rate of retirement account ownership is not substantially different from that of the general U.S. population, 49% of whom had retirement accounts in 2013 (Federal Reserve, 2013). Of the clients with retirement accounts, the median amount of retirement savings they have accumulated is $10,000. By way of contrast, the median amount these clients believe they will need to have saved for retirement is around $205,000, indicating that there may a substantial deficit between current retirement savings and expected needs in retirement.

<table>
<thead>
<tr>
<th>MyMoneyCheckup Retirement Indicators</th>
<th>% Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Have a retirement account</td>
<td>43%</td>
</tr>
<tr>
<td>Currently saving for retirement</td>
<td>38%</td>
</tr>
<tr>
<td>Employer offers a retirement plan</td>
<td>51%</td>
</tr>
<tr>
<td>Currently participating in the plan†</td>
<td>65%</td>
</tr>
<tr>
<td>Making automatic retirement contributions</td>
<td>31%</td>
</tr>
</tbody>
</table>

\[n=16,227\]

Source: MyMoneyCheckUp Data

†Asked of those offered a retirement plan through an employer

Table 2.11: Retirement Savings Behaviors

Fifty-one percent of respondents have employers offering some form of retirement plan. Of respondents offered plans through their employers, 65 percent are participating in the plan. Only about a third are making automated contributions to their retirement accounts (though this jumps to nearly 60 percent for those with retirement plans offered through their employer). This low rate of automatic retirement contributions is potentially troubling, as shifting to a plan of automatic deductions into retirement accounts can often take advantage of an employer’s matching contributions (where available) and can also serve as a method of building long-term assets that is more reliable than ad hoc retirement contributions.

What Changes Do Clients Report After Credit Counseling?
This section presents the results of a follow-up survey administered by the NFCC three months after a client completed the Sharpen program. Data are available for 777 survey respondents. Tables 2.12 and 2.13 of this section summarize the survey results, with Table 2.12 covering self-reported behavioral changes and actions and Table 2.13 covering changes in clients’ financial conditions and their relationship with financial institutions.

*Perceptions of improved financial behaviors*

Generally speaking, Sharpen clients report improvements in their financial behaviors, as shown in Table 2.12. Notably, almost two-thirds of clients report better managing their money, and two-thirds also assert that the program improved their overall financial confidence and helped them set financial goals. Nearly three-fourths of responding clients claim to pay their debts more consistently, while over 40 percent have ordered or viewed their credit report.\(^2^4\) Less positively, almost 30 percent of clients still report paying late fees on their payments.

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\(^{2^4}\) This is likely due in part to the fact that participation in the Sharpen program comes with a year’s subscription to Experian’s freecreditscore.com service, which allows participants to view their credit report.
Table 2.12: Self-Reported Changes in Financial Behaviors

Table 2.12 also explores these survey responses for a variety of subgroups: Respondents with monthly incomes below the median for Sharpen clients ($2,820), female clients, minority clients, and clients recommended into debt management plans. Generally speaking, these subgroups have similar response profiles to the general Sharpen client base and overall report positive behavioral changes after their credit counseling sessions. There are some significant differences between these subgroups and the total group of survey respondents, however.

Significantly fewer respondents with below-median incomes report better managing their money, having improved financial confidence, and paying their debt more consistently; though fewer of these clients report paying late fees (p<0.1). Female clients are very similar to male clients in terms of their survey responses, though they do report ordering their credit report at significantly
lower rates than male clients (p<0.05). Minority clients report paying late fees and taking out payday loans significantly more than non-minority clients; though only eight percent of minority clients report taking out payday loans, this represents a sixty percent increase relative to the general client base. Finally, while clients recommended into a DMP report ordering their credit report less frequently and taking out payday loans more frequently than non-DMP clients, they also report paying their debt more consistently at a significantly higher rate.

Changes in financial conditions

Table 2.13 outlines client responses to several questions about the changes in their financial conditions since credit counseling. A strong majority of survey respondents are in a similar employment position as they were during program enrollment, with 20 percent of respondents reporting that their situation has improved three months after the time of credit counseling and seven percent reporting that it has worsened. Given the relative stability of the employment situation for these clients, it is unsurprising that two-thirds report that their available income has stayed the same while a fifth report that it has increased.

Around half of survey respondents report a decrease in credit card debt three months after credit counseling while only nine percent report an increase and most respondents have not really changed their savings behavior (almost as many report a decrease in savings as report an increase). While this may be evidence that the program is better at changing debt behaviors than savings behaviors, it could also capture clients shifting their focus toward paying down debt and away from building savings.

Seventeen percent of clients also reported using new financial products that they had not used prior to credit counseling. New product use was about evenly split between checking accounts, savings accounts, and credit/debit cards (five percent each), with an additional two percent reporting use of some “other” financial product.
<table>
<thead>
<tr>
<th>Sharpen Client Survey Responses</th>
<th>% Answering Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>Has your employment situation in your household...</em></td>
<td></td>
</tr>
<tr>
<td>Improved</td>
<td>20%</td>
</tr>
<tr>
<td>Stayed the Same</td>
<td>73%</td>
</tr>
<tr>
<td>Worsened</td>
<td>7%</td>
</tr>
<tr>
<td><em>Has the available income...</em></td>
<td></td>
</tr>
<tr>
<td>Increased</td>
<td>21%</td>
</tr>
<tr>
<td>Stayed the Same</td>
<td>66%</td>
</tr>
<tr>
<td>Decreased</td>
<td>13%</td>
</tr>
<tr>
<td><em>Would you say that the total amount of credit card debt that your household carries has...</em>†</td>
<td></td>
</tr>
<tr>
<td>Increased</td>
<td>9%</td>
</tr>
<tr>
<td>Decreased</td>
<td>49%</td>
</tr>
<tr>
<td>Stayed the Same</td>
<td>39%</td>
</tr>
<tr>
<td><em>Would you say that the total amount of money you are able to save on a regular basis has...</em>†</td>
<td></td>
</tr>
<tr>
<td>Increased</td>
<td>26%</td>
</tr>
<tr>
<td>Decreased</td>
<td>16%</td>
</tr>
<tr>
<td>Stayed the Same</td>
<td>55%</td>
</tr>
</tbody>
</table>

Source: NFCC Post-Counseling Survey

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

†Responses do not add to 100% because a small subset of respondents answered "Don't know".

Table 2.13: Self-Reported Changes in Financial Conditions

How Do Credit Counseling Client Indicators Evolve from Pre- to Post-Counseling?

This section traces credit outcomes for 8,963 Sharpen clients from baseline to six quarters post-counseling. This analysis is descriptive and is not intended to estimate the causal impact of the Sharpen program (Chapter Three of this dissertation provides the results of the impact evaluation).

Baseline Credit Characteristics
Table 2.1 describes the credit characteristics of Sharpen clients before the program began. Clients had an average credit score of about 590\textsuperscript{25} and had almost 10 accounts open with positive balances. This credit score is markedly lower than that of the average American, which was 669 in 2015 (Experian, 2015). Including mortgages, the average Sharpen client held a little over $100,000 in debt prior to credit counseling. When only looking at revolving debt, however, clients hold around $13,300 for open revolving accounts and $20,600 for any revolving account (including revolving accounts that have been subsequently closed by clients or their creditors). For reference, the average level of credit card debt (a major component of revolving debt) for households with credit card debt was only $5,700 in 2013 (Bricker et al., 2014), indicating that Sharpen clients have substantially higher revolving debt than the general U.S. population. Thirty-five percent of Sharpen clients have a mortgage and those with mortgages have an average balance of about $180,000.\textsuperscript{26} Seven percent of clients have ever declared bankruptcy, and clients on average had 1.4 payments at least 30 days delinquent in the prior year, with 0.8 payments at least 60 days delinquent.

\textsuperscript{25} The credit score used in this analysis is Experian’s Vantage 3.0 credit score, which is a similar metric to the FICO credit score and spans an identical range (scores are between 300 and 850).

\textsuperscript{26} The mortgage debt level reported here is higher than that reported by clients in the MyMoneyCheckUp survey. It is possible that this gap stems from the fact that the MMCU relies on self-reports while the credit data is more objective. Another explanation is that those for whom MMCU data were available had higher levels of mortgage debt than the general Sharpen client base. However, financial differences were compared between clients based on MMCU data availability and generally speaking those for whom MMCU data were available had a similar financial profile to other Sharpen clients.
<table>
<thead>
<tr>
<th>Sharpen Client Credit Indicators</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit Score</td>
<td>586.4</td>
<td>588.0</td>
<td>73.1</td>
</tr>
<tr>
<td># of Accounts with Balance &gt; 0</td>
<td>9.8</td>
<td>9.0</td>
<td>6.0</td>
</tr>
<tr>
<td># of Revolving Accounts with Balance &gt; 0</td>
<td>4.9</td>
<td>4.0</td>
<td>3.9</td>
</tr>
<tr>
<td>Total Debt</td>
<td>$107,709</td>
<td>$47,498</td>
<td>$146,304</td>
</tr>
<tr>
<td>Revolving Debt on Accounts Updated in Last 12 Months</td>
<td>$20,610</td>
<td>$10,111</td>
<td>$36,857</td>
</tr>
<tr>
<td>Aggregate Balance For Open Revolving Trades</td>
<td>$13,307</td>
<td>$7,264</td>
<td>$16,944</td>
</tr>
<tr>
<td>Own a Mortgage</td>
<td>35%</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Total Mortgage Debt‡</td>
<td>$179,562</td>
<td>$147,142</td>
<td>$140,476</td>
</tr>
<tr>
<td>Ever Bankrupt</td>
<td>7%</td>
<td>n/a</td>
<td>n/a</td>
</tr>
<tr>
<td>Number of Payments 30 Days Delinquent in Prior 12 Months</td>
<td>1.44</td>
<td>0</td>
<td>2.37</td>
</tr>
<tr>
<td>Number of Payments 60 Days Delinquent in Prior 12 Months</td>
<td>0.80</td>
<td>0</td>
<td>1.84</td>
</tr>
</tbody>
</table>

n=8,963

Source: Credit Attributes Data

| Table 2.14: Baseline Credit Characteristics‡ |

Change in credit scores

The average credit score for the full sample increased by 14 points one and a half years after enrollment in Sharpen. The score increased more substantially for clients towards the bottom of the credit score distribution, increasing by 50 points for those in the bottom quartile of credit scores at baseline. The trends in these two groups also differ, as can be seen in Figure 2.3. For the average Sharpen client, the trend indicates a declining credit score around the time of enrollment, followed by a recovery and eventual increase. For clients in the bottom credit quartile, the credit score increased across all periods.²⁷

²⁷ The trend in credit scores was also examined based on the reasons clients gave for seeking counseling. Regardless of the reason given for entering counseling, the trend was the same and was very similar to the overall trend for Sharpen clients in this analysis.
The distribution in credit score change is also of interest. While the average change in credit scores was a 14 point increase, Figure 2.4 shows that the range of changes is wide. While credit score changes tend to cluster between 50 and -50 points, there were a substantial number of clients who experience extreme shifts in credit scores over the study period (±100 points). These wide swings in credit scores over the evaluation period illustrate the degree of the financial volatility faced by many credit counseling clients in the Sharpen program.
Debt levels

For this analysis, three different indicators of debt are measured: (1) total debt, which includes the combined balance of revolving and installment debt, including both open and closed accounts with a remaining balance; (2) total revolving debt, which includes outstanding balances on credit cards and revolving home equity lines of credit (HELOCs); and (3) open revolving debt, which includes balances on open revolving accounts only, excluding accounts that have been closed by a consumer or creditor as well as HELOCs.
<table>
<thead>
<tr>
<th>Credit Indicator</th>
<th>Pre-Counseling Quarter</th>
<th>First Quarter</th>
<th>Second Quarter</th>
<th>Third Quarter</th>
<th>Fourth Quarter</th>
<th>Fifth Quarter</th>
<th>Sixth Quarter</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total Debt</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>25th Credit Percentile</td>
<td>$72,093</td>
<td>$70,733</td>
<td>$68,838</td>
<td>$65,283</td>
<td>$62,390</td>
<td>$59,678</td>
<td>$57,228</td>
</tr>
<tr>
<td>All Clients</td>
<td>$107,709</td>
<td>$106,787</td>
<td>$104,667</td>
<td>$99,354</td>
<td>$95,836</td>
<td>$93,199</td>
<td>$90,625</td>
</tr>
<tr>
<td><strong>Total Revolving Debt</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>25th Credit Percentile</td>
<td>$11,940</td>
<td>$10,778</td>
<td>$8,587</td>
<td>$6,815</td>
<td>$6,078</td>
<td>$5,383</td>
<td>$4,999</td>
</tr>
<tr>
<td>All Clients</td>
<td>$20,610</td>
<td>$20,071</td>
<td>$18,482</td>
<td>$16,014</td>
<td>$14,310</td>
<td>$13,274</td>
<td>$12,576</td>
</tr>
<tr>
<td><strong>Open Revolving Debt</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>25th Credit Percentile</td>
<td>$6,546</td>
<td>$4,284</td>
<td>$3,263</td>
<td>$2,646</td>
<td>$2,392</td>
<td>$2,140</td>
<td>$1,949</td>
</tr>
<tr>
<td>All Clients</td>
<td>$13,307</td>
<td>$10,694</td>
<td>$8,271</td>
<td>$7,064</td>
<td>$6,475</td>
<td>$6,012</td>
<td>$5,672</td>
</tr>
</tbody>
</table>

\( n=8,963 \)

*Source: Credit Attributes Data*

Table 2.15: Change in Debt Levels Over the Evaluation Period
Table 2.15 shows that there was a substantial decline in the amount of debt held by clients post-enrollment. The average decrease in total debt across all clients was around $17,000 while the average decrease in total *revolving* debt was about $8,000. The average decrease in debt held in *open* revolving accounts was close to $7,600. For clients in the bottom quartile of the credit score distribution at baseline, the reduction in total debt was around $15,000, while the average decrease in total revolving debt was around $7,000 and the decrease in open revolving debt was around $4,600.

The distribution in debt changes is also wide. Figure 2.5 demonstrates the distribution of change for open revolving debt.\(^{28}\) While the majority of Sharpen clients had modest changes in open revolving debt, there were a number of clients with more extreme debt reductions. Only 21 percent of Sharpen clients had an open revolving debt increase over this period.

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\(^{28}\) Open revolving debt was chosen as the debt measure of interest here because of the absence of HELOC debt in this metric. Taking on (or eliminating) HELOC debt can cause large swings in debt levels, which make the interpretation of histograms difficult. In this case, the open revolving debt histogram is similar to the total revolving debt histogram excluding any clients with HELOCs.
Overall, the median change for both revolving debt measures was about -$2,000 for credit counseling clients and the median change in total debt was -$5,089. While this analysis demonstrates that Sharpen clients reduced their debt levels, there remains a question of how much of this debt reduction stemmed from behavioral changes such as paying off more debt or reducing expenses and how much stemmed from the declaration of bankruptcy or debt charge-offs. Chapter Three of this dissertation explores this question in detail.

*Delinquent payments*

The metric used to measure payment delinquencies here is the number of tradelines, or credit accounts, on a client’s credit file that are 60 days or more past due in the last six months. The average decline in delinquent payments was about 0.18 for all clients and 1.13 for those in the bottom quartile of the credit distribution at baseline; though the large drop in the bottom
quartile may in part be driven by the high baseline delinquencies for these clients. The trend in payment delinquencies can be seen in Figure 2.6. On this metric, an inverse pattern to that of the credit score trend develops: The average client experienced a sharp increase in payment delinquencies, followed by a steady decline through the end of the evaluation period.

![Figure 2.6: Change in Payments 60 Days Past Due Over the Evaluation Period](image)

$n=8,963$
Source: Credit Attributes Data

Discussion

This chapter has shown that, relative to the U.S. population, credit counseling clients appear to be in an extremely vulnerable position. Their incomes are smaller, their savings levels are dramatically lower, and their credit usage is exceptionally high. In this, American counseling clients are similar to the British counseling clients studied by Disney and Gathergood (2009). Though these clients are substantially different from the general population, their circumstances
are likely not uncommon in an era of high credit usage, persistently low savings, and economic volatility driving households into distress. Given that these dynamics may persist well into the future, it is important to understand what populations can be served by credit counseling, and the degree to which their outcomes improve as a result of these services. By providing a detailed examination of the individuals who voluntarily sought credit counseling for debt and credit issues, this chapter has contributed to that understanding.

Most importantly, this work has demonstrated the degree of credit distress faced by credit counseling clients around the time they seek credit counseling. While Collins (2010) found a positive link between having a large income drop in the prior year and seeking credit counseling, Wang (2010) used interviews to demonstrate that many credit counseling clients take on unsustainable debt in response to income or expense shocks, and (Disney et al., 2015) found significant associations between having income, employment, or health shocks and seeking counseling, the analysis in this chapter allows for a more detailed look at these dynamics. Three-fourths of credit counseling clients report seeking credit counseling for income- or expense-related issues, most commonly from job loss (or underemployment), medical expenses, or domestic conflicts. These shocks are reflected in their credit profiles, as around the time clients are seeking credit counseling they are also exhibiting spikes in payment delinquencies and a drop in their overall credit scores. These metrics return to their baseline values about a year after credit counseling.

From a policymaker’s standpoint, this finding is important in determining whom to target with these (or related) programs. The evidence in this chapter shows that clients are seeking credit counseling from job loss and that clients may be spending down their savings before seeking credit counseling, leaving them less capable of weathering future income or expense shocks. To offset this possibility and to reach this key population at an earlier stage, policymakers could tie
credit counseling initiatives to other programs associated with experiencing income or expense shocks, such as unemployment programs or disability programs.

This finding is also relevant for future evaluations of credit counseling programs and other programs dealing with clients in financial distress. As these services cannot often be randomly assigned (which would require credit counseling agencies to turn away services from clients in need), evaluations tend to either rely on matching approaches (Elliehausen et al., 2007; Chapter Three of this dissertation) or on pre- and post-counseling surveys (Bagwell, 2000; Kim et al., 2003). These approaches may not account for the presence of unobservables such as job loss or medical issues, which may confound any evaluation of credit counseling’s impact on self-reported outcomes.

From a program design standpoint, this finding also has important implications. Credit counseling services are often oriented toward the long-term: Budget counseling seeks to stabilize household finances to make existing debts more manageable (and prevent the accumulation of future debts), financial education seeks to help clients avoid damaging financial behaviors like participating in payday loans or using high-interest credit cards, and debt management plans restructure client debt in such a way that clients can pay it down over the span of several years. But clients are demonstrably facing circumstances at the time of credit counseling that can harm their long-term financial welfare; payment delinquencies can remain on credit reports for years and the associated reduction in credit scores can prevent clients from accessing necessary financial products (such as mortgages), or only accessing them at higher interest rates. Given this, consumer credit counseling agencies should seek ways to stem the degradation of client credit profiles in the short-term, perhaps through working with creditors to forgive client payment delinquencies under certain circumstances or through the provision of low-interest emergency loans to prevent clients from falling behind on payments. Products of this type are already being explored by banks and employers (FDIC, 2010) but credit counseling agencies and other related
service providers could uniquely benefit clients through these products by offering them to clients in moments of distress.

The demographic and credit profile observed for credit counseling clients in this chapter is largely in-line with the limited prior work discussing client characteristics. Like Bagwell (2000), this chapter finds that credit counseling clients tend to be white, female, relatively well-educated, and lower-income, and like Elliehausen, Lundquist, and Staten (2007) it finds that clients hold high levels of debt prior to credit counseling and have a history of payment delinquencies. While the gender disparity in seeking credit counseling is similar to that seen in other work, the degree of the disparity is striking: Credit counseling clients are almost two-thirds female. The source of this disparity is unclear. It could be that men have higher levels of financial literacy (Lusardi & Mitchell, 2014) and so perceive that credit counseling will provide less benefit to them, but it could also be that males suffer from overconfidence when it comes to their finances (Barber & Odean, 2001; Collins, 2010), leading males to not seek credit counseling when it might otherwise benefit them. However, one key attribute of credit counseling clients described here and omitted in other research is the relatively dire savings levels of Sharpen clients; three-fourths of these clients report having no liquid savings. While this could be from a lack of savings behavior in general, it could also indicate that clients are exhausting their liquid savings before seeking credit counseling. Regardless of the motivation, this finding demonstrates that credit counseling clients have very little financial slack available to weather future income or expense shocks.

This analysis has also described the behavioral profile of credit counseling clients, finding that their budgeting behavior is relatively inconsistent (only about a third keep a budget and only 60 percent of those keeping a budget follow it “most of the time”), only a fourth of clients are actively saving money, and the majority of clients are paying the minimum or less on their credit card bills. Each of these findings provide guidance on the troubles facing credit
counseling clients. A lack of budgeting may make it difficult for clients to live within their means, a lack of savings reduces clients’ ability to weather unforeseen shocks like the ones driving them to seek credit counseling, and paying the minimum or less on their credit cards subjects them to high interest payments that compound over time. In each of these areas financial education and direct guidance can play a role, either through advice on how to construct a budget, education on how interest accumulates and the importance of paying down the principal on debt, or advice on where to cut expenses to build emergency savings to weather shocks. There is also evidence of ample room for relatively simple improvements in clients’ financial behaviors through the use of automated payments; a significant majority report not using automated deposits for their liquid savings, their retirement savings, or their mortgage payments. Relying on automated payments can overcome problems of inattention (Stango & Zinman, 2014), allowing clients to build savings or make timely payments without having to make the conscious decision to engage in these behaviors at multiple intervals in a given year.

Interestingly, this chapter has also shown that mortgage-owning clients seem relatively secure in issues related to housing: They are confident in making their mortgage payments and the vast majority report staying current with their mortgage payments (even though a subset of these clients struggle to do so). At the same time, a majority of clients also report receiving calls from bill collectors, which is a concrete indicator of financial distress. Given these two results, it seems reasonable to say that clients are prioritizing essential expenses like housing even as they fall behind on their other debts.

Finally, this chapter has also presented results from both client surveys and credit attributes data capturing client changes over several post-counseling periods. Though these analyses are not intended to make any causal claims for the impact of credit counseling (the impact of credit counseling is analyzed in Chapter Three of this dissertation), they do provide a sense of how clients perceive their financial state soon after credit counseling and how their
overall credit profiles change in the year and a half after counseling. From these data sources, it is clear that clients perceive themselves to be in a stronger financial state three months after credit counseling than they were at the time of counseling; strong majorities report better managing money, having more overall financial confidence, paying their debts more consistently, and setting financial goals, though around 40 percent still report paying late fees. From the credit data, it is also clear that clients are shedding a substantial amount of debt over the evaluation period, though this debt reduction could be attributable to either behavioral changes or debt write-offs from bankruptcies, foreclosures, or creditors charging off accounts. Chapter Three of this dissertation explores the question of what is driving these debt reductions in more detail.

While this chapter has presented an analysis of credit counseling clients with a high level of detail, the limitations are clear. This analysis is purely descriptive: There is no non-counseled comparison group used (though an analysis of client outcomes relative to a comparison group follows in the next chapter), the survey is self-reported and has a relatively low response rate (Appendix B compares the characteristics of survey respondents and non-respondents), and the administrative and MyMoneyCheckUp data are not intended to make any causal arguments about what drives clients to seek credit counseling. Regardless of these limitations, this work contributes to the credit counseling literature specifically and the literature on consumer financial programs generally by providing an in-depth look at these highly vulnerable individuals and providing guidance for the development of future research in this area.
Chapter 3: Credit Counseling’s Impact on Client Outcomes: Evidence from the Sharpen Your Financial Focus Program

Introduction

While the previous chapter outlined the characteristics of credit counseling clients and descriptively traced their credit outcomes over 18 months after they received counseling, this chapter presents an impact analysis assessing outcomes for credit counseling clients relative to counterfactual outcomes measured for a comparison group. 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 evidence that credit counseling generally had the potential to improve the credit scores of high-risk borrowers in the long-term, while the results were more mixed for the general credit counseling population (Elliehausen et al., 2007). That evaluation, however, only focused on credit indicators at two points in time (the year a client received credit counseling and three years after they received counseling), which may ignore critical shorter-term changes in consumer credit profiles. It also does not control for the impact of debt repayment plans or debt write-offs (e.g. from bankruptcy, foreclosure, or debt charge-offs by creditors), which are often associated with credit counseling clients.

This chapter addresses these gaps in the extant 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, 2013.29 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

29 The NFCC is an umbrella membership organization representing more than 70 affiliate nonprofit financial and credit counseling agencies nationwide.
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. This chapter evaluates the impact of the nationwide Sharpen Your Financial Focus credit counseling program on counseling clients and tracing the evolution of key credit indicators for those clients over time. It seeks to answer the following questions:

1. How do credit outcomes for credit counseling clients differ from a comparison group with similar credit profiles at baseline (prior to the intervention)?
2. To what extent are client credit outcomes attributable to debt write-offs (from bankruptcy, foreclosure, and creditor charge-offs)?
3. How do client credit outcomes differ based on debt management plan enrollment?
4. How do these outcomes differ among clients with different credit risk profiles at baseline?

To answer these questions, this research uses administrative data collected by 13 nonprofit consumer credit counseling agencies combined with longitudinal credit data on clients receiving counseling in those agencies to assess the quarterly impact of participation in the credit counseling program over the period of a year and a half after counseling. The aim of this chapter is to contribute to the understanding of the financial circumstances faced by credit counseling clients and evaluate the potential for counseling programs to benefit these clients. The working hypotheses underlying this research are that clients’ credit profiles will deteriorate in the short-term due to the presence of income and expense shocks that drive clients to seek counseling, but in the longer-term client credit outcomes will improve relative to a non-counseled comparison
group and these impacts will be robust to controlling for debt write-offs (e.g. bankruptcy) and participation in a debt management plan.

In partnership with Experian, a matched comparison group is generated through Coarsened Exact Matching (CEM). Using fixed effects panel regression, a series of differences-in-differences models are then estimated 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 credit counseling, this data and modeling approach accounts for other time-varying credit interventions post-counseling, including bankruptcies, charge-offs, and foreclosures. In an alternative specification, outcomes are separately traced for counseling clients who were recommended for DMPs and those who were not.

This longitudinal analysis reveals that credit counseling clients tend to experience large income and/or expense shocks around the time of their entry into credit counseling programs, as indicated by an increase in account delinquencies and declines in credit scores around the time of credit counseling. Administrative data from the credit counseling sessions indicate these shocks are often driven by job loss or unexpected expenses. Relative to the comparison group, Sharpen clients make significant reductions in their debt balances after credit 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 prior to credit counseling also demonstrate improvements in payment delinquency and credit score metrics relative to the comparison group.

The remainder of this chapter proceeds as follows: The next section reviews the relevant literature on credit counseling and related programs. After the literature review, the mechanisms by which credit counseling may impact client outcomes are discussed and hypotheses are described. The fourth section provides a description of the program under study. The fifth section outlines the data and methods to be employed in this chapter. The sixth section presents the results of the differences-in-differences analyses. Finally, findings are discussed and the limitations of the analysis are detailed, followed by the conclusion and policy implications of the study.

Literature Review

There are several existing streams of literature to draw from in order to understand how credit counseling services may impact overall financial behaviors and short- and long-term outcomes. This section provides a detailed review on credit counseling research and briefly touches on related research emerging from financial education and financial coaching programs. This section will also cover research on the behavioral impact of income and expense shocks (which often drive individuals to seek credit counseling services) to provide a foundation for understanding how credit counseling may benefit households facing these shocks.

The Credit Counseling Research Literature

While the credit counseling industry has been around for a long time, relatively few formal evaluations of credit counseling’s impacts on household outcomes exist. Indeed, much of
the general financial counseling literature is focused less on credit counseling explicitly and is instead focused on targeted education or credit counseling programs such as pre- or post-purchase homeownership counseling. Results from these targeted programs are mixed, with some studies on mortgage 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).

Several studies seek to measure the impact of credit counseling directly. In an analysis linking financial literacy to credit outcomes, Courchane and Zorn (2005) found that credit counseling could improve credit outcomes through its contribution to financial knowledge (in a structural model) but in a reduced form model they found that credit counseling was actually negatively related to creditworthiness (a result attributed to the possibility that households with credit issues are more likely to self-select into counseling programs, a characteristic that impaired their subsequent credit scores). Additionally, Kim, Garman, and Sorhaindo (2003) used pre- and post-counseling surveys and found that while enrollment in a credit counseling program had no direct effects on financial behaviors, credit counseling participants did have a lower propensity to experience future financial stressor events like collection calls or foreclosures and that those who remained active in debt management plans had better self-assessed financial outcomes than those who did not. Bagwell (2000) used a similar research design and found that credit counseling participants reported improved financial behaviors post-counseling relative to their pre-counseling behaviors and also showed improvements in financial stress levels one year after credit counseling. Barron and Staten (2011) did not test the overall impacts of credit counseling but rather explored the relative effectiveness of “technology-assisted” credit counseling (counseling done over the phone or online) versus in-person counseling by using the change in
credit scores from pre-counseling to post-counseling and found few differences between the modes of delivery on client outcomes. While these studies can provide descriptive assessments of credit counseling’s potential impact, they do not measure outcomes against a comparison group, which is necessary for evaluating counterfactual outcomes.

Other descriptive work has assessed the factors associated with completing debt management plans. Xiao and Wu (2008) incorporated the Theory of Planned Behavior (Ajzen, 1991) into a survey of credit counseling clients and found that client attitudes and perceptions about the likelihood and desirability of completing a DMP were correlated with actually completing the DMP. Tang and Xiao (2007) used a similar approach and found that factors like satisfaction with credit counseling services, client perceptions of control, and client attitudes toward remaining in DMPs correlated with successfully completing a DMP.

Only one study to date has evaluated the impact of credit counseling itself on client credit outcomes in a rigorous way. Elliehausen, Lundquist, and Staten (2007) employed a quasi-experimental research design explicitly developed to offset the selection problems that plague other studies of credit counseling and related interventions (i.e. the decision to enter into a credit counseling program is potentially correlated with the error term; Meier & Sprenger, 2010). Using credit bureau data that included clients receiving credit counseling in 1997 and a matched comparison group of uncounseled individuals, the study employed a two-stage least squares model to first predict selection into the credit counseling program and then used a selection-corrected model to predict the impact of the receipt of credit counseling on an array of credit indicators. While they found that the impact on credit scores was relatively minimal once selection was taken into account, they did find positive impacts from credit counseling on debt

Credit counseling agencies, like many financial institutions, appear reluctant to share client data widely with researchers.
levels, accounts held, and bank card use (as well as more general positive effects for those with
the weakest credit profiles prior to credit counseling).

Despite its strengths relative to the few other existing analyses, the Elliehausen, Lundquist, and
Staten (2007) work did not account for debt reductions stemming from charge-offs or
bankruptcies (rather than client or program-driven debt reductions) and did not investigate
the differences between DMP participants and those not recommended into DMPs. Further, it
did not investigate the pattern in credit outcomes for credit counseling clients over time, which
may yield valuable insights into the circumstances facing credit counseling clients. This last point
requires additional explanation. Credit counseling clients typically do not enter in to credit
counseling solely because of unsustainable debt levels or general credit problems but because
they are facing some financial hardship such as job loss or an expense shock33 (i.e. from a major
medical emergency) that has left them unable to pay their debts (Wang, 2010). Given this,
analyses of credit outcomes (e.g. Elliehausen et al., 2007) that only look at two points in time
may miss the initial declines in credit scores faced by clients around the time they seek credit
counseling, while analyses of self-reported financial outcomes (Bagwell, 2000; Kim et al., 2003)
may not account for the fact that many clients are going through periods of exceptional financial
hardship at the time of credit counseling; reports of improved financial well-being post-
counseling may simply reflect the fact that many clients are out of the crisis period that caused
them to seek out credit counseling.

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33 The issue of unobserved shocks correlating with selection into social programs has been discussed in the
program evaluation literature (e.g. Ashenfelter, 1978; Heckman & Smith, 1995) and provides a strong
argument for randomized, controlled trials in evaluating these programs. Due to the nature of credit
counseling programs, such an approach is unlikely to be implemented, as it requires agencies to turn away
services from potential clients. An alternative option would be to only advertise or explicitly offer credit
counseling services to a randomized sample of individuals (i.e. a subset of student loan holders on a college
campus) and measure outcomes for this sample relative to a control group but, as the Sharpen Your
Financial Focus program was advertised nationally, establishing such a control group was not possible.
Evidence from Related Programs

While this chapter is concerned with evaluating the impact of the Sharpen Your Financial Focus credit counseling program, there are other related interventions that provide guidance on 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 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 that 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 skills and also provide 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 and Mitchell (2014) noted 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 tied financial illiteracy to paying higher fees in financial transactions and an increased propensity to use high-cost services like payday lenders. The authors also showed that

34 The target population for these programs likely differs as well, as these programs are not oriented toward managing immediate financial issues in the same way that credit counseling services are.
sub-optimal borrowing behaviors such as late bill payments, going over credit limits, or paying minimum amounts on credit card debt are also associated with lower levels of financial literacy.

There is little consensus as to whether 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, and 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. This study was later contradicted by Cole and Shastry (2013), which analyzed Census data to show that states with high savings and investment rates due to economic growth were more likely to impose a financial education mandate, indicating that the imposition of mandates that the Bernheim, Garrett, and 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 that systematically assess the potential impacts of these programs. Miller, Reichelstein, Salas, and Zia (2014) reviewed 188 studies and found that a majority of articles reported positive financial outcomes for participants in education programs including increased savings and improved financial skills but that these positive impacts notably diminished 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 did, 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 Fernandes, 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 evaluating the impact of coaching on financial outcomes. Collins and O’Rourke (2010) detailed three small field studies in financial coaching, including a coaching program for community college students, a program for low-income clients 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) assessed 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, Collins, Loibl, and Samak (2015) also 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.

*The Impact of Income and Expense Shocks on Client Behavior*

The decision to seek out the services of credit counseling agencies does not happen in a vacuum, and this decision can be associated with other factors that can damage long- and short-term financial health. A survey by Visa (1999) showed that around half of credit counseling clients have experienced financial struggles for over a year prior to their seeking credit counseling and both Wang (2010) and Collins (2010) illustrated that clients often seek out credit counseling in response to income or expense shocks that may have made their credit situation untenable. Chapter Two of this dissertation reinforces this, showing that many clients report seeking credit counseling because they have suffered an income loss, often through unemployment or divorce, or had an increase in their expenses, often from healthcare costs.

There exists a growing body of work on how shocks such as these can alter behavior. Experiencing shocks such as loss of income can increase discount rates and make individuals more present-biased (Haushofer & Fehr, 2014; Haushofer et al., 2013), which can manifest itself in an increased willingness to pursue high-cost, short-term resolutions to their debt problems such as payday loans (Mullainathan & Shafir, 2013). Individuals facing income shocks or other economic constraints must also think much more intensely about how to make purchases and responsibly allocate their money, which drains cognitive resources (Spears, 2011), diminishing behavioral control and increasing the likelihood that people under these conditions make poor financial decisions (Muraven & Baumeister, 2000). Yet inasmuch as these shocks can drain
cognitive resources, they also can elicit large amounts of focus on the problems they face (Shah et al., 2012). This focus on the problem of debt management in times of crisis may result in credit counseling yielding dividends for those undergoing shocks relative to those who are not. Enhanced focus means that the various behavioral and educational interventions such as the financial review, the development of action plans, and the identification of financial problem areas may have more potential to cause behavioral shifts among these individuals, even as programmatic interventions like debt management plans make the management of existing debts easier and provide individuals with more cognitive “slack” (Mullainathan & Shafir, 2013) vis a vis their finances.

Theoretical Framework and Hypotheses

Taken together, the literature on credit counseling (and related programs) and the literature on the behavioral impact of shocks allows for the outlining of a general framework detailing the relationship between credit counseling and client outcomes, as well as the formulation of several hypotheses. First, the nature of credit counseling programs provides a sense of how credit outcomes for credit counseling clients, which include credit scores, debt and liquidity metrics, and making on-time payments, may evolve in the subsequent periods after the receipt of credit counseling. Individuals seeking credit counseling are often spurred on by some event that necessitates their seeking help to manage their credit and/or debt. These events could include foreseeable events like the inability to access certain financial products due to persistently low credit scores but could also include difficult-to-predict shocks like medical expenses due to health emergencies, divorce, or job loss. From this, it stands to reason that credit counseling clients are disproportionately likely to be facing an immediate crisis relative to the general population and this will be reflected in their credit outcomes around the time they are seeking credit counseling.

35 This section can be viewed as an application of the framework developed in Chapter One.
Hypothesis 1: *In the short-term, credit outcomes for counseled clients will decline relative to the comparison group.*

Once the shock subsides, credit indicators are expected to begin improving. Much of this improvement may be attributable to a regression to the mean effect independent of credit counseling. For example, clients impacted by unemployment may find another job and start making debt payments again, or clients impacted by medical expenses may find ways to offset those unexpected expenses (such as reducing expenses elsewhere or taking a second job). However, there are many aspects of credit counseling that may lead to longer-term improvements in credit outcomes above and beyond the regression to the mean effect: The educational aspects of credit counseling may lead to improved financial behaviors for all clients (not just those experiencing a shock) through several avenues: Increases in knowledge from the educational components or tailored financial advice provided to clients may help clients manage their finances more responsibly; the action plans developed in credit counseling may help guide client behaviors by providing a framework outlining their financial goals and the means by which they can achieve these goals; counselors may encourage clients to close several existing accounts leading to less debt-financed consumption; clients may receive information on how to access social services or other community programs; and enrollment in debt management plans may lead to fewer missed payments and possibly an accelerated debt reduction schedule.

Hypothesis 2: *In the long-term, credit outcomes for counseled clients will improve relative to the comparison group.*

Additionally, the subset of clients undergoing economic shocks from loss of income or increased expenses may benefit the most from credit counseling, particularly relative to the comparison group. Experiencing a shock resulting in an inability to pay one’s debts is difficult for anyone, but having a timely intervention by a trained counselor who can potentially provide program support, advice, education, and access to other resources may allow individuals
undergoing a shock to recover more quickly than those who do not seek credit counseling. Credit counseling may also provide alternatives to high-cost borrowing options like payday lenders, which are disproportionately appealing to those facing short-term crises. These alternatives may stem from better information about social services and other resources, advice on how to handle expenses and reduce existing debts, or from enrollment in debt management plans.

Hypothesis 2a: Counseling clients undergoing an economic shock will exhibit stronger credit improvements than non-counseled individuals undergoing similar shocks.

Beyond the relationship between clients undergoing shocks and credit counseling, it is also possible that credit counseling has a disproportionate impact on individuals with the weakest credit profiles. Inasmuch as low credit scores are often reflective of a history of financial mismanagement, clients with low credit scores may benefit more from access to the variety of educational services and programs offered by credit counseling agencies; a disproportionately weak credit profile may lead to disproportionately large benefits from credit counseling interventions.

Hypothesis 2b: Counseling clients with the lowest baseline credit scores will exhibit stronger credit improvements than non-counseled individuals with similar baseline credit profiles.

While measuring any credit indicator is not without its difficulties (the persistence of a missed payment’s impact on credit scores, for example, prevent behavioral improvements from manifesting fully in those scores), the measurement of debt for financially-distressed individuals is particularly complicated. Reductions in debt may stem from changes in financial behaviors such as incurring fewer expenses, making higher monthly payments on credit cards, or switching to lower-interest debt instruments, but they may also stem from creditors deciding to charge-off an individual’s debts, the declaration of bankruptcy, home foreclosure, or the renegotiation of debts with creditors as part of a debt management plan. This analysis will assess the relative
contribution of each of these potential factors by controlling for their occurrence in the post-counseling period.

*Hypothesis 3a:* Individuals who did not declare bankruptcy, experience foreclosure, or have debts charged off by creditors in the post-counseling period will exhibit lower levels of debt reduction than those who did have debts written off.

*Hypothesis 3b:* Counseling clients enrolled in DMPs after counseling will have higher levels of debt reduction than those not enrolled in DMPs.

*Hypothesis 3c:* Controlling for post-counseling debt write-offs and DMP enrollment, counseling clients will still exhibit improved debt reduction relative to the comparison group.

**Program Description**

The Sharpen Your Financial Focus campaign examined in this chapter is a nationwide effort coordinated by the National Foundation for Credit Counseling that is intended to standardize credit counseling programs among participating agencies and takes place over the course of three years (beginning in 2013). The initiative features what is referred to as a “Three-Step Personal Financial Stabilization Program” consisting of (1) a financial stress test (the MyMoneyCheckUp instrument examined in Chapter Two of this dissertation), 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 in the vein of typical credit counseling efforts, 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”) that provide additional resources and education on
specific areas of interest or concern to a client.\textsuperscript{36} The member agencies have discretion in how they implement the Sharpen program so the delivery of all three elements of the program was not universal and was often contingent on available funding. Only the financial review was delivered to every client in the program. There are also sub-programs within this initiative targeting specific groups, such as the Hands-On Banking program aimed at providing services to members of the military, but these efforts are not a focus of this research.

\textbf{Data and Methods}

\textit{Sample}

This chapter employs data from clients in the Sharpen credit counseling program, which has reached over 40,000 clients at the time of this writing. Despite being managed at the national level by the NFCC, the Sharpen program was implemented through a network of nonprofit counseling agencies operating at either the local, state, or regional levels. This evaluation was conducted using clients from 13 of these nonprofit agencies, which submitted proposals to the NFCC in order to be selected for the evaluation.\textsuperscript{37}

Data for these clients are generated from two sources: Administrative data compiled by the agencies on their clients, measuring demographic and financial data as well as the clients’ reasons for seeking credit counseling; and longitudinal credit report data pulled on each Sharpen client in the participating agencies, which reports each client’s status across a variety of credit indicators (credit score, debt level, payment delinquencies, etc.). The administrative data are cross-sectional and recorded at the time clients enroll in credit counseling, while the credit data are pulled at quarterly intervals across six quarters beginning with August of 2013.

\textsuperscript{36} Per information provided by the NFCC, the typical budget counseling and financial review session takes about an hour while additional financial education courses take about a half an hour. The MyMoneyCheckUp instrument takes approximately thirty minutes to an hour to complete.

\textsuperscript{37} These agencies are the same agencies featured in the descriptive credit analysis in Chapter Two.
<table>
<thead>
<tr>
<th>Reason For Seeking Counseling′</th>
<th>#</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Reduced Income</strong></td>
<td>4,804</td>
<td>79 %</td>
</tr>
<tr>
<td>Reduced Income</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Domestic Conflict</td>
<td>390</td>
<td>6 %</td>
</tr>
<tr>
<td>Un/underemployment</td>
<td>1,762</td>
<td>29%</td>
</tr>
<tr>
<td>Other</td>
<td>2,652</td>
<td>44%</td>
</tr>
<tr>
<td><strong>Increased Expenses</strong></td>
<td>1,321</td>
<td>22%</td>
</tr>
<tr>
<td>Increased Expenses</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Costs of death in family</td>
<td>35</td>
<td>1%</td>
</tr>
<tr>
<td>Creditors increased interest rates</td>
<td>148</td>
<td>2%</td>
</tr>
<tr>
<td>Increased family size</td>
<td>128</td>
<td>2%</td>
</tr>
<tr>
<td>Medical/Disability expenses</td>
<td>404</td>
<td>7%</td>
</tr>
<tr>
<td>Other</td>
<td>606</td>
<td>10%</td>
</tr>
<tr>
<td><strong>Other Reasons</strong></td>
<td>1,350</td>
<td>22%</td>
</tr>
<tr>
<td>Other</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bad credit</td>
<td>149</td>
<td>2%</td>
</tr>
<tr>
<td>Previous bad experience</td>
<td>45</td>
<td>1%</td>
</tr>
<tr>
<td>Other</td>
<td>1,156</td>
<td>19%</td>
</tr>
</tbody>
</table>

n=6,094 credit counseling clients

Source: NFCC Administrative Data

†Respondents could select multiple reasons for seeking counseling

Table 3.1: Reason for Seeking Counseling

The individuals comprising the sample in this analysis are the 6,094 clients who sought credit counseling over the three-month period between September and November of 2013 and who were able to be matched to a non-counseled individual based on their pre-counseling credit characteristics, a process described below. As shown in Table 3.1, individuals in this analysis often report seeking credit counseling due to a loss of income (79 percent), most typically from unemployment or underemployment, or increased expenses (22 percent) most typically from healthcare expenses or higher interest rates on their debt.38

38 The prior chapter explores counseling motivations for the full array of Sharpen clients and further examines client responses in the “other” categories.
<table>
<thead>
<tr>
<th>Selected Client Characteristics</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender</strong></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>31%</td>
</tr>
<tr>
<td>Female</td>
<td>69%</td>
</tr>
<tr>
<td><strong>Marital Status</strong></td>
<td></td>
</tr>
<tr>
<td>Single</td>
<td>39%</td>
</tr>
<tr>
<td>Separated</td>
<td>6%</td>
</tr>
<tr>
<td>Divorced</td>
<td>13%</td>
</tr>
<tr>
<td>Married or Living with a Partner</td>
<td>39%</td>
</tr>
<tr>
<td>Widowed</td>
<td>3%</td>
</tr>
<tr>
<td><strong>Race</strong></td>
<td></td>
</tr>
<tr>
<td>Asian</td>
<td>3%</td>
</tr>
<tr>
<td>Black</td>
<td>22%</td>
</tr>
<tr>
<td>White</td>
<td>64%</td>
</tr>
<tr>
<td>Other</td>
<td>12%</td>
</tr>
<tr>
<td><strong>Education</strong></td>
<td></td>
</tr>
<tr>
<td>Less than High School</td>
<td>3%</td>
</tr>
<tr>
<td>High School Graduate</td>
<td>30%</td>
</tr>
<tr>
<td>Two Year College/Technical School</td>
<td>34%</td>
</tr>
<tr>
<td>Four Year Degree</td>
<td>21%</td>
</tr>
<tr>
<td>Graduate Degree</td>
<td>12%</td>
</tr>
<tr>
<td><strong>Region</strong></td>
<td></td>
</tr>
<tr>
<td>Midwest</td>
<td>18%</td>
</tr>
<tr>
<td>Northeast</td>
<td>25%</td>
</tr>
<tr>
<td>South</td>
<td>30%</td>
</tr>
<tr>
<td>West</td>
<td>26%</td>
</tr>
<tr>
<td>Age</td>
<td>42.8</td>
</tr>
<tr>
<td>Average Monthly Income</td>
<td>$3,093.2</td>
</tr>
<tr>
<td>Savings</td>
<td>$559.0</td>
</tr>
<tr>
<td>Household Size</td>
<td>2.5</td>
</tr>
<tr>
<td>Number of Children Under 18</td>
<td>0.8</td>
</tr>
</tbody>
</table>

n=6,094 credit counseling clients

Source: NFCC Administrative Data

Table 3.2: Client Demographic and Financial Characteristics
Table 3.2 outlines key characteristics of credit counseling clients included in this analysis. 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 households with 2.5 individuals on average. Clients appear to be relatively low-income, with an average gross monthly income of around $3,000. Their savings levels are also particularly anemic, with an average of $500 saved; the median Sharpen client in this analysis has no savings whatsoever.

Coarsened Exact Matching

To assess counterfactual outcomes in this chapter, a non-counseled comparison group was generated based on the similarity of their credit attributes to the counseled clients’ attributes in the pre-counseling period. The credit indicators used to match the credit counseling and uncounseled comparison individuals included revolving debt levels, bankruptcy history, the age of the oldest account on record, 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. These indicators were selected for the matching process because they represent a diverse array of elements that 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

39 See the prior chapter of this dissertation for a discussion of how Sharpen client characteristics differ from the general U.S. population, as measured by the Census and the Survey of Consumer Finances.

40 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 3.3, the comparison and counseled groups are still extremely well matched on total revolving debt.

41 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.
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 that may be relevant, such as the employment conditions of a state.

Counseling and comparison group clients are matched through a process known as Coarsened Exact Matching (CEM), a method of data processing that uses Monotonic Imbalance Bounding to match treated and untreated observations and allows for causal analyses through 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 are 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). Observations in both the treated and untreated groups are then sorted into “strata” based on the values of these coarsened categories and are subsequently matched based on the presence of an exact match between the counseling and comparison groups within these strata. As a result clients with similar credit scores, debt levels, debt payment histories, debt types, account ages, bankruptcy history, and states of residence are matched to each other. Any individuals from the treatment or comparison groups who do not have an equivalent match in the other group are excluded from the analysis. This process thus allows for an estimation of counterfactual outcomes by only comparing counseled clients to similar non-counseled individuals. Relying on exact matching also restricts the observations in the analysis to a common support area and lessens the need to rely on parametric approaches to assess the treatment effect.42

42 A related advantage of this approach is that the appropriate functional form of the variables in the model does not need to be determined, as many of the relevant variables are “controlled” for through the exact matching procedure.
The comparison group was identified using Experian’s credit database, which contains credit information for 220 million individuals actively using credit in the United States (Experian.com, 2016). From this database, a five percent random sample of U.S. individuals was generated and comparison group members were selected from this sample of millions of individuals based on their similarity to counseled individuals across the matching covariates referenced above. Despite the presence of these millions of individuals in the Experian database, matches were not found for all credit counseling clients. Out of 8,963 credit counseling clients, exact matches were found for 6,297, or 70 percent.\textsuperscript{43} While finding an exact match for every credit counseling client (a 100 percent match rate) is plausible, it would require a tradeoff of the specificity of the matching procedure (i.e. certain matching variables would need to be dropped or be coarsened into fewer categories). As having a highly-specific matching criteria resulting in well-balanced groups is necessary for strong estimates of counterfactual outcomes, losing some potential matches in order to retain this specificity was deemed an acceptable tradeoff. Further, an examination of non-matched credit counseling clients revealed that these clients were relatively idiosyncratic (see Appendix E), exhibiting even more signs of credit distress than the already-distressed Sharpen client base in general and showing signs of housing-related financial issues in particular.

Once the match was completed, a small subset of comparison group individuals were identified as having gone through the Sharpen initiative (these clients could not be identified prior to the match) and were thus in both the counseling and comparison group samples.\textsuperscript{44} After

\textsuperscript{43} 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 four-year degree. They also had less average monthly income than counseling clients for whom no match was available.

\textsuperscript{44} As the data were de-identified before being delivered by Experian, counseling clients who were included in both the counseling and comparison group were identified based on having identical credit indicators across all available measures. If a client and comparison observation were identical across all indicators for multiple quarters, it is extremely likely that they are simply duplicate observations, meaning that the counseling client was included in the comparison group. There remains a small chance that an individual in
excluding these duplicates and any observations with additional data issues, 6,094 Sharpen clients remained matched with 6,005 non-counseled individuals.45

Comparison individuals were matched to each counseled individual using a 1:1 matching procedure, meaning that all counseled individuals have a weight of one. However, due to the elimination of a handful of comparison observations, which were confirmed to have gone through the Sharpen credit counseling program, a small number of counseled individuals were weighted to ensure that the numbers of credit counseling and comparison individuals are balanced in each matching stratum and across the total sample. Any individuals in unmatched strata are given a weight of zero.

Similarity Between the Counseling and Comparison Groups

In order to determine 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 3.3. At baseline, individuals 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.

...the comparison group did receive credit counseling at an agency outside of those included in this analysis, but if that is the case then any measured treatment effect will simply be slightly lower than the true effect (assuming a positive impact from counseling). 45 137 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. See Appendix D for a guide to the sample used in this analysis.
<table>
<thead>
<tr>
<th>Matching Variable</th>
<th>Counseled Mean (St. Dev)</th>
<th>Comparison Mean (St. Dev)</th>
<th>% Difference (Treatment/Comparison)</th>
<th>Balance‡</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit Score (Vantage 3.0)</td>
<td>594 (77.1)</td>
<td>597 (80.3)</td>
<td>-1%</td>
<td>0.04</td>
</tr>
<tr>
<td>Open Revolving Debt ($)</td>
<td>10,582 (15,346)</td>
<td>10,248 (14,947)</td>
<td>3%</td>
<td>0.02</td>
</tr>
<tr>
<td>Total Revolving Debt ($)†</td>
<td>16,612 (35,612)</td>
<td>16,453 (38,893)</td>
<td>1%</td>
<td>0.00</td>
</tr>
<tr>
<td>Total Installment Debt ($)</td>
<td>20,425 (34,647)</td>
<td>21,113 (44,461)</td>
<td>-3%</td>
<td>0.02</td>
</tr>
<tr>
<td>Mortgage Debt ($)</td>
<td>44,021 (104,449)</td>
<td>46,565 (131,740)</td>
<td>-5%</td>
<td>0.02</td>
</tr>
<tr>
<td>Total Debt ($)†</td>
<td>81,059 (129,829)</td>
<td>84,130 (159,032)</td>
<td>-4%</td>
<td>0.02</td>
</tr>
<tr>
<td>Number of Bankruptcies</td>
<td>0.30 (1.6)</td>
<td>0.29 (1.6)</td>
<td>3%</td>
<td>0.01</td>
</tr>
<tr>
<td>Age of Oldest Account (Months)</td>
<td>182 (105.4)</td>
<td>183 (109.5)</td>
<td>-1%</td>
<td>0.01</td>
</tr>
<tr>
<td>Payments 60 Days Delinquent (Last 12 Months)</td>
<td>0.58 (1.6)</td>
<td>0.59 (1.7)</td>
<td>-1%</td>
<td>0.01</td>
</tr>
<tr>
<td>Payments 60 Days Delinquent (Last 6 Months)†</td>
<td>0.46 (1.4)</td>
<td>0.45 (1.5)</td>
<td>1%</td>
<td>0.00</td>
</tr>
<tr>
<td>Mortgage Payments 90 Days Delinquent (Last 24 Months)</td>
<td>0.11 (1.2)</td>
<td>0.12 (1.4)</td>
<td>-8%</td>
<td>0.01</td>
</tr>
<tr>
<td>Available Open Credit Ratio†</td>
<td>0.48 (0.4)</td>
<td>0.49 (0.4)</td>
<td>-1%</td>
<td>0.01</td>
</tr>
<tr>
<td>Balance to Credit Ratio on Revolving Debt</td>
<td>0.52 (0.4)</td>
<td>0.52 (0.4)</td>
<td>1%</td>
<td>0.01</td>
</tr>
</tbody>
</table>

**Observations** 6,094 6,005

*Source: Credit Attributes Data*

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

‡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.

Table 3.3: Summary Statistics for Treatment and Comparison Groups in Coarsened Exact Matching Analysis
To assess the balance between the two groups, Table 3.3 also compares 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, between counseling and comparison groups (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 chapter. 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 credit counseling and comparison groups.

Additionally, several variables are included in Table 3.3 that were not matching variables but are dependent variables used in the analysis: The total revolving debt (including closed accounts), the 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, credit counseling clients and the comparison group are still very well-balanced 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.

Subsample Specification

Beyond the analysis of the evolution of credit indicators for the total sample of matched credit counseling clients relative to the uncounseled comparison group, supplemental analyses will be conducted for subgroups of analytical interest. These include clients in the bottom 50th and 25th credit score percentiles at baseline, clients holding debt at baseline, and clients either recommended or not recommended into debt management 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. To illustrate, a subgroup analysis of clients in the bottom 50th credit percentile at baseline would proceed in the following way:

1. Exclude any clients and comparison individuals not in the bottom 50th credit percentile at baseline from the sample.
2. Exclude any individuals in this sample who no longer had a matched equivalent.
3. Re-weight the counseling and comparison groups based on the new ratio between counseled clients and comparison group individuals.

**Method**

With the similarity between the counseled and comparison groups at baseline established, the next step in the evaluation is to trace the difference in credit indicators for these two groups over time. To identify the impact of Sharpen on client outcomes over the evaluation period, this analysis tracks credit indicators at quarterly intervals between the counseled and comparison groups. This approach (1) tracks the change in indicators from quarter to quarter within the counseled group and (2) compares this change to changes within the comparison group of non-counseled individuals. This is known as a difference-in-difference comparison. The analysis starts in the baseline quarter, which is the period prior to a client enrolling in credit counseling. The baseline quarter for all clients in the full analysis is August, 2013. This baseline contains any clients enrolling in Sharpen between September and November of 2013. The standard difference-in-difference model for credit counseling clients relative to non-counseled individuals can be described as:

\[
(1) \text{Counseling Impact} = [Y_{t0+q}\text{Client} - Y_{t0}\text{Client}] - [Y_{t0+q}\text{Comparison} - Y_{t0}\text{Comparison}]
\]

where \(Y_{t0}\) is the value of a credit report indicator (Y) at baseline (t0), and \(Y_{t0+q}\) is the value of the same credit report indicator (Y) at some quarter (q) post-baseline.
This analysis estimates the above differences using a fixed effects panel regression model. The credit outcome of interest is measured at baseline and for six subsequent quarters for each individual as follows:

\[(2) \ y_{it} = \alpha_i + \pi_{Counseling} + \lambda_{Quarter_t} + \delta(Counseling_{it} \times Quarter_t) + \beta_j x_{it} + \epsilon_{it}\]

where \(y\) is the credit outcome of interest, the coefficient \(\pi\) captures the overall impact of receiving credit 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 chapter control for bankruptcies, charge-offs, and foreclosures). \(\epsilon\) is the error term of the model, and \(\alpha\) is a constant representing the average value of the outcome variable for the full sample. The subscripts \(i\) and \(t\) represent the individuals in the analysis and the observed quarters, respectively. The model is estimated using a fixed effects panel regression with standard errors clustered on each individual.\(^{47}\)

**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 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 analysis (Experian).

\(^{46}\) Several alternative specifications of models in this analysis also control for the amount of HELOC debt, though these models are only referenced descriptively as they do not notably change the results.\(^ {47}\) As a robustness check, the models were also estimated using bootstrapped standard errors. This alternate approach revealed no notable differences in the standard errors of the estimates when compared to the clustered standard errors employed in this analysis.
With regard to debt measurement, a number of debt indicators can be used to assess consumer financial health. The level of consumer revolving debt, installment debt, or total debt can be used to get a sense of the consumer’s overall debt profile.\(^4\) For the purposes of this analysis, the most attention will be paid to consumer revolving debt levels (including debt held in closed accounts and HELOCs), as revolving debt typically carries higher interest rates than installment debt and is the debt indicator likely to be most responsive to consumer behavioral changes or programmatic interventions.\(^5\)

The matching portion of the analysis will also trace the evolution of total debt for both counseling and comparison groups. 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 credit counseling interventions and subsequent behavioral changes, understanding how credit counseling clients’ total debt profiles change provides a more robust sense of their overall financial state.

In addition to debt levels, this chapter considers 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 revolving balance to credit ratio, which measures the total balance on all revolving accounts (open and closed), as a percent of the total 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. Liquidity access has been described as a type of financial “slack” allowing individuals a degree of flexibility in managing their finances, reducing financial stress and helping avoid expensive financial mistakes like bouncing

\(^4\) Elliehausen, Lundquist, and Staten (2007) similarly employed revolving debt as a measure of client outcomes in their study of credit counseling, but it is not readily apparent if their measure of revolving debt only includes debt on open accounts or debt held in open or closed accounts, as is the case with this chapter.

\(^5\) As shown in the previous chapter, much of the reduction in overall debt is driven by changes in revolving debt.
checks or making late payments (Mullainathan & Shafir, 2009, 2013). Liquidity access has also been associated with general increases in debt, however, which implies that it may act as both a lifeline and temptation for individuals (Gross & Souleles, 2002; Laibson, 1997). 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 are explored. While the counseling and comparison groups are matched based on the number of payments 60 days delinquent within the last 12 months (to capture a longer history of potential delinquency), this chapter 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.50

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 chapter will control for three time-varying covariates that 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 seeking credit counseling and influence dependent variables of interest in this analysis.51 For example,

---

50 Given the quarterly nature of this analysis, the ideal would be to track the number of delinquent payments made within the last three months but these data were not available. 51 An alternate possibility is that these debt write-offs could occur immediately prior to clients seeking counseling. If this is the case the presence of these write-offs would likely still be controlled for in the analysis, as the quarterly data would also pick up an increase in bankruptcies, charge-offs, or foreclosures so long as they happened after the baseline measurement. If a client sought counseling in October 2013 and declared bankruptcy in September 2013, for example, this new bankruptcy would be picked up in this analysis as the baseline quarter would be August 2013. There may be exceptions to this. For example, if a client declared bankruptcy in August 2013 and sought counseling in September 2013, that bankruptcy would not be picked up through this approach. However, even if this approach misses a subset of pre-
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 credit 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.

Results

The first results presented are for the full sample of counseled clients and the matched comparison group. Subsequent comparisons will be made for specific subgroups of the counseled and comparison groups.

counseling debt write-offs, this may not substantially influence the estimates of counseling’s impact. If clients have already experienced debt write-offs at the time of counseling, then their baseline levels of debt will be lower due to those write-offs, and any change in debt will be measured in relation to that lower baseline.

Indeed, a preliminary analysis used logistic regression to assess the relative likelihood of having a charge-off, bankruptcy, or foreclosure after the baseline period contingent on an individual seeking credit counseling. This analysis found that the odds of having a post-baseline charge-off were 2.2 times higher for counseling clients, while the odds of having a bankruptcy or foreclosure in the post-baseline period were 4.0 and 1.1 times higher for counseling clients, respectively.

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.
The full analysis sample contains 6,094 counseled clients and 6,005 individuals in the comparison group. Every credit counseling client in the subsample received the financial stress test and budget counseling session, while 16 percent of clients received additional targeted education programs and 62 percent of clients were recommended into a debt management program. For simplicity, each table presented in main analysis includes only the overall difference in outcomes between credit counseling clients and the comparison group over the entire 18-month evaluation period. To this end, each table suppresses the model output for the quarterly coefficients and counseling/quarter interaction coefficients. Appendix F includes the full output for selected models as well as a comment on the interpretation of the quarterly coefficients. In the tables presented in the main analysis, the highlighted coefficients should be understood to represent the average change in the counseling group’s credit metrics relative to the comparison group over the full evaluation period. For example, if the comparison group reduced their total debt by $1,000 and the counseling group reduced their debt by $6,000 over the same period, the coefficient on “Counseling Client” in the tables below would be -$5,000.

**Consumer Debt**

A number of debt indicators can be used to assess consumer financial health. First, the impact of credit counseling on overall debt levels (revolving and total debt) is estimated. Figures 3.1 and 3.2 show the quarterly changes in these debt metrics for the counseling and comparison groups. For both total debt and revolving debt, the counseling and comparison groups have similar trajectories through the first post-counseling quarter, but in subsequent quarters the counseling group exhibits substantial declines in their debt levels relative to the comparison group; these declines continue through the end of the evaluation period.
**Figure 3.1: Total Debt Over the Evaluation Period**

**Figure 3.2: Revolving Debt Over the Evaluation Period**
Table 3.4 reports the estimated impact of credit counseling on client debt levels using a fixed effects panel regression. For both total and revolving debt, Sharpen clients have significantly lower levels of debt eighteen months after credit counseling (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.

<table>
<thead>
<tr>
<th>Model (Standard Errors in Parentheses)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable</td>
<td>Total Revolving Debt</td>
<td>Total Revolving Balance-to-Credit Ratio</td>
<td>Open Revolving Credit Ratio</td>
<td>Total Debt</td>
</tr>
<tr>
<td>Counseling Client</td>
<td>-3,637.18***</td>
<td>-11,341.00***</td>
<td>0.04***</td>
<td>-0.04***</td>
</tr>
<tr>
<td></td>
<td>(341.88)</td>
<td>(1368.07)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Constant</td>
<td>16,532.97***</td>
<td>82,582.95***</td>
<td>0.49***</td>
<td>0.52***</td>
</tr>
<tr>
<td></td>
<td>(100.2)</td>
<td>(406.35)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.04</td>
<td>0.01</td>
<td>0.04</td>
<td>0.03</td>
</tr>
<tr>
<td>Observations</td>
<td>84,693</td>
<td>84,693</td>
<td>84,693</td>
<td>84,693</td>
</tr>
<tr>
<td>(Individuals*Quarters)</td>
<td>12,099</td>
<td>12,099</td>
<td>12,099</td>
<td>12,099</td>
</tr>
<tr>
<td>Unique Individuals</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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 not shown. Full results can be seen in the Appendix.

Source: Credit Attributes Data

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

Table 3.4: Differences-in-Differences Analysis - Client Outcomes on Key Debt Indicators

54 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. The models in Table 3.10 exclude these consumers to provide a more detailed examination of the debt metrics.

55 There is evidence that some of the change in total debt is driven by extreme changes in debt levels from a relatively small group of individuals. See Tables 3.13 and 3.14 for an examination of this metric excluding extreme values.
In addition to debt levels, two debt ratio measures are considered in Table 3.4: The open revolving credit ratio, which measures available revolving credit as a percent of the credit limit on revolving accounts; and the total revolving balance to credit ratio, which measures the total balance on all revolving accounts, as a percent of the total credit limit. 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 four 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 full analysis is not featured 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).56

As a note, the R-squared measures in the full sample models without controls are relatively low, ranging from 0.01 to 0.04. This low R-squared is only concerning inasmuch as the weak fit of the models is associated with inconsistent estimation of the treatment effect. However, the treatment effects of credit counseling are robust to the inclusion of a number of controls that also substantially improve the fit of the models; the fit of the debt models is improved substantially by the inclusion of controls for bankruptcies, charge-offs, foreclosures, and HELOC debt, and the treatment effect remains largely consistent with the basic models excluding controls. Given this, the low R-squared values are likely not a major concern.

*Credit Score and Debt Payments*

In addition to overall debt levels, the impact of counseling on overall consumer credit (measured by the credit score) and debt payment delinquencies is estimated. Figures 3.3 and 3.4

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56 This impact remains significant when controlling for bankruptcies and charge-offs over the evaluation period.
explore the trends in these metrics over the evaluation period. Figure 3.3 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 that persists through the second quarter. The comparison group by contrast has a modest upward trend over this same interval and this trend continues across all quarters. The counseled group begins to recover in the third quarter after the receipt of credit 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 increase for the comparison group.

![Credit Score Graph](image)

*Figure 3.3: Credit Scores Over the Evaluation Period*

Similarly, the trends in sixty-day delinquencies over time are plotted. Figure 3.4 shows an inverted pattern to the credit score trend seen in Figure 3.3. The baseline delinquencies between the two groups are roughly identical (~0.45 delinquent payments on average for each person in

\[ n=11,837 \]

*Source: Credit Attributes Data*
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) that 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 roughly at parity with the comparison group.\(^{57}\)

\[ n=12,099 \]

*Source: Credit Attributes Data*

**Figure 3.4: Sixty Day Payment Delinquencies Over the Evaluation Period**

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 credit counseling caused drops in credit scores. Rather, the evidence is in-line with a counseled client

\(^{57}\) 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 analysis is not featured here, the payment delinquency spike for current delinquent payments is over by the third post-counseling quarter and by the fourth post-counseling quarter the level of current delinquencies is actually *lower* than it was at baseline. This decline persists for the rest of the evaluation period.
experiencing a debt- or income-based shock (such as a hospitalization or the loss of a job) around the time of credit counseling (perhaps motivating them to seek counseling), resulting in a downward trend in their credit score that persists for the first quarter after credit counseling.

There is some evidence of a shock driving participation into credit counseling, as indicated in Table 3.1 of this chapter. The majority of clients (almost two-thirds) reported seeking credit counseling because of reduced income, while another ~30 percent reported facing increased expenses. When Figures 3.3 and 3.4 are paired together, it appears that the drop in credit score is likely driven in part by clients’ inability to meet their debt payment obligations.

Table 3.5 investigates the overall impact on client outcomes relative to the comparison group for credit score and debt payment measures. When measured as the total change over the evaluation period, receiving credit counseling is negatively associated with the change in credit score (Model 1), and there is no significant difference between credit 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.

58 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.
<table>
<thead>
<tr>
<th>Model (Standard Errors in Parentheses)</th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable</td>
<td>Credit Score</td>
<td>Payments 60 Days Delinquent (Past 6 Months)</td>
</tr>
<tr>
<td><strong>Counseling Client</strong></td>
<td>-6.76***</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>(1.23)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Constant</td>
<td>595.12***</td>
<td>0.46***</td>
</tr>
<tr>
<td></td>
<td>(0.39)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.03</td>
<td>0.01</td>
</tr>
<tr>
<td>Observations (Individuals*Quarters)</td>
<td>82,859</td>
<td>84,693</td>
</tr>
<tr>
<td>Unique Individuals</td>
<td>11,837</td>
<td>12,099</td>
</tr>
</tbody>
</table>

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 not shown. Full results can be seen in the Appendix.

**Source:** Credit Attributes Data

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

Table 3.5: Differences-in-Differences Analysis - Client Outcomes on Key Credit Indicators

**Outcomes for Debt-Holding Clients**

For this portion of the analysis, the evolution of revolving debt indicators is examined only for those individuals who *had debt at the baseline period*. Given the nature of credit counseling, debt-holding clients are likely a more relevant target population than those clients who have no debt in the period prior to receipt of credit counseling. It is also possible that debt-holding 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 ten credit counseling clients does not have *any* debt in the quarter prior to the receipt of credit counseling and slightly over one out of five matched clients do not have *revolving* debt in the baseline period.

Figures 3.5 and 3.6 respectively trace the evolution in total revolving debt and the available open credit ratio for credit 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 that 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 nine percent higher than the comparison group six quarters after counseling (a relative difference of 19 percent).

\[ n=9,015 \]

*Source: Credit Attributes Data*

**Figure 3.5: Revolving Debt Over the Evaluation Period (For Those with Debt at Baseline)**
Table 3.6 presents the difference-in-difference analysis for debt-holding Sharpen clients compared to their debt-holding 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 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.
By the end of the evaluation period, debt-holding counseling clients experience improvements across all four metrics relative to the comparison group. Indeed, the results here are relatively similar to those in Table 3.4, although the magnitude of the differences between counseling and comparison groups is 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 individuals who did not have any debt at baseline causes the magnitude of the change between counseling and comparison groups to more than 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.

*Clients in the Bottom 50th Credit Percentile*
This section and the following section will explore key credit indicators for two different sub-groups defined by their baseline credit score. This section covers those in the bottom 50\textsuperscript{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\textsuperscript{th} percentile of credit scores (a credit score of 540 or below). 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 2,700 counseled clients in the bottom 50\textsuperscript{th} percentile of baseline credit scores and 2,605 individuals in the comparison group. For those in the bottom 50\textsuperscript{th} credit percentile at baseline, the pattern in credit scores (shown in Figure 3.7) 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 credit 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.

![Credit Scores Over the Evaluation Period (Bottom 50\textsuperscript{th} Credit Percentile)](image)

\textit{Source: Credit Attributes Data}

Figure 3.7: Credit Scores Over the Evaluation Period (Bottom 50\textsuperscript{th} Credit Percentile)
### Table 3.7: Differences-in-Differences Analysis - Client Outcomes on Key Credit Indicators (50th Credit Percentile at Baseline)

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Total Revolving Debt</th>
<th>Credit Score</th>
<th>Payments 60 Days Delinquent (Past 6 Months)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Counseling Client</strong></td>
<td>-1,973.05***</td>
<td>0.86</td>
<td>-0.13**</td>
</tr>
<tr>
<td></td>
<td>(404.15)</td>
<td>(1.82)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Constant</td>
<td>7,195.09***</td>
<td>526.27***</td>
<td>0.96***</td>
</tr>
<tr>
<td></td>
<td>(115.89)</td>
<td>(0.55)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.03</td>
<td>0.08</td>
<td>0.02</td>
</tr>
</tbody>
</table>

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 not shown. Full results can be seen in the Appendix.

Source: Credit Attributes Data

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

Table 3.7 shows the outcomes for credit counseling clients in this subgroup relative to the non-counseled comparison group across several key metrics. The amount of total revolving debt for credit 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 50th credit percentile also have less than half the revolving debt of the full sample at baseline.\(^{59}\) The change in credit score for credit 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.

\(^{59}\) This can be seen in comparing the constants for the full sample and 50th credit percentile subsample.
**Clients in the Bottom 25th Credit Percentile**

This portion of the analysis covers clients and comparison group individuals who fall in the bottom 25th percentile of the baseline credit distribution (a credit score at or below 540). For this subgroup, there are 1,328 counseled clients and 1,257 individuals in the comparison group. Figure 3.8 traces the change in credit scores for clients in the bottom 25th 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.

![Credit Scores Over the Evaluation Period (Bottom 25th Credit Percentile)](image)

*Source: Credit Attributes Data*

**Figure 3.8: Credit Scores Over the Evaluation Period (Bottom 25th Credit Percentile)**

Table 3.8 presents the difference-in-difference results across several metrics for this subgroup. There are two notable differences between this analysis and the analysis of the 50th credit percentile above. First, while credit counseling clients do reduce their revolving debt by over 500 dollars relative to the comparison group, this change is not statistically significant at conventional levels. 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 credit counseling population). The other major change compared to the samples assessed above is that credit 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’ average credit scores have grown 7.5 points higher relative to the comparison group’s scores (p<0.01). The delinquency metric directionally improves for this group and the change in delinquent payments is similar to the 50th credit percentile group but the difference is not significant for those in the 25th credit percentile at baseline.

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

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 not shown. Full results can be seen in the Appendix.

Source: Credit Attributes Data

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

Table 3.8: Differences-in-Differences Analysis - Client Outcomes on Key Credit Indicators (25th Credit Percentile at Baseline)
Controlling for the Credit “Shock”

As detailed in the full sample analysis, 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 credit counseling (or in the periods prior to credit counseling) and that this is reflected on their credit report data in the first quarter after credit counseling. Indeed, this explanation tracks with the reasons clients give for seeking out credit counseling: The majority of clients are facing job losses, income reductions, or sudden expenses that 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 change in credit scores and payment delinquencies from pre-counseling to the first post-counseling quarter was measured for the credit counseling group and a shock was defined as having a credit score that decreased by more than one standard deviation from baseline to the first post-counseling period, or having payment delinquencies that increased by more than one standard deviation over the same time period. This isolates the credit counseling clients who were undergoing exceptional credit shocks around the time of credit counseling and matches them to comparison group individuals going through similarly exceptional shocks. To quantify this, a person was identified as having gone through a shock if their credit score dropped by 48 points,

---

60 The quarterly nature of the credit data in this chapter 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 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.

61 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.
or if their number of payment delinquencies 60 days past due increased by more than 1.2.

Individuals were also considered to have undergone a shock if they experienced a similar drop in the second post-counseling period.62

Figure 3.9 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 defined 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

---

62 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.
this, their scores recover quicker and end up higher than the comparison by the end of the evaluation period.

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, as shown in Table 3.9.

<table>
<thead>
<tr>
<th>Model (Standard Errors in Parentheses)</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable</td>
<td>Credit Score</td>
</tr>
<tr>
<td><strong>Counseling Client</strong></td>
<td>5.85</td>
</tr>
<tr>
<td></td>
<td>(5.53)</td>
</tr>
<tr>
<td>Constant</td>
<td>594.56***</td>
</tr>
<tr>
<td></td>
<td>(1.76)</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.18</td>
</tr>
<tr>
<td>Observations (Individuals*Quarters)</td>
<td>4,438</td>
</tr>
<tr>
<td>Unique Observations</td>
<td>634</td>
</tr>
</tbody>
</table>

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 credit counseling clients relative to a matched non-counseled comparison group. Output for the quarter indicators and counseling/quarter interactions is not shown.

* Source: Credit Attributes Data

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

Table 3.9: Differences-in-Differences Analysis - Credit Outcomes for Individuals Matched by Presence of Credit Shock

A supplemental analysis on the credit score trend controlling for variables that might be correlated with a credit shock (charge-offs, bankruptcies, and foreclosures) was also conducted.
but the inclusion of these controls did not notably alter the credit score outcomes for credit counseling clients seen in the credit score analysis for the full sample (Table 3.5). Without controlling for these factors, the credit score for credit 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).

*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 re-estimates the models for revolving and total debt, controlling for the initiation of a bankruptcy, charge-off, or foreclosure over the evaluation period. Additionally, the amount of HELOC debt is included as a time-varying control variable in alternative specifications, as HELOC debt can cause large fluctuations in an individual’s debt profile.

Table 3.10 presents the results when controlling for any bankruptcies, charge-offs, or foreclosures. Specifically, Models 1 and 2 estimate changes in revolving debt while controlling for new bankruptcies and charge-offs in the post-counseling period, while Models 3 and 4 estimate 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.

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63 Preliminary analyses revealed that certain individuals were either opening HELOCs during the study period (leading to large increases in revolving debt) or closing HELOCs during the study period (leading to large decreases in revolving debt). The opening and closing of HELOCs is potentially problematic for an analysis of revolving debt as these actions can cause large shifts in the overall debt profile of an individual that is not necessarily indicative of an actual reduction or increase in debt. However, controlling for HELOCs does not make a substantial difference in the size or significance of the treatment effect.
Table 3.10: Differences-in-Differences Analysis - Client Outcomes Controlling for Debt Write-Offs

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Total Revolving Debt</th>
<th>Total Revolving Debt (Had Debt at Baseline)</th>
<th>Total Debt</th>
<th>Total Debt (Had Debt at Baseline)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Counseling Client</td>
<td>-1,988.54***</td>
<td>-2,659.47***</td>
<td>-6,604.27***</td>
<td>-7,614.55***</td>
</tr>
<tr>
<td></td>
<td>(322.99)</td>
<td>(424.72)</td>
<td>(1,305.71)</td>
<td>(1,410.92)</td>
</tr>
<tr>
<td>Bankruptcy Post-Baseline†</td>
<td>-13,972.72***</td>
<td>-16,966.38***</td>
<td>-58,237.28***</td>
<td>-60,858.06***</td>
</tr>
<tr>
<td></td>
<td>(1,002.68)</td>
<td>(1,183.58)</td>
<td>(3,859.80)</td>
<td>(3,998.96)</td>
</tr>
<tr>
<td>Charge-Offs Post-Baseline†</td>
<td>-5,778.28***</td>
<td>-6,563.97***</td>
<td>-9,852.71***</td>
<td>-9,801.84***</td>
</tr>
<tr>
<td></td>
<td>(312.75)</td>
<td>(375.06)</td>
<td>(841.14)</td>
<td>(877.36)</td>
</tr>
<tr>
<td>Foreclosures Post-Baseline†</td>
<td>-64,529.61***</td>
<td>-64,555.67***</td>
<td>(11,665.13)</td>
<td>(11,739.10)</td>
</tr>
<tr>
<td>Constant</td>
<td>16,532.97***</td>
<td>22,051.75***</td>
<td>82,582.95***</td>
<td>90,989.41***</td>
</tr>
<tr>
<td></td>
<td>(98.36)</td>
<td>(128.86)</td>
<td>(397.55)</td>
<td>(429.51)</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.08</td>
<td>0.10</td>
<td>0.04</td>
<td>0.05</td>
</tr>
<tr>
<td>Observations</td>
<td>(Individuals*Quarters)</td>
<td>84,693</td>
<td>63,105</td>
<td>84,693</td>
</tr>
<tr>
<td>Unique Individuals</td>
<td>12,099</td>
<td>9,015</td>
<td>12,099</td>
<td>11,031</td>
</tr>
</tbody>
</table>

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 not shown.

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.

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.

The models in Table 3.10 were also estimated controlling for changes in HELOC debt. This additional control made relatively little difference to the overall results (not featured here), reducing the difference between the counseling and comparison groups by about $200 in each model. However, the inclusion of HELOC debt did affect the overall fit of the revolving debt models substantially, increasing the R-squared from 0.08 in Model 1 and 0.1 in Model 2 to 0.53 and 0.54 respectively.

Client Outcomes Based on DMP Status

Finally, Tables 3.11 and 3.12 present the results examining the relative changes in debt and credit outcomes based on client DMP status. While this analysis cannot track who entered into a DMP, information on which clients were recommended into a DMP is available. To assess the outcomes for those recommended into DMPs and those not recommended into DMPs, Tables 3.11 and 3.12 separate DMP and non-DMP clients into two separate models, with DMP clients only compared to their matched equivalents (as are the non-DMP clients).64

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64 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 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.
<table>
<thead>
<tr>
<th>Model (Standard Errors in Parentheses)</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variable</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Counseling Client (DMP Recommendation)</td>
<td>-3,340.09***</td>
<td>-2,095.31***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(366.44)</td>
<td>(350.46)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Counseling Client (No DMP Recommendation)</td>
<td>-4,129.67***</td>
<td>-1,766.30***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(674.14)</td>
<td>(629.30)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bankruptcy Post-Baseline†</td>
<td>-12,061.03***</td>
<td>-16,071.73***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1,187.47)</td>
<td>(1,654.86)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Charge-Offs Post-Baseline‡</td>
<td>-5,244.10***</td>
<td>-6,598.26***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(387.07)</td>
<td>(516.31)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>17,563.18***</td>
<td>14,818.66***</td>
<td>17,563.18***</td>
<td>14,818.66***</td>
</tr>
<tr>
<td></td>
<td>(98.46)</td>
<td>(212.04)</td>
<td>(96.95)</td>
<td>(208.00)</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.05</td>
<td>0.03</td>
<td>0.09</td>
<td>0.07</td>
</tr>
<tr>
<td>Observations</td>
<td>54,089</td>
<td>33,145</td>
<td>54,089</td>
<td>33,145</td>
</tr>
<tr>
<td>(Individuals*Quarters)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unique Individuals‡</td>
<td>7,727</td>
<td>4,735</td>
<td>7,727</td>
<td>4,735</td>
</tr>
</tbody>
</table>

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 not shown.

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.

Table 3.11: Differences-in-Differences Analysis - Debt Outcomes for Samples Split by Client DMP Recommendation

As can be seen in Table 3.11, the non-DMP group actually reduces their debt more than the DMP group in the models with no controls (Models 1 and 2). 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 (Model 2) leads to greater debt reductions for DMP clients than non-DMP clients and DMP clients have around $300 more in debt reduction than non-DMP clients in these models.
Table 3.12 shows the credit score outcomes for DMP and non-DMP clients. While both groups show declines in their credit scores relative to their comparison groups, the DMP clients experience less of a drop than the non-DMP group; DMP clients see a credit score decline of five points while non-DMP clients see a decline of almost ten points. An alternative set of models controlling for bankruptcies, charge-offs, and foreclosures reproduced these results very closely.

<table>
<thead>
<tr>
<th>Model (Standard Errors in Parentheses)</th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable</td>
<td>Credit Score</td>
<td></td>
</tr>
<tr>
<td><strong>Counseling Client (DMP Recommendation)</strong></td>
<td><strong>-5.12</strong>*</td>
<td><strong>-9.51</strong>*</td>
</tr>
<tr>
<td></td>
<td>*(1.54)</td>
<td>*(2.02)</td>
</tr>
<tr>
<td><strong>Counseling Client (No DMP Recommendation)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>595.56***</td>
<td>594.51***</td>
</tr>
<tr>
<td></td>
<td>*(0.48)</td>
<td>*(0.63)</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.04</td>
<td>0.02</td>
</tr>
<tr>
<td>Observations (Individuals*Quarters)</td>
<td>53,039</td>
<td>32,165</td>
</tr>
<tr>
<td>Unique Individuals †</td>
<td>7,577</td>
<td>4,595</td>
</tr>
</tbody>
</table>

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 not shown.

* 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.

Source: Credit Attributes Data

Table 3.12: Differences-in-Differences Analysis - Credit Outcomes by DMP Status

**Alternative Model Specifications**

**Outliers and Influential Observations**

Each of the basic treatment effect models in this analysis (shown in Tables 3.4 and 3.5) were assessed for the possible influence of outliers. Outliers are defined as any observation with exceedingly high residuals relative to the overall residual distribution of the panel regression.
model. Only the two debt models (revolving debt and total debt) have clear outliers, and only one observation in each of these models is identifiable as an outlier. As a robustness check, these models were re-run excluding the outlier individuals. The exclusion of these individuals did not substantially impact the coefficients, significance, or overall fit of the models.

**Extreme Values**

Given the relatively high levels of debt held by individuals in this analysis and large changes in other credit indicators such as credit scores, it is important to check to verify that extreme values are not influencing the analysis. To address this, extreme values were identified based on exceedingly large changes in outcome measures from baseline to the end of the evaluation period.

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Full Sample</th>
<th>Excluding 1% Highest/Lowest Change</th>
<th>Excluding 5% Highest/Lowest Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Revolving Debt</td>
<td>-3,637***</td>
<td>-2,861***</td>
<td>-1,663***</td>
</tr>
<tr>
<td>Total Debt</td>
<td>-11,341***</td>
<td>-5,809***</td>
<td>-2,441***</td>
</tr>
<tr>
<td>Available Open Credit Ratio</td>
<td>0.04***</td>
<td>0.06***</td>
<td>0.08***</td>
</tr>
<tr>
<td>Balance-to-Credit Ratio</td>
<td>-0.04***</td>
<td>-0.06***</td>
<td>-0.07***</td>
</tr>
<tr>
<td>Credit Score</td>
<td>-6.76***</td>
<td>-5.93***</td>
<td>-4.06***</td>
</tr>
<tr>
<td>60-Day Payment Delinquencies</td>
<td>-0.01</td>
<td>0.04**</td>
<td>0.04***</td>
</tr>
</tbody>
</table>

This table presents a comparison of client outcomes based on the exclusion of extreme values, defined by the overall change in the outcome measure over the evaluation period. This table includes results for the full sample, the sample excluding the highest and lowest one percent of outcome changes, and the sample excluding the highest and lowest five percent of outcome changes.

*Source: Credit Attributes Data*

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

Table 3.13: Results Excluding Extreme Changes in Outcome Measures
Table 3.13 presents a comparison of the full sample models (shown in Tables 3.4 and 3.5) in this evaluation when excluding those in both the highest and lowest one percent of changes in outcome measures and the highest and lowest five percent of changes in outcome measures. These results reveal that the total debt measure in particular is influenced by extreme changes, as the reduction in total debt falls by almost 50 percent when excluding the highest and lowest one percent of total debt changes (and by over three-fourths when excluding the highest and lowest five percent). However, total debt is still negative and statistically significant with these sample restrictions. The revolving debt measure also exhibits some sensitivity to large changes, as excluding the highest and lowest one percent of changes results in slightly more than a 20 percent drop in the debt reduction. The balance-to-credit, available open credit, and credit score outcome measures show modest improvements when excluding extreme changes and the payment delinquency metric becomes slightly positive (and statistically significant).

The sample excluding the highest and lowest one percent of outcome changes was also examined using every model in this evaluation (i.e. controlling for debt write-offs, restricting the sample by baseline credit score percentile, etc.). This analysis found that the removal of the most extreme values affects the coefficients on credit counseling participation for every model in roughly similar ways as those seen in Table 3.13. In each model, the magnitude of the change for total and revolving debt is reduced to a similar degree and there are relatively modest fluctuations for all other measures. Notably, the revolving debt reduction for those in the 25th credit score percentile at baseline becomes statistically significant at the five percent level (driven by a reduction in the standard error) and the reduction in 60-day payment delinquencies for those in the 50th credit score percentile loses statistical significance.

An alternative way of accounting for extreme values excludes observations based on their pre-counseling debt measures, as the variability in debt levels was extremely large at baseline. Table 3.14 presents the results when excluding individuals based on this criterion. The changes in
total and revolving debt are less sensitive to exclusions based on pre-counseling debt levels; while both measures show less reduction in debt in the restricted samples than the full sample, these changes are relatively modest when compared to the impacts seen when restricting samples based on the change in outcome measures.

<table>
<thead>
<tr>
<th>Sample Restriction Criteria</th>
<th>Full Sample</th>
<th>Excluding Highest 1% at Baseline</th>
<th>Excluding Highest 5% at Baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Revolving Debt</td>
<td>-3,637***</td>
<td>-3,444***</td>
<td>-2,768***</td>
</tr>
<tr>
<td>Total Debt</td>
<td>-11,341***</td>
<td>-9,954***</td>
<td>-8,516***</td>
</tr>
</tbody>
</table>

This table presents a comparison of client outcomes based on the exclusion of extreme values, defined by the value of revolving debt and total debt measures at baseline. This table includes results for the full sample, the sample excluding the highest one percent of baseline debt, and the sample excluding the highest five percent of baseline debt.

*Source: Credit Attributes Data*

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

Table 3.14: Debt Results Excluding Large Baseline Values

**Agency-Level Effects**

An additional set of models was constructed to account for the possibility of any agency-specific effects in the results. Specifically, indicators were created to identify the counseling agency for each client (coded ‘0’ for all individuals pre-counseling and ‘1’ for every client in a specific agency post-counseling) and these indicators were used as controls in every model presented in this analysis. When controlling for agency-level effects, the results are largely unchanged for every model.

65 A separate set of models clustering standard errors at the agency level was also considered but this presented two issues. First, the relatively small number of agencies limits the utility of clustering at this level. Second, the individuals in the comparison group did not interact with the agencies in any way, so clustering this group by agency (or clustering the standard errors for all comparison individuals as one group) would be inappropriate.
Discussion

From this analysis, it is clear that Sharpen clients are uniquely distressed at baseline relative to individuals 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 credit counseling as their credit profiles have already begun to deteriorate—confirming Hypothesis 1—may indicate that future credit 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 clients 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 approximates a counterfactual outcome for Sharpen clients and compares 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 and the structure of this analysis allows for the establishment of a range on the overall treatment effect of counseling. For the full sample, the average change in revolving debt is -$3,637. When only examining those in the middle 90th percentile of changes, however, the revolving debt reduction is a more modest but still significant -$1,663 (as in Table 3.13). The average change in total debt is -$11,341, though this change decreases substantially to -$2,441 when only considering those in the middle 90th percentile of debt changes. This large shift in total debt when excluding those with the largest changes indicates that much of the reduction in total debt is coming from a minority of clients.
Even so, there is still statistically significant debt reduction in total debt when excluding these clients. Conversely, the debt ratio metrics actually improve when considering only those in the middle 90th percentile of outcome changes: The decrease in the balance-to-credit ratio grows from -0.04 to -0.07 while the increase in the available open credit ratio doubles from 0.04 to 0.08. What these results demonstrate is that, though the treatment effect of counseling may be driven somewhat by those at the extremes of the distribution in outcome changes, the benefits of counseling are also being experienced by those towards the middle of the distribution as well.

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. Some of the decline in total debt is influenced by extreme values. However, even when accounting for these extreme values the reduction in total debt is always statistically significant and greater than the reduction in revolving debt for credit counseling clients in all models covered in this evaluation. Additionally, credit 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, partially confirming Hypothesis 2, the question of what drives this decline is less clear. To explore the answer this question, this chapter 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 debt management plan...
enrollment. Overall, the results show that both of these sources contribute significantly to client
debt reduction and confirm Hypothesis 3a. When controlling for bankruptcies, charge-offs, and
foreclosures over the study period, the relative difference in debt levels is smaller but is still
significant, confirming Hypothesis 3c. It is worth noting here that client bankruptcies do not exist
in isolation from credit counseling. Sharpen clients can, as part of the credit 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, both groups experience significant revolving debt reductions even when
controlling for bankruptcies or charge-offs and DMP clients exhibit higher rates of debt reduction
than those not recommended for DMPs, confirming Hypothesis 3b.

For client credit scores, the results are mixed. For the full sample of counseled
individuals there is a substantial credit decline that only begins to recover in the third post-
counseling quarter. The comparison group by contrast 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 total, the comparison group has a credit
score 6.8 points higher than the counseling group eighteen months post-counseling (while those
in the middle 90th percentile of the change in credit scores see a decline of around four points). 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 clients 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.) that 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, meaning that Hypothesis 2a cannot be confirmed.

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 clients. For those who had credit scores in the bottom half of the credit distribution (a credit score at or below 601) at baseline, counseled clients 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 (see Appendix F for the full regression output providing quarterly changes in the key outcomes), 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, though it remains unclear if the increased credit gains relative to the comparison group are due to the counseling program or from factors outside of credit counseling. Thus, for the clients in the bottom quartile of credit scores, Hypothesis 2b is confirmed.

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 credit counseling for “bad credit” at twice the rate of the general Sharpen clientele (though overall their motivations appear largely similar).

Summarizing these results, there are indications 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 debt management plans see stronger improvements in their credit scores than those clients not recommended for debt management plans. 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 the bottom quartile of credit scores at baseline 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 credit counseling that recover by the end of the evaluation period, though as with the credit score metric it is not clear if credit 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 (those in the bottom 25th
percentile of the credit distribution prior to credit counseling) experience more substantial credit gains post-counseling than the general credit counseling population. In this, the chapter 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, the Elliehausen, Lundquist, and Staten analysis found that credit 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. This chapter also reinforces the more descriptive analyses of credit counseling initiatives (Bagwell, 2000; Kim et al., 2003), which found that clients had better self-assessed financial behaviors and outcomes after going through credit counseling.

Even as this analysis has reinforced the findings of existing studies of credit counseling programs, it also substantially extends them. In particular, the tracking of outcomes on a quarterly basis has illustrated the risks of descriptive analyses that only examine outcomes for counseling clients before and after counseling. As illustrated in this analysis (and in Chapter Two of this dissertation), client credit profiles are already starting to deteriorate at the time they are seeking counseling. Given this, research designs that survey clients immediately prior to counseling and then compare their pre-counseling outcomes to their outcomes at some point in the future may overstate the impact of counseling on client well-being—improvements seen over this timeframe may just be due to clients having more time to recover from the shocks driving them into counseling rather than any impact of counseling itself. This underscores the importance of using comparison groups to assess the impact of these types of programs.

This chapter has also notably extended the work done by Elliehausen, Lundquist, and Staten (2007), specifically by assessing outcomes for both DMP and non-DMP clients, examining clients from a wider array of agencies, tracking client outcomes at multiple points in time (rather than one pre-counseling and one post-counseling period), and perhaps most importantly by
controlling for post-counseling indicators of financial distress (e.g. bankruptcies, foreclosures, and charge-offs). In doing so, this work provides additional context around client credit dynamics after clients seek counseling and allows for the improved isolation of the behavioral component driving outcomes in counseling programs. The isolation of this behavioral component is important in determining credit counseling’s potential impact on individual and social welfare. As counseling clients have an increased propensity to experience debt write-offs (particularly bankruptcies and debt charge-offs) in the post-counseling period, it is not enough to simply track debt outcomes over time relative to a comparison group (unless clients can be matched on shock-related factors like unemployment or health expenses; something not feasible in this analysis) as has been done in prior work. The level of financial distress clients face around the time they seek counseling must be accounted for to get a strong read on the relationship between credit counseling and outcomes. In modeling indicators associated with financial distress, including going through bankruptcies, debt charge-offs, and foreclosures, this chapter has made perhaps the strongest case yet for credit counseling’s potential to benefit its recipients.

**Limitations**

A few cautions should be noted when interpreting the results from this analysis. First, there may be unobserved differences between counseled individuals and the matched comparison group, limiting the ability of the analysis to estimate causal impacts. 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 consumer credit counseling industry, it is unlikely that credit counseling services would be withheld from a random subset of consumers in distress (as withholding services runs counter to their mission), which would be necessary to establish a randomized control group. While the alternative of creating a matched comparison group allows for the approximation of a counterfactual outcome, the only traits of the counseled and comparison groups that can be matched upon are those traits that are observable for both
groups. This means that the analysis cannot match on motivational or behavioral traits, and 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, the estimate of the counterfactual outcomes is incomplete.

Another issue is the limited array of financial indicators that can be directly observed through credit data. As this analysis relies on credit data, it cannot measure outcomes not captured in these data. These outcomes include psychological outcomes such as lower financial stress, behavioral outcomes like avoiding high-cost lenders, and financial outcomes like savings rates and savings levels. As such, the analysis of the overall impact of credit counseling is incomplete. Importantly, the available credit outcome measure in this analysis is also only a partial measure of liquidity, as liquidity can be measured through both available liquid savings levels and available credit.

It is also possible that the non-counseled group took measures to address any financial difficulties they may have faced. If the individuals in the comparison group sought credit counseling at agencies outside of the agencies participating in the analysis, participated in related programs such as debt settlement programs, or sought financial advice from professionals, these behaviors would not be picked up in the analysis. However, if individuals in the comparison group did seek credit counseling or related services elsewhere this would bias the impact estimates in a conservative direction (assuming beneficial impacts from these related services).

Caution should also be exercised when interpreting the evolution of credit and payment delinquency indicators. Many credit counseling clients appear to go through some form of shock impacting their credit indicators around the time of credit counseling. Ideally, one would construct a comparison group of consumers experiencing a similar shock but who did not receive counseling. Future analyses could address this by using a “dynamic baseline” approach wherein credit 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 sample of credit counseling agencies used in this analysis. A subset of 13 NFCC-affiliated credit counseling agencies volunteered and were 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 are compared in Appendix C of this dissertation. 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 chapter 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 the matching criteria no match was found 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 that the analysis fails to capture Sharpen’s impacts on these relatively idiosyncratic clients. A comparison of the characteristics and credit outcomes between matched and unmatched clients in Appendix E of this dissertation shows that unmatched counseling clients are relatively distressed compared to matched counseling clients, with lower credit scores and higher debt levels, though trends in credit scores and debt levels for the unmatched group are similar to those of the matched counseling clients. This analysis also
Partially addresses Sharpen’s impact on clients 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.

**Conclusion and Policy Implications**

As individuals continue to struggle with high debt levels, employment volatility, anemic savings levels, and inadequate retirement assets, both policymakers and creditors are examining a variety of options for addressing these problems and their associated risks. This chapter 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 credit counseling (i.e. clients taking on less debt or paying down existing debt more rapidly) on credit indicators for these clients, or the degree to which credit counseling itself may impact people’s financial behaviors and thus their long-term outcomes. This chapter 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 credit counseling (particularly on the levels of revolving debt held by clients) remains.

What this analysis cannot explain is the exact source of this change. Perhaps credit 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; or perhaps the credit counseling agency acts as a hub to provide clients with additional resources such as other nonprofit 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 credit counseling. By virtue of being the type of person to seek credit counseling, one may also be the type of person likely to responsibly manage one’s 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 likely seek out credit 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 feasible.

From the policymaker’s perspective, the benefits demonstrated in this chapter 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 in the present likely mean less propensity to declare bankruptcy in the future, which can prevent individuals from taking on “healthier” debt that can enhance personal welfare such as car loans, mortgages, or student debt. However, there is also some risk to an accelerated debt reduction schedule if debt is being paid down at the expense of savings contributions. Chapter Two presented some survey-based evidence that this may be happening (Table 2.13 in particular), but since savings could not be directly observed for this analysis it is not possible to assess the overall change in credit counseling clients’ savings behaviors. The increases in liquidity seen among credit counseling clients also 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

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66 See the framework presented in Chapter One for a more thorough discussion of the change mechanisms in counseling programs.
will not be prevented from accessing a wide variety of potentially beneficial financial instruments including mortgages.

Though this chapter is not intended to provide a cost-benefit analysis of credit counseling, it is worth briefly discussing the implications of this study from a cost-benefit perspective. The cost of each counseling session administered as part of the Sharpen program was $125 to $150 (though none of the cost is borne by the client; counseling services in nonprofit agencies are typically free to clients and funded through the revenue streams available to the nonprofit credit counseling agencies). There are also additional fees to set up DMPs, though these are typically low—agencies may charge start-up fee and monthly fees that are often around $50 and are sometimes adjusted based on client needs. In the absence of robust DMP enrollment information (the data in this study only capture DMP recommendations) it is difficult to estimate how much clients spend monthly on DMP programs, but since this chapter has taken steps to isolate credit counseling’s impact outside of DMP enrollment it is still possible to get an overall sense of the relative costs and benefits of counseling. By the end of the evaluation period, the Sharpen program had enrolled around 40,000 clients. At $150 per counseling session, the Sharpen program spent six million dollars on client counseling (absent any DMP expenditures). Taking the most conservative estimate of credit counseling’s debt impact in this study, which is the impact for non-DMP clients controlling for bankruptcies and debt charge-offs, the average reduction in revolving debt is $1,766.3 eighteen months after counseling. If the reduction seen among the clients in this study is the same for all Sharpen clients (which is plausible, as Appendix C demonstrates that clients from agencies participating in this analysis do not substantially differ from those agencies not participating), this translates to around 70.7 million dollars in revolving debt reduction over the evaluation period. Put differently, credit counseling programs have the potential to drive almost 12 dollars in debt reduction for every dollar spent on service delivery; an outcome that may be a conservative estimate. Given the potential benefits from this relatively low
cost investment, credit counseling programs should be seriously considered by policymakers seeking to address issues of consumer debt.

This work also contributes to the research on consumer financial interventions generally. Credit counseling contains elements of financial coaching, behavioral monitoring, and financial education programming. Each of these types of programs have been studied to varying degrees but evidence for their ability to improve client outcomes is either limited (as is the case with financial coaching and monitoring) or mixed (as is the case with financial education). In establishing the ability for credit counseling programs, which are also substantially under-studied given their long history and extensive reach, to drive client outcomes, this work helps develop the broader discourse in consumer financial policy concerning the relative efficacy of various program types.

From a broader policy studies perspective, this chapter contributes to the emerging research combining behavioral economics with public policy concerns. Credit counseling has within it a number of embedded mechanisms that can overcome behavioral biases leading to sub-optimal financial behaviors, including problems of inattention, self-regulation, present-biased preferences, and cognitive drain. Though the research in this chapter was not designed as an explicit test of the individual behavioral mechanisms embedded in credit counseling, the fact that the combined bundle of these mechanisms yields positive client outcomes demonstrates the potential for behaviorally-oriented interventions to accomplish policy-relevant goals. In doing so, this research follows in the vein of other behaviorally-oriented research that has addressed public issues in such disparate areas as retirement savings (Benartzi & Thaler, 2007; Madrian & Shea, 2001), poverty-related issues (Shah et al., 2012), employment discrimination (Krieger & Fiske, 2006; Pager, 2003), health policy (Elbel et al., 2009; Wansink et al., 2009), and education policy (Cohen et al., 2009). As such, the work in this dissertation not only has implications for the narrower fields of consumer financial policy and credit counseling initiatives but also provides
empirical support for the use of behaviorally-oriented interventions in the pursuit of public policy solutions.

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 credit counseling agencies), access to appropriate public or nonprofit 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 credit counseling framework through additional program enhancements.
Chapter 4: Unpacking Program Implementation: The Impact of Frontline Worker Engagement on Household Financial Outcomes

Introduction

While the previous chapter of this dissertation investigated the overall impact of a credit counseling program, this chapter takes a more narrow focus by assessing the impact that practices within a credit counseling agency can have on client outcomes. Specifically, this chapter examines the role that client-worker interactions have on program success. These interactions are often characterized as the “frontlines” of policy and program implementation and understanding how dynamics at the frontlines impact the nature of policies and programs is instrumental to understanding the drivers of program success. This of course is not a novel point; the frontlines of implementation have been recognized as important to understanding policies and their outcomes for over three decades (Lipsky, 1980), and there has been ample research demonstrating that frontline workers often determine how (and if) services are provided to clients (e.g. Maynard-Moody & Musheno, 2003; Maynard-Moody & Portillo, 2010; Meier & Nicholson-Cotty, 2006; Watkins-Hayes, 2011). The relationship between frontline workers and target populations is often understood as being a function of the complex interplay between routine and discretion; frontline workers exhibit varying degrees of discretion over specific decisions within the context of their established work routine. The discretionary decisions made by frontline workers can influence the ways in which services are provided to clients (Feldman & Pentland, 2003; Hasenfeld, 2010) and the quality and quantity of service provision are both subject to frontline worker discretion in the implementation of many programs (Weiss, Bloom, & Brock, 2014). Further, these decisions are often mediated by the relationships between clients and workers and
between workers and the programs they are implementing. Thus, understanding how discretion shapes the decisions of workers in how to engage both clients and the programs themselves is essential to understanding how the frontlines impact program success.

Despite the recognition of the frontlines as important to the successful implementation of a program, a recent content analysis of the implementation literature found that the frontlines of the implementation system were only explored in less than a fifth of implementation studies from 2004 to 2013 (Sandfort, Roll, & Moulton, 2014). While frontline implementation research has made substantial contributions to understanding the broader implementation system and the policy process generally, it suffers from several gaps. Two of these gaps are addressed in this work. The first is that implementation research often does little to empirically link implementation dynamics to target group outcomes (i.e. changes in the behavior or conditions of the external group targeted for the intervention; Domitrovich & Greenberg, 2000; Durlak & DuPre, 2008; Dusenbury, Brannigan, Falco, & Hansen, 2003). Even when target group outcomes are evaluated through a randomized controlled trial of an intervention, the link between frontline conditions and outcomes remain largely a black box (Durlak & DuPre, 2008). Instead, frontline implementation research often concerns itself with programmatic components and activities--how frontline workers choose to engage clients and how these varying levels of engagement lead to clients receiving different levels of services. While understanding the link between frontline dynamics and service provision is valuable, the emphasis on program activities rather than program outcomes remains a weakness of this research stream.

Additionally, much of the research on policy and program implementation in public affairs has focused on what might be considered “traditional” public service implementation contexts: Face-to-face interactions between frontline workers in public agencies, where target populations often have little to no choice in interacting with the frontline worker (for example, students in a classroom or a parent applying for public assistance; e.g. Brodkin, 1997; Maynard-
Moody & Musheno, 2003; Schram et al., 2009). But despite this focus, many programs affiliated with public agencies, particularly those administered through contracts with private or nonprofit organizations, do not operate with captive target populations or in coercive settings (Maynard-Moody & Portillo, 2010).

This paper directly addresses these gaps by presenting a unique analysis of frontline dynamics in a publicly-funded personal financial management program implemented by a nonprofit organization. It is motivated by the following question: How do differing implementation approaches among frontline workers impact key program outputs and subsequent target group outcomes? This question is answered through a multi-method approach using a sequential exploratory strategy (Cresswell, 2009) that employs the deductive/inductive coding of frontline workers’ program session notes to identify variations in workers’ implementation approaches. Differences in implementation approaches are linked to both program outputs and target group outcomes through basic statistical tests and probit regression while exploiting the strength of a randomized controlled study design; a relative rarity in frontline implementation studies.

The analysis first demonstrates that both program outputs and target group outcomes vary by the worker implementing the program. It then explores the sources of this variation and finds that these differences in outputs and outcomes are associated with differing approaches to client engagement, as well as different levels of worker engagement with the “program technology”, or the mechanisms a program uses to drive change in a target population. These findings contribute to the literature by showing that not only do frontline workers influence client outcomes but also that there are important differences in outcomes based on (1) worker engagement with the client and (2) worker engagement with the program technology. Workers who are capable of successfully engaging clients are significantly more capable of driving program take-up rates and promoting the program, while workers who are more engaged with the program technology and
the people-changing process of the technology are significantly more capable of driving improved client outcomes. An ability to engage clients is not sufficient to drive program outcomes; the competencies required to drive program take-up and program outcomes are separate but not incommensurate.

The remainder of this chapter proceeds as follows: The next section reviews relevant streams of literature, including a brief overview of frontline implementation studies generally, a review of the literature on engagement and client-worker relationships in implementation contexts, and a review of the research on frontline worker engagement with program technologies. Following the literature review, several assumptions are outlined and hypotheses are developed. A description of the program and a summary of program and participant characteristics comprise the fourth section. The methods and data used in this chapter are described in the fifth section, including a detailed description of the coding scheme employed for the qualitative portion of this chapter. The sixth section covers the results of the analysis. The final section provides a discussion around these findings and covers both the limitations and contributions of this chapter.

**Literature Review**

**Frontline Implementation**

Beginning with Lipsky’s (1980) work, it has been well-established that the dynamics influencing workers at the frontlines of policies or programs can have a substantial impact on the success of that policy. The major finding of Lipsky’s that is relevant to this research is how goal complexity and environmental complexity create a system in which frontline workers are often given high levels of discretion over their work and in their pursuit of organizational goals. Implementation at the frontlines, particularly in human service-oriented fields, often involves nuanced and highly contextual problems. Engaging with other individuals exposes the work to human demands and human nature and it is incumbent on individual frontline workers to navigate
that complexity in the way they see fit. Given this, the work cannot be completely automated nor can every contingency be planned for; discretion is required in order to implement the program.

Discretion is often a central focus of frontline implementation studies. In a framework developed by Hasenfeld (2010), frontline worker discretion allows workers to develop individualized routines to navigate the realities of their day-to-day work, including how they manage cases and relate to clients. Similarly, Feldman and Pentland’s (2003) framework for understanding organizational routines treats frontline worker behavior as a function of both the basic requirements of the work and of the frontline worker’s choices in determining how to perform that work. Indeed, a key area in implementation research is how factors that influence the individual street-level worker such as program constraints (e.g. time or funding), workload demands, worker competence, or competing goals, impact the implementation of policies and programs. Brodkin (1997), in a case study of welfare reform, found that a lack of staffing, funding, training, and skills in welfare offices led to caseworkers rarely doing more than the required minimum to help clients, despite the hopes of reformers. Jewell and Glaser (2006) interviewed welfare workers and found that the complexity and difficulty of the tasks put before the workers resulted in their developing simplifying procedures to process clients, again resulting in a focus on the achievable goals of processing clients rather than the overarching goals of welfare system, in this case promoting long-term employment among welfare recipients. Similar research later reinforced this, showing that frontline welfare workers did not fully implement a policy intended to change clients’ behavior due to the bias of frontline workers toward performing manageable tasks like client processing or rule enforcement (Meyers, Glaser, & Donald, 1998).

The need to navigate these constraints leads to different compensatory behaviors in frontline workers. Within human services organizations, workers are often expected to perform both routinized tasks, such as those involving client processing, and tasks requiring the
development of a relationship with the client. Hasenfeld (1983, 2010) characterized these tasks as “people-processing” and “people-changing”, with the former involving reliance on forms and rules to govern the interaction and the latter involving highly contextual worker/client interactions that cannot be routinized. While public organizations may face pressures to retain the bureaucratic people-processing model due to lack of funding, training, and a bias toward quantifiable performance measures (Hasenfeld, 2010), discretion allows for workers to go above and beyond the routinized tasks of clearing client lists and rule enforcement.

These findings indicate that, in the absence of strict oversight, the workers implementing programs at the frontlines must often determine their own means of achieving the program’s goals. This discretion can lead to variations in the way the program is delivered, even as frontline workers are operating within the broader framework of the program’s established routine (as in Feldman and Pentland (2003)). Though this research establishes that discretion shapes frontline practices, the link between discretionary frontline behaviors in social service programs and program outcomes remains underexplored within the implementation literature. To that end, the remainder of this literature review will outline two key elements of frontline implementation commonly referenced in the literature: The engagement between frontline workers and their clients, and the engagement frontline workers feel with the program itself. These research streams will then inform the development of hypotheses linking frontline behaviors and program impacts.

Client-Worker Engagement and Implementation

While the above research into frontline implementation often focuses on the worker and the organizational and institutional context in which they operate, there is also a body of implementation research focusing specifically on the interactions and relationships of frontline workers and their clients. A common focus in public service frontline implementation research is the role that the identities of clients and workers play in frontline worker engagement and behavior. Maynard-Moody and Musheno (2003) provided an in-depth qualitative study of this
through a large number of interviews with police officers, school teachers, and job counselors. One of the major ideas behind their work is that relationships between the client and the worker matter: Clients’ identities, or at least how these identities are perceived by the frontline worker, impact how those workers treat clients and thus impact the level of services clients receive from the government; it is repeatedly shown that the formation of relationships between frontline workers and their clients lead to higher levels of engagement not only on the part of the worker but also the client. In a similar vein, Radey (2008) conducted a literature review of studies of worker-client interactions in a welfare system and concluded that relationship-building (and workers with relationship-building skills) are a key factor in achieving program aims, as these relationships can enhance trust and lead to more accurate assessments that will appropriately identify client needs and solutions to those needs. These skills can also help overcome the complications that hierarchical power arrangements and the routinization of many tasks cause worker-client relationships (Lurie, 2006; Radey, 2008; Thompson et al., 2001). This research indicates that both client and worker identities and practices augment the ability to form a relationship at the frontlines of program implementation and that different approaches to relationship-building can lead to different levels of client/worker engagement and different outcomes.

Building off this, other research shows that the relationship between clients and workers can have immediate and substantial consequences. Lindhorst and Padgett (2005) conducted interviews with welfare workers and their clients to examine the implementation of a domestic violence protocol and found major issues in how frontline workers handled the new protocol. These issues largely stemmed from poor relationships and trust issues between clients and workers, which led to clients not disclosing sensitive information about their family dynamics to workers, preventing them from accessing domestic violence services. Schram et al. (2009) presented welfare workers with a series of vignettes that varied the race and social status of
imaginary clients and found that the identity of clients substantially impacts the likelihood of clients receiving sanctions. How workers relate to clients and perceive their identities can fundamentally alter the services received in a program, a finding reinforced by a number of other studies, often under the moniker of “representative bureaucracy” research (e.g. Meier & Nicholson-Crotty, 2006; Watkins-Hayes, 2011).

The importance of relationships in implementation has also made its way into program evaluations. Clark et al. (2002) conducted a qualitative study focusing on the experiences of clients, clinicians, and program directors in implementing a rural substance abuse treatment protocol and found that strong relationships between the program implementers and their clients was important to program success, or at least the perception of success for the clients. Tout et al. (2012) evaluated the impacts of an early childhood education program that utilized coaches to assist organizations entering into the program and found that relationships between these coaches and their clients, as well as the ability of coaches to identify the unique needs of clients, was integral to the success of the program. Hall et al. (2012) presented a case study of a social service agency in Australia that implemented a program explicitly designed to shift the focus of the agency away from people-processing behaviors and more towards forging relationships with its clients and found that, while this shift in perspective can take time, it can also provide resolutions to many issues faced by welfare agencies that adopt a purely efficiency-based approach to service provision.

While the above research often focuses on traditional public sector settings (welfare offices, schools, law enforcement) in which clients do not have much (or any) choice in interacting with the frontline worker, the expansion of government services into other areas and the increasing propensity for government services to be provided by private or nonprofit organizations has led to customer-centered approaches (in which workers focus on client satisfaction, their individual needs, and overall responsiveness) becoming more common.
Though there are few studies of the implementation of these customer-centered approaches from a frontline perspective in the public affairs literature, the literature on customer-centered and relationship-building approaches in frontline worker interactions has been covered in the private sector literature. Bettencourt and Gwinner (1996), for example, conducted interviews with customer service employees in a private retail organization, finding that the ability for frontline workers to personalize services and tailor communication style for the client is important for making sales and getting clients to commit to a service. Similarly, Hurley (1998) used two qualitative studies in a large convenience store chain to link the service quality provided by frontline workers to workers’ levels of extroversion and agreeableness. Frontline worker commitment to their job has also been linked to customer loyalty and improved business outcomes through those employees providing improved service quality, as demonstrated by Loveman (1998) who analyzed employee satisfaction, customer satisfaction, and financial performance data in bank branches. The literature on relationship banking or relationship lending also focuses on these issues and finds that treating customers as clients and relying on long-term repeated interactions (and, potentially, contacts outside of the context of the banking relationship) can yield benefits for both the bank and the client (Boot, 2000; Elyasiani & Goldberg, 2004; Everett, 2010).

Finally, work also exists on the role that client-worker relationships play in financial advising, which has some additional relevance to this chapter due to similarities between financial advising and financial coaching. Sharma and Patterson (1999) used survey data to link the ability to effectively communicate with clients to the level of trust that exists between clients and

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67 This finding also has relevance to the subsequent discussion on technology-worker engagement by showing that employees’ commitment to the organization can drive improvements in outcomes.

68 Though there is some conceptual overlap between financial coaching and advising, in that they both deal with financial issues and provide guidance on pursuing financial goals, there are also notable differences. Financial advising often deals with relatively affluent clients and often focuses on investment advice rather than working with clients to pursue shorter-term financial goals and assist with behavioral or knowledge deficits in money management, as is the case in financial coaching (Collins, 2010).
advisors. Dubowsky and Sussme (2010) found that while relatively few financial advisors have “strong” bonds with their clients (defined as having some sort of role in a client’s personal life, such as being an emergency contact), the strength of the bonds in these relationships is linked with advisors acting in more of a coaching role to address their clients’ psychological needs; behavioral and demographic traits of the advisors are also linked to the propensity to form strong bonds. Brown and Brown (2008) found that financial investment clients have different “styles” of forming relationships and argued that successful financial advisors are able to take different approaches to engage these different personalities.

Taken together, these streams of literature reveal that the relationship between clients and workers in program implementation is of central importance. In contexts where the client has little to no choice in interacting with a frontline worker (e.g. welfare workers or police officers), relationships matter in that they can lead to differential levels of engagement and trust for the workers and clients, which can impact the type and quality of service provided. In contexts where the client is not “captive” and can choose to enroll in a program, such as the program under study in this chapter, relationships matter because the ability to effectively communicate with clients, generate trust, and promote the program is necessary for driving enrollment in the program; knowing how to functionally sell the program and get client “buy-in” may be one of the key factors driving program outputs.

*Technology-Worker Engagement and Implementation*

While client buy-in to a given program is important, worker buy-in to that program is also relevant to understanding the relationship between implementation and program success. In addition to the literature on how client-worker relationships and engagement impact frontline implementation and program outcomes, a literature on how frontline workers’ perceptions of the program or program technology impact implementation dynamics has also emerged over the last several decades. The “technology” of a program can be understood as the mechanisms a program
uses to drive change in a target population. Thus, an engagement with program technology can be understood as the degree to which a worker buys in or commits to a program and its goals; a disconnect between the type of work being done and frontline workers’ preferences can lead to shirking behavior or absenteeism (Lipsky, 1980; Wilson, 1989). Put simply, if a worker is not committed to the goals of a program (or the goals of her agency), she will be less likely to put forth as much effort in fully implementing that program than a worker who is committed and believes in the mission of the agency or the program’s aims.

This disconnect between the goals of the frontline worker and the goals of the program often occurs when established organizations seek to implement new innovations (Klein & Knight, 2005). Resistance to new programs may stem from several sources: It may be a function of the difficulty frontline workers have in acquiring the knowledge and skills used to implement the new program technology, which can be exacerbated by program complexity (Aiman-Smith & Green, 2002); it may stem from status quo bias in frontline workers, skepticism of the merits of the program, and the fact that decisions to pursue new innovations often come from higher up in the organizational hierarchy (Nutt, 1986); it could emerge from organizational climates that do not emphasize innovation or learning (Holahan, et al., 2004); or resistance may occur due to an absence of social pressures within the organization to adopt a given innovation (Frank, Zhao, & Borman, 2004).

As frontline worker commitment to a given program or policy is directly related to her willingness to implement it fully and enthusiastically, a direct link can thus be drawn between this and program outcomes. May and Winter (2009) conducted a survey of municipal caseworkers and found that frontline workers’ understanding of a policy, their professional knowledge, and their endorsement of an employment reform positively impacted their willingness to implement these reforms. Jones (2003) noted that frontline worker identification with a given approach or program can bolster a manager seeking to push workers beyond typical performance levels but
can hinder a manager seeking to shift strategies or implement new programmatic innovations. Brehm and Gates (1997) focused on organizational culture as one of the defining elements governing frontline worker compliance in implementing programs—a culture that does not incentivize the adoption of new innovations may lead to workers who refuse to actively implement programs or who may outright sabotage efforts at program innovation. When taken together, this work indicates that there is a very real threat to program success when frontline workers are either unwilling or unable to fully embrace a given program technology.

**Theoretical Framework and Hypotheses**

At its core, this chapter is concerned with how different implementation approaches lead to variation in program outputs and outcomes and the above literature review of frontline implementation research helps develop testable hypotheses to assess this relationship. First, the literature establishes that the various and often unique attributes of frontline implementers, such as their identities, abilities, and constraints, govern their decisions and behaviors in implementing policy at the frontlines and potentially impact outcomes. While one of the goals of this chapter is to understand how these behaviors and decisions can be systematically characterized, it is important to first assess the veracity of the chief underlying assumption behind this research.

*Assumption 1: Program outputs and client outcomes will differ depending on the frontline worker administering the financial coaching program.*

Specifically, this chapter is exploring the chief program output of program take-up and the chief outcome of a reduction in client mortgage payment delinquencies. As frontline workers were randomly assigned to clients, any variation in client behaviors or characteristics should be non-systematic between coaches; this implies that any differences in outputs or outcomes is attributable to differences in frontline worker approaches.
A corollary to Assumption 1 is that, inasmuch as frontline implementation dynamics are related to outcomes, implementation approaches will differ depending on the coach administering the program.

Assumption 2: Systematic differences can be identified among frontline workers in their implementation approach.

Embedded within Assumptions 1 and 2 are tests of the relationship between routine and discretion in this chapter as well. Assuming that the inputs are roughly homogenous across frontline workers (as is the case in this chapter; see the next section for additional detail), a lack of evidence for differences in outcomes, outputs, and implementation approaches would indicate that the frontline workers in this program are largely implementing the program in a similar fashion and not relying on their discretion to individualize the delivery of the program.

The existing literature on frontline implementation also provides a framework containing assumptions about the types of implementation approaches that may be observed in this analysis. The research on client-worker relationships in program implementation (e.g. Lurie, 2006; Maynard-Moody & Musheno, 2003; Radey, 2008; Thompson et al., 2001) emphasizes the ubiquity and importance of relationship formation between frontline workers and clients even in otherwise highly routinized environments and demonstrates that the ability to form relationships and engage clients is heavily dependent on the characteristics of the frontline worker. This finding is reinforced by the private sector literature on client engagement, which treats the ability to effectively communicate with clients as a skill that varies from worker to worker (e.g. Bettencourt & Gwinner, 1996; Hurley, 1998; Sharma & Patterson, 1999). Similar variations in frontline workers’ ability to engage clients can be expected to emerge in this analysis.

While variations in client characteristics may also lead to differing levels of program engagement, these differences should not impact the analysis of this chapter so long as clients do not differ systematically between frontline workers. As clients were randomly assigned to frontline workers in this chapter, any variations in engagement stemming from client characteristics or behaviors should be random. Table 4.4 in this chapter largely confirms that clients do not differ between coaches.
Assumption 2a: Frontline workers will exhibit differing levels of engagement with program clients.

While the ability to engage clients is key to the success of many programs, the literature also demonstrates that the frontline workers themselves must be engaged with the program technology (the mechanisms of client change embedded in the program); their support for and belief in a program, its goals, and the means of accomplishing those goals is essential for the successful implementation of a program (Klein & Knight, 2005; Lipsky, 1980; May & Winter, 2007; Wilson, 1989). Further, they must also be comfortable with the program technology itself and have the skills and training to effectively implement it (Aiman-Smith & Green, 2002; May & Winter, 2007).

Assumption 2b: Frontline workers will exhibit differing levels of engagement with the program technology.

If the above assumptions hold true, it will allow for the identification of commonalities in implementation strategies. Once these commonalities have been assessed, it is then possible to group the workers based on their common approaches and test the impact of these approaches on client outcomes.

Assumption 3: Differences in implementation strategies in the financial coaching program will lead to differential outcomes and outputs among clients in the program.

However, implementation approaches are likely not equal in their relation to outcomes and outputs. Worker-client relationships and the level of engagement with program technologies are functions of the use of discretion at the frontlines and these factors are integral to implementing people-changing programs and policies. Thus it can be hypothesized that workers who use their discretion to develop a more individualized and relationship-oriented approach to pursue client change and who demonstrate heightened engagement with the change process embedded in the program will also exhibit improved outcomes for their clients relative to workers who implement
the program in a routine fashion. Yet these types of engagement may impact the success of the program in different ways. For programs involving a non-captive target population, the ability to quickly and effectively engage clients may function chiefly to drive program take-up; clients who feel engaged with the frontline worker may be more likely to commit to the program administered by that worker, though engagement with clients may only be a partial driver of program success. Once engaged, client success in the program may be driven by the ability of the frontline worker to effectively deliver the program technology. Put differently, a frontline worker’s engagement with the change process embedded in the program (through either the willingness or the ability to engage with the change process) may be a direct determinant of program outcomes. The proposed link between these types of engagement is the basis for the central hypotheses of this chapter:

*Hypothesis 1: Increased frontline worker engagement with clients is positively associated with improvements in program outputs (e.g. program take-up).*

*Hypothesis 2: Increased frontline worker engagement with the program technology is positively associated with improvement in program outcomes (e.g. fewer mortgage payment delinquencies).*

While the literature provides guidance on the types of implementation approaches that may be found, it should be noted that this chapter takes an exploratory approach and will also examine the data for any other systematic implementation approaches beyond those implied by the extant literature.

**Data**

*Research Context and Sample*

To explore these hypotheses, this chapter uses data collected through a program called MyMoneyPath, which was developed in a partnership between researchers at The Ohio State University and the Ohio Housing Finance Agency (OHFA). In an effort to reduce mortgage defaults and foreclosures in a publicly-funded program aimed at lower-income first-time
homebuyers, OHFA developed this program to offer a financial assessment and financial coaching to borrowers in the program after they had purchased their home. The MyMoneyPath program began in August, 2011 and enrolled clients over the first three quarters of the initiative.

Clients randomly selected for the treatment group were randomly assigned to one of four coaches. Coaches all received the same training to implement the program and were given a standardized protocol for contacting clients. This protocol specified the timing and frequency of calls, emails, and voicemail messages; agency records were reviewed to ensure that coaches conformed to the contact protocol. Coaches were also provided with a guidebook that provided an overview of the expected structure of the coaching sessions, covering subjects such as making introductions, shifting the conversation toward finances, helping the client develop goals and action plans, follow-ups, and guides for future coaching sessions. Appendix G features an excerpt from this guidebook covering the development of clients’ action plans.

Clients received a 25 dollar gift card in exchange for their participation for each coaching session. In order to participate in the program, households must have had incomes lower than 115 percent of their area’s median income and must not have owned a home in the past three years (National Council of State Housing Agencies, 2011). After their completion of an initial financial health assessment, individuals randomly selected into the treatment group were then contacted for coaching at quarterly intervals through August 2012. Clients who completed at least one session were contacted in every possible quarter, while clients who did not complete any coaching sessions were contacted a maximum of three quarters. Due to rolling client enrollments over the study period, the number of quarters in which a client was in the program varied. A total of 295 individuals were offered coaching and 108 individuals actually went through the coaching process; a takeup rate of 37 percent. Of these 108 clients, 61 completed a second session, 23 completed a third session, and two completed a fourth session. The extreme drop-off in fourth session enrollments was likely due to two factors outside the normal attrition effect seen in other
quarters: First, not all clients were in the program long enough to be contacted for a fourth quarter; and second, funding concerns limited the number of contacts provided to clients in the final quarter of the program. Table 4.1 summarizes client enrollments and the takeup of coaching over the four quarters of the study.

Table 4.1: Client Enrollments and Treatment Takeup by Quarter

<table>
<thead>
<tr>
<th></th>
<th>Quarter 1</th>
<th>Quarter 2</th>
<th>Quarter 3</th>
<th>Quarter 4</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Client Enrollment</td>
<td>162</td>
<td>80</td>
<td>53</td>
<td>n/a</td>
<td>295</td>
</tr>
<tr>
<td>Total Coaching</td>
<td>33</td>
<td>56</td>
<td>65</td>
<td>40</td>
<td>194</td>
</tr>
<tr>
<td>Sessions</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1st Coaching</td>
<td>33</td>
<td>43</td>
<td>32</td>
<td>0</td>
<td>108</td>
</tr>
<tr>
<td>Session</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2nd Coaching</td>
<td>13</td>
<td>26</td>
<td>22</td>
<td>61</td>
<td></td>
</tr>
<tr>
<td>Session</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3rd Coaching</td>
<td>7</td>
<td>16</td>
<td>23</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Session</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4th Coaching</td>
<td>2</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Session</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

This table summarizes the number of total client enrollments into the MyMoneyPath financial coaching program, as well as the number of clients that took up coaching in each quarter.

Program Context

Financial coaching is a type of program that has grown out of the more general field of “coaching” (other examples of which include life coaching and health coaching). Financial coaching is a relatively new field; Collins and O’Rourke (2012) define financial coaching as “a collaborative solution-focused, result-oriented, systematic, and strengths-based process in which the coach facilitates the enhancement of personal financial management practices” (p. 42).

Coaching programs are intended to provide participants with support in developing or maintaining positive financial behaviors and the coach also ideally monitors client behaviors over time to help clients reach their financial goals. Several coaching programs have recently been evaluated in an experimental setting and have demonstrated the potential to drive improvements in both financial and psychological outcomes for clients (Collins, 2013; Moulton et al., 2015;
The coaching program under study, the offer to participate in financial coaching was randomized and the coaching itself was administered by a nonprofit credit counseling agency. For the coaching sessions themselves, the major goal for coaches was to help clients formulate financial goals, translate these goals into concrete action plans, and subsequently re-contact clients at set intervals to monitor client progress and provide additional coaching. In this, it follows models of financial coaching described elsewhere (Collins, 2010; Collins, Baker, & Gorey, 2007).

The central logic of this program is that the purchase of a new home poses a relatively unique set of challenges to households, as they are likely dealing with a variety of new financial issues—issues that may be exacerbated given the lower incomes of program participants. Because these households have entered new financial territory, the purchase of a home serves as a teachable moment where they are more focused on their finances than they otherwise might be and interventions like financial coaching can capitalize on this teachable moment to help clients improve their financial behaviors. Programs exploiting these key moments in household financial decision making are of particular interest for both researchers and social service agencies; a recent quantitative meta-analysis by Fernandes, Lynch Jr, and Netemeyer (2014) found few impacts among financial education programs generally but noted that “just-in-time” interventions coinciding with key decision points show the potential to drive outcomes; financial coaching in particular was cited in this research as a promising intervention. These improvements in financial behaviors are intended to help clients adjust to the financial realities of owning a home and avoid missing any mortgage payments (with the longer-term goal of avoiding foreclosure); the avoidance of mortgage payment delinquencies is the key program outcome in this chapter. This program can thus be described as a people-changing program technology that works by the

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70 Chapter Three features a more in-depth discussion of the financial coaching literature.
71 People-changing technologies are defined as those in which the relationships between clients and workers are the primary driver of program outcomes (Hasenfeld, 2010).
coach and their client identifying specific client needs and collaboratively generating detailed plans to achieve those goals, a process supplemented by coaching follow-ups to motivate the client and help them maintain financial stability while diligently making their new mortgage payments.

The current study is part of a larger analysis of this pilot program. Moulton et al. (2015) investigated the overall impact of this program on the likelihood of default for new homebuyers and found positive and significant treatment effects on savings, credit scores, installment and revolving debt, and the propensity to have a serious delinquency in mortgage payments (defined as being 60 days or more behind in mortgage payments), establishing the link between coaching and improved client outcomes. While the larger study found positive treatment effects, it did not explore the relationship between these effects and dynamics at the frontlines. This paper by contrast is not concerned with the overall efficacy of the program (which has been established) but rather uses this program as a means to explore how different implementation dynamics at the frontlines impact key program outputs and outcomes.

Data Collection and Summary Statistics

The data for this analysis come from a number of sources and are both qualitative and quantitative in nature. The first data source comes directly from the financial coaching agency itself and contains a number of variables relevant to the administration of the coaching session, such as the number of coaching sessions received, contact attempts per quarter, the coach assigned to the client, and the date of coaching. This data source also contains the notes on the sessions from the financial coaches, which not only contains records of call attempts, messages left, and session completions, but also includes detailed notes about their interaction with the client. These notes cover a wide array of topics but in general nearly all of the notes touch on common themes, including the total time spent in session, the financial goals each client has, how they plan to achieve those goals, and (for those clients who received more than one coaching
session) whether or not the client has made progress on those goals. These data were collected from August 2011 through August 2012; a timeframe that covered the full duration of the coaching program. For the purposes of this chapter, each of the four coaches has been given a pseudonym: Beverly, Katherine, Diana, and Tasha. All four coaches are female and English is the native language for three of the four coaches; English is a second language for Diana. The coaches worked out of an accredited nonprofit credit counseling agency in Columbus, Ohio, and were employed as National Foundation for Credit Counseling-certified counselors before receiving training in financial coaching.

During these sessions and pre-coaching attempts to encourage program take-up, coaches kept detailed notes of their interactions with the clients. These notes include logging every call, email, voicemail, and conversation with clients, as well as the goals and action plans generated during the coaching session. Coaches often (though not always) recorded important details about the clients emerging from these sessions: Their financial concerns, major life events, or key characteristics of their identity were common subjects of note.
### Program Characteristics†

<table>
<thead>
<tr>
<th>Metric</th>
<th># of clients</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clients Receiving Treatment</td>
<td>108</td>
<td>37%</td>
</tr>
</tbody>
</table>

#### Contacts Prior to Takeup

<table>
<thead>
<tr>
<th>Metric</th>
<th></th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Contacts Per Client</td>
<td>n/a</td>
<td>7.8</td>
</tr>
<tr>
<td>Number of Direct Voice Contacts Per Client</td>
<td>n/a</td>
<td>0.4</td>
</tr>
<tr>
<td>Voicemails Left Per Client</td>
<td>n/a</td>
<td>3.3</td>
</tr>
<tr>
<td>Emails Sent Per Client</td>
<td>n/a</td>
<td>4.1</td>
</tr>
</tbody>
</table>

#### Coaching Assignment

<table>
<thead>
<tr>
<th>Coach</th>
<th># of Clients</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Katherine</td>
<td>77</td>
<td>26%</td>
</tr>
<tr>
<td>Beverley</td>
<td>60</td>
<td>20%</td>
</tr>
<tr>
<td>Diana</td>
<td>78</td>
<td>26%</td>
</tr>
<tr>
<td>Tasha</td>
<td>80</td>
<td>27%</td>
</tr>
</tbody>
</table>

### Session Characteristics‡

<table>
<thead>
<tr>
<th>Metric</th>
<th></th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coaching Time Per Session (Minutes)</td>
<td>n/a</td>
<td>22.9</td>
</tr>
<tr>
<td>Number of Sessions Per Client</td>
<td>n/a</td>
<td>1.80</td>
</tr>
<tr>
<td>Number of Goals Set Per Session</td>
<td>n/a</td>
<td>2.58</td>
</tr>
<tr>
<td>Client Made Progress Toward Goal</td>
<td>48</td>
<td>44%</td>
</tr>
</tbody>
</table>

#### Types of Goals Set

- **Save Money**: 84 (78%)
- **Pay Down Debt**: 66 (61%)
- **Pay Down Mortgage**: 19 (18%)
- **Save for Retirement**: 22 (20%)
- **Manage Expenses**: 46 (43%)
- **Make a Budget**: 35 (32%)
- **Automate Mortgage Payments**: 7 (6%)

†Statistics for the general treatment group itself (n=295)
§Statistics for those opting to receive treatment (n=108)

Table 4.2: Coaching Program and Session Characteristics

Table 4.2 details the key statistics for the coaching sessions. Thirty-seven percent of the clients who were offered coaching agreed to at least one coaching session and on average clients went through 1.8 sessions. Client assignment to coaches was roughly equal, with Beverly having fewer assigned clients than the rest due to falling ill for a brief period during the program period. The typical coaching session lasted around 23 minutes and had around three goals set per session. In terms of the goals themselves, despite the mortgage and homeownership focus of the program, the most prevalent goal type was around saving money, with almost 80 percent of clients...
identifying this as a goal. Paying down debt was the next largest focus with 60 percent of clients identifying this as a goal, while paying down the mortgage (18 percent), saving for retirement (20 percent), managing expenses (43 percent), making a budget (32 percent), and automating mortgage payments (six percent) were less prominent goals.

The second data source comes from the post-treatment MyMoneyPath financial assessment. For the broader study, all program participants had to complete an initial financial assessment prior to coaching, then one year later were re-contacted to take a follow-up financial assessment. These surveys collected a wide variety of self-reported financial information, attributes, and behaviors. Most relevant to this current analysis is an array of questions in the post-treatment survey asked of those respondents who received the financial coaching treatment. These questions cover the general impressions participants had of the coaching sessions, as well as the perceived usefulness of the sessions and coaches. For the follow-up financial health assessment, 69 of the 108 coaching clients responded (a response rate of 64 percent).

Objective data on the financial state of the participating households were collected through administrative data from OHFA, mortgage origination data provided by the master loan servicer, and credit report data. These data capture important household attributes not collected by the survey (such as race) and also provide a measure of household resources and credit status that does not rely on self-reports. Beyond that, the OHFA data tracks the mortgage payment history of each household including payment delinquencies, the avoidance of which is the key focus of the MyMoneyPath program.

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72 This assessment is very similar to the MyMoneyCheckUp self-assessment described in Chapter Two of this dissertation.
<table>
<thead>
<tr>
<th>Client Characteristics</th>
<th>Offered Coaching Mean (S.D.)</th>
<th>Received Coaching Mean (S.D.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>White</td>
<td>82% (0.38)</td>
<td>77%* (0.43)</td>
</tr>
<tr>
<td>Male</td>
<td>54% (0.5)</td>
<td>42%*** (0.5)</td>
</tr>
<tr>
<td>Age</td>
<td>32.64 (9.98)</td>
<td>32.99 (10.96)</td>
</tr>
<tr>
<td>College Degree</td>
<td>67% (0.47)</td>
<td>71% (0.45)</td>
</tr>
<tr>
<td>Monthly Income</td>
<td>$3,529 (1,271)</td>
<td>$3,424 (1,252)</td>
</tr>
<tr>
<td>Number of People in Household</td>
<td>2.48 (1.31)</td>
<td>2.49 (1.33)</td>
</tr>
<tr>
<td>Credit Score</td>
<td>665.2 (48.94)</td>
<td>669.1 (49.36)</td>
</tr>
<tr>
<td>Observations</td>
<td>295</td>
<td>108</td>
</tr>
</tbody>
</table>

This table presents the summary statistics for all program clients and the subset of clients who took up coaching. Significant differences between those who took up coaching and those who did not are tested via Chi-squared tests (for proportional variables) and t-tests (for continuous variables).

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

Table 4.3: Summary Statistics for Selected Client Characteristics Prior to Treatment

Table 4.3 details the characteristics for both the clients who were offered the program and the subset of clients choosing to take-up coaching. Eighty-two percent of clients in the program were white, while 54 percent were male and the average age was 33 years old. Clients offered coaching were relatively highly educated, with 67 percent having some type of college degree. The typical household size was 2.5 people and the monthly household income of clients was $3,529. The average credit score of clients in the program was 665. For those who actually took up the coaching program, the demographic makeup was roughly similar, though the proportion of
males enrolling in the treatment was only 42 percent, which significantly differs from those who did not take up coaching (p<0.01).

73 Interestingly, the higher propensity for women to take-up coaching is reminiscent of the disproportionate number of women who seek credit counseling services relative to men, as shown in Chapter Two of this dissertation.
had a slightly greater propensity to have a college degree (p<0.1); and Beverly’s clients were somewhat more likely to be non-white (p<0.1).

Method

This research is couched in a sequential exploratory strategy (Cresswell, 2009). First, quantitative analysis is conducted to test the central assumption underlying this chapter: That outputs and outcomes differ by the frontline worker implementing the program. Once this assumption is tested and verified, a qualitative analysis of the frontline workers’ notes is undertaken to assess systematic differences in implementation approaches. Finally, this qualitative work is integrated into a quantitative analysis using statistical tests to link the approaches emerging from the qualitative work with program outcomes. The qualitative and quantitative elements of the analysis thus complement each other and allow for a richer triangulation on the implementation approaches used in this program.

Quantitative Analysis

The quantitative leg of this research proceeds in stages. The first stage assesses whether there are substantial differences among the frontline workers on the outcome of interest for this program, as well as the major output. The primary outcome variable in this research, as indicated above, is whether a person has been seriously delinquent on their mortgage payment since taking out a mortgage. Serious mortgage delinquency is defined here as being behind on payments by 60 or more days in the first year after receiving coaching and is coded as ‘1’ if an individual meets this criterion and ‘0’ otherwise. Mortgage payment delinquency is pulled from payment records from the Ohio Housing Finance Agency, which tracked each participant’s mortgage payment performance. The primary output is the coaching sessions themselves, measured by whether or not a potential client completed at least one coaching session with a coach (the number of sessions is also recorded). Differences in coaches on these measures are explored both descriptively and through chi-squared tests to assess statistical significance.
The next leg of the quantitative analysis proceeds after the qualitative coding of the coaching data (see next section) is complete. This portion of the chapter seeks to provide an understanding of why the key outputs and outcomes differ and so explores the differences in coaching approaches based on the key metrics outlined in the qualitative analysis section below. Similar to the first stage, differences in these approaches will be assessed descriptively and through the use of t-tests and chi-squared tests. Once the differences in coaching approaches have been illustrated, the next step in the research will be to detail different commonalities in implementation approaches and then to group coaches according to those approaches. Once coaches have been grouped based on their implementation approach, tests will be run to see if any of these different approaches are correlated with the key outcome variable. Given the relatively low number of people who were seriously delinquent in their mortgage, a confirmatory probit will be run at this stage. The probit model is specified as

\[ \Pr(Y_i = 1) = \alpha_0 + \beta_1 \text{Approach}_i + \sigma X_i + \epsilon_i \]

where \( Y \) is the chief outcome variable in this chapter: An indicator variable for severe mortgage delinquency; \( \beta_1 \) is the average effect of being assigned to a coach using a given implementation approach for borrower \( i \), \( \alpha \) is the constant for borrower \( i \), and \( \sigma \) is the coefficient for a control variable \( X \) (in this case an indicator capturing subprime credit scores, defined as any credit score less than 640).

As the participants in this study are not only randomly assigned to the treatment but are also randomly assigned to the coaches, the use of control variables to assess the differential effects of the treatment is not required; the comparison of the distribution of mortgage delinquency by the assigned coach can be considered the average “treatment effect” of being assigned to that coach. However, as a robustness check a secondary probit model controlling for subprime credit scores is presented in addition to the primary treatment effect model that features
only the implementation approaches as independent variables. The subprime credit score indicator is included to control for any differential impact that client pre-treatment risk profiles (as measured by credit scores) may have on the overall propensity to have a mortgage payment delinquency. Even though clients are assigned randomly to coaches, controlling for this variable helps account for the possibility that pre-treatment credit behaviors may impact post-treatment outcomes. The cutoff of 640 for the low credit score indicator is because a credit score less than 640 has commonly been considered “subprime” (Lo, 2012), and these subprime households may differ systematically from the general treatment group.

**Qualitative Analysis**

To transform the coaching notes into a format suitable for analyzing the relationship between coaching approaches and program successs, a combined deductive/inductive attribute coding approach (Saldaña, 2012) was used to operationalize the content of the coaches’ notes. The attribute coding approach is a good fit for this analysis, as the goal of the analysis is to quantitatively measure concrete differences in implementation approaches and link them with measurable outcomes. As such, relying on the more “structured” data emerging from the notes (such as the number of goals set, session length, types of contact made, etc.) is appropriate and attribute coding is more conducive to this type of data than other more “interpretivist” coding approaches. The coding began with a codeframe centered on areas in which coaches were assumed to focus based on the design of the program, such as the number and type of goals set. The coding also captured the structure of the coaching sessions themselves, such as the time spent in each coaching session and whether or not additional ad hoc coaching or contact was requested outside of the formalized, quarterly coaching sessions. Additional codeframes were developed based on commonalities observed in the coaching sessions and the coaching notes were iteratively recoded as these additional frames were generated.
A number of other attributes of the coaching sessions were coded, including the level of detail in the coaching notes and whether coaches recorded a “personal” comment during their sessions. The level of detail in coaching notes is recorded for two reasons: The first is that it can be argued that coaches who record more information about their clients may be more engaged with the sessions themselves as they are more likely to focus on details; the second is that coaches who record the sessions in more detail can use that information to help build the relationship with their client in future sessions, for example by referring back to some detail about that client’s life that would perhaps make the client feel the coach was attentive and delivering a personalized service. Note detail is operationalized here as a straightforward word count of the notes emerging from the coaching sessions (not including the documented contact attempts).

Coding personal comments works on a similar logic. Coaches who are engaged with clients may be more likely to elicit personal comments and coaches who record personal comments may be able to use those to help identify with the client during that session or in future sessions. For example, if a coach referenced that a client is concerned about her son’s ability to be self-sufficient, or is caring for a sick husband, this would count as a personal comment. Comments like these may help build rapport and lead to higher engagement on the part of both the client and the worker.\textsuperscript{74} For the purposes of this analysis, personal comments count as any note that reveals some important detail of the client’s life outside of the typical development of goals and action plans. It does not include simple descriptors of the client’s life, such as if they have kids or the type of work they do.

\textsuperscript{74} While coaches were not explicitly instructed to record personal comments, they were provided space to record additional notes about the clients and were instructed to build trust with clients by engaging in non-financial conversations and sharing details about their own lives. However, given that recording personal comments was not required, this may indicate that some coaches simply chose not to record these details even though they may have come up during the session. Though this is a possibility, the data show that all coaches recorded personal comments fairly regularly, with personal comments recorded for between 42 percent and 80 percent of clients (depending on the coach).
Another central element of the coaching sessions is the development of an action plan to help clients achieve their goals. Unlike many of the other elements of the coaching program, the development of action plans has not been quantified through coding, as the recording of action plans for some coaches did not lend itself well to operationalization due to an occasional conflation of goals and action plans. Further, in reviewing the notes, it quickly became clear that there was not only variation in the use of action plans by coaches but there was also substantial variation in the detail of the action plan provided by the coaches. These differences in detail do not lend themselves well to quantification, thus the portion of the analysis concerning action plans will be purely qualitative in nature. For the purposes of comparison, representative notes from the coaches will be presented in the text to illustrate the differences among the coaches in terms of developing action plans with clients.

Beyond the topical content of the coaching sessions themselves, a wide array of other key pre-coaching attributes were recorded and coded. First, the number and types of contacts with clients were recorded. These include the number of voicemails left, emails sent, and number of times coaches made direct voice contact with clients (i.e. the client picked up the phone and had a conversation with the coach). Additionally, the number of times the client responded to coach contacts, either by replying to emails or returning phone calls was recorded. For all of these types of contacts, instances in which multiple contacts were made as part of an exchange were only counted as one contact.\textsuperscript{75,76}

\textsuperscript{75} By way of example, if a client returned an email saying she was interested in coaching, then the coach asked her about availability for a session, and she responded with the times she was available, this exchange would only be counted as one instance of a coach emailing and a client responding. Similarly, if a client asked a coach to call her at a given time and the coach called but received no response, a coach might leave more than one voicemail to follow-up on the missed appointment. This too would be counted only as one contact attempt. The logic behind this coding is that these exchanges only represent one overall attempt at contact or communication and, for an analysis that seeks to understand differences in implementation approaches and client relationships, it is important to only focus on specific instances of contact, rather than the total number of communications in a given exchange.

\textsuperscript{76} Attempts were also made to code the total number of calls made by coaches to clients where they did not leave any message but the data strongly suggest that one coach inconsistently recorded these attempts early on in the program, so those codes are not included in the analysis. It should be noted that the issue of
Results

The first step in the analysis is to explore whether the key outcome (mortgage delinquency) and key output (takeup of coaching) differ by the frontline worker. Establishing these differences is the first step in linking differences in implementation approaches to differences in these key metrics of program success. Figure 4.1 illustrates that three coaches (Diana, Katherine, and Beverly) have clients with mortgage delinquencies at rates that do not differ significantly from the average, while Tasha has clients with significantly higher than average delinquency rates ($\chi^2=4.56$ and $p<0.05$ for those offered coaching; $\chi^2=3.49$ and $p<0.1$ for those receiving coaching). Indeed, clients who were assigned to Tasha and took up coaching had delinquencies at twice the rate of all other coached clients, thus confirming Assumption 2.

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77 Inconsistent recording of contact attempts should not be a concern for contacts where concrete messages or exchanges were involved, as a condition of funding for this program was that these contacts be recorded. If a client did not have these contact attempts on record, the agency implementing the program would run the risk of losing funding for that client.

77 Given the relatively low prevalence of severe mortgage payment delinquencies, Fisher’s exact test was considered to assess significance. However, Fisher’s exact test is considered inappropriate for tests in which all parameters of an experiment are not fixed (e.g. unconditional tests; Lydersen, Fagerland, & Laake, 2009). While chi-squared tests are sometimes considered inappropriate for tests with small expected cell counts, the chi-squared results are presented here as the $p$-values are similar to those of other tests, including the unconditional Fischer-Boschloo test and Pearson’s ($z$-pooled) chi-squared statistic, as well as probit regression.
As a note, the possibility was considered here that Tasha received clients who were more prone to delinquency by random chance. Though not presented in this paper, this possibility was tested by examining the coach-specific default rates of clients who did not participate in the treatment. If delinquency was substantially higher among Tasha’s untreated clients than among the other coaches’ untreated clients, this would indicate that Tasha was assigned more delinquency-prone clients at random. However, no significant differences among the non-treated clients for Tasha were found in terms of delinquency rates, indicating that initial client differences do not explain the difference in outcomes.

Takeup rates, here defined as the percent of each coach’s clients who opted to participate in a coaching session, can be understood as the key program output of this initiative. As shown in Figure 4.2, there are also large differences by frontline worker. Though Tasha’s clients had the highest rate of mortgage delinquencies (the key program outcome), at a 45 percent takeup rate she is significantly stronger than the average of 36 percent in terms of getting clients to actually participate in the coaching treatment ($\chi^2=3.42; p<0.1$). Beverly is a very strong performer on this
metric as well, with 55 percent of her clients ($\chi^2=11.13; p<0.01$) enrolling in the program. By contrast, Diana and Katherine perform relatively poorly on this front, with Diana enrolling only 24 percent of her pool of clients ($\chi^2=6.72; p<0.01$) and Katherine enrolling 26 percent ($\chi^2=4.96; p<0.05$). Given these results, it can be safely said that the key outcome and program participation rates differ substantially based on the frontline worker involved, validating Assumption 1.

![Client Takeup Rates by Coach](image-url)

Figure 4.2: Client Takeup Rates by Coach

Having established the differences in program success criteria for individual coaches and confirming Assumptions 1 and 2, the next step is to examine the differences in the specific elements of each worker’s approach and look for commonalities that explain these differences in performance. To do this, first the factors most likely to be related to program takeup (i.e. the elements of the program taking place outside of the sessions themselves, most notably the coaches’ contact strategies) will be explored and then the factors most likely to be linked to client outcomes (i.e. the elements of the coaching sessions themselves) will be assessed.
Table 4.5 summarizes the difference in contact approaches by coach, with the different modes of contact being leaving a phone message, sending an email, or making direct contact with a client over the phone. Significance is measured via t-test. The proportion of contacts is described here rather than the aggregate number of contacts because analysis revealed that the raw number of contacts differs substantially by worker and is also influenced by each worker’s takeup rates. For example, if a coach can successfully get a client to enroll in the treatment early on, they are not going to need to contact that client as much as a coach who is less successful in enrolling clients and so must contact them over longer intervals to try and enroll them. Further, these contacts are measured only prior to the initial takeup of coaching. This is done because coaches often had multiple sessions with their clients over the course of the program and the contact approach (and client responsiveness) likely differs for those clients who already participated in the initial session. As such, it is appropriate to only measure contacts up to the first session or, in the case of those who never enroll, all total contacts. Table 4.5 also breaks out contact approaches by those clients receiving treatment and clients who never receive treatment in order to control for differences in takeup rates among coaches. As all clients were required to receive phone calls and emails and the contact procedure for phone messages and emails was the same for all coaches, the chief variable of interest in Table 4.5 is the proportion of total contacts that are direct voice contacts; a higher percentage of voice contacts indicates a stronger propensity for coaches to directly engage clients.\(^78\)

\(^{78}\) There may be several factors driving this difference. Coaches making more frequent direct contacts may have made more call attempts beyond the minimum requirements, or they may have left more engaging messages that made the program more appealing.
<table>
<thead>
<tr>
<th></th>
<th>Total Clients</th>
<th>Treated Clients</th>
<th>Untreated Clients</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Voice Contact</td>
<td>Emails</td>
<td>Phone Messages</td>
</tr>
<tr>
<td>Total</td>
<td>10%</td>
<td>57%</td>
<td>33%</td>
</tr>
<tr>
<td>Diana</td>
<td>8%</td>
<td>59%</td>
<td>33%</td>
</tr>
<tr>
<td>Katherine</td>
<td>5%***</td>
<td>49%***</td>
<td>45%***</td>
</tr>
<tr>
<td>Beverly</td>
<td>16%***</td>
<td>60%</td>
<td>24%</td>
</tr>
<tr>
<td>Tasha</td>
<td>12%</td>
<td>60%</td>
<td>28%</td>
</tr>
<tr>
<td>Observations</td>
<td>295</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* p<0.1; ** p<0.05; *** p<0.01
Significance measured through t-tests comparing each coach with the average metrics for all other coaches.

Observations by coach: Diana (78 offered coaching; 19 received coaching); Katherine (77 offered; 20 received); Beverly (60 offered; 33 received); Tasha (80 offered; 36 received)

Table 4.5: Proportion of Contact Types Prior to Takeup
There are a couple major takeaways from Table 4.5. The first is that the chief difference in contact approach appears to be that coaches differ in their ability to make direct voice contact with clients. When looking at the total pool of clients, Katherine is significantly less capable of engaging clients directly than her associates, as direct voice contact comprised only five percent of her total contacts ($t=-2.46; p<0.05$). This is also true for those clients who never received coaching, with whom only one percent of her contacts involved voice communication ($t=-2.54; p<0.05$). As such, a relatively high proportion of her contacts with clients were passive in nature and involved sending or leaving messages, which inherently engage the client less than direct contact. The second major takeaway is that for clients who received coaching, the contact approaches do not differ among coaches and a much higher proportion of those contacts involve direct voice communication. This indicates that treated clients are all recruited in similar ways and that direct voice contact is likely the most effective means of enrolling them, as around a fifth of the contacts for enrolled clients were direct voice contacts compared to four percent of contacts for unenrolled clients. The differences in other contact types are not nearly as pronounced.
Contacts were not only made by coaches, as each email or voice message left also informed the client that they could contact the coach directly. The propensity for coaches to elicit client responses also differs substantially by coach, as can be seen in Figure 4.3. Interestingly, Katherine (who had the poorest record of making direct contact with clients) did not differ substantially from average in terms of eliciting client response, while Diana (who was less capable of directly engaging clients on average) elicits a client response about half as much as the average ($\chi^2=8.48; p<0.01$) and a third as much as Tasha, who elicited responses from thirty-five percent of clients ($\chi^2=5.74; p<0.05$). This is particularly interesting because Diana was the only coach for whom English was not a first language and, while the impact of this on client responses is difficult to measure, it may have some bearing on this result.

Figure 4.3: Eliciting Client Responses
Table 4.6: Average Number of Sessions per Client

The final aspect of the contact approaches explored here is the average number of sessions held per client, shown in Table 4.6. As might be expected, the results here roughly track the results for coaching takeup in general, as coaches more capable of encouraging takeup are perhaps more capable of engaging clients for multiple sessions as well. Katherine performs the worst on this metric, having on average 1.35 sessions per client ($t=-2.79; p<0.01$) while Tasha is the strongest performer at 2.06 sessions per client ($t=2.38; p<0.05$). Beverly has an above average (though not significant) 1.88 sessions per client, while Diana has a below average (and non-significant) 1.63 sessions per client.

Coaching Approaches and Frontline Workers

Whereas the previous section explored differences in frontline implementation prior to the coaching session, this section covers coaching differences within the sessions themselves. Specifically, it explores variation in the average session time, the level of detail in coaching notes, the presence of personal comments in the notes, the number of goals set per session, and the average number of sessions per client. The intent of this section is thus to explore key elements of the coaching sessions with the final aim of assessing commonalities in coaching approaches in order to link these approaches with client outcomes.
The first key aspect of the sessions explored is the session length. At the end of each session, coaches recorded the length of the session in minutes, though there were a small number (four) of clients for whom no session length data were recorded. Table 4.7 outlines the differences in coaching time by coach and reveals notable differences on this metric. Most notably, sessions with Tasha are significantly ($t=-6.73; p<0.01$) shorter than sessions with other coaches. Indeed, at an average length of 17.3 minutes, her sessions are over 20 percent shorter than the nearest coach (Diana, at 22 minutes) is and almost 40 percent shorter than the coach with the longest session time (Beverly, at 27.8 minutes). Katherine also has a comparatively long session time at 25.8 minutes ($t=1.97; p<0.1$).

<table>
<thead>
<tr>
<th>Coaches</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diana</td>
<td>22.0</td>
<td>5.6</td>
<td>13.5</td>
<td>30.0</td>
</tr>
<tr>
<td>Katherine</td>
<td>25.8*</td>
<td>8.5</td>
<td>15.0</td>
<td>40.0</td>
</tr>
<tr>
<td>Beverly</td>
<td>27.8***</td>
<td>6.5</td>
<td>20.0</td>
<td>40.0</td>
</tr>
<tr>
<td>Tasha</td>
<td>17.3***</td>
<td>3.3</td>
<td>12.7</td>
<td>26.0</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>22.9</td>
<td>7.3</td>
<td>12.7</td>
<td>40.0</td>
</tr>
</tbody>
</table>

*n=104 (4 clients did not have session times noted for at least one session)*

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

Significance measured through t-tests comparing each coach with the average metrics for all other coaches.

Table 4.7: Average Coaching Session Time (Minutes)
### Average Financial Goals Per Session

<table>
<thead>
<tr>
<th>Coaches</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diana</td>
<td>2.40</td>
<td>0.79</td>
<td>1.0</td>
<td>4.0</td>
</tr>
<tr>
<td>Katherine</td>
<td>2.53</td>
<td>0.92</td>
<td>1.0</td>
<td>4.0</td>
</tr>
<tr>
<td>Beverly</td>
<td>2.23**</td>
<td>1.16</td>
<td>0.5</td>
<td>5.0</td>
</tr>
<tr>
<td>Tasha</td>
<td>3.01***</td>
<td>0.81</td>
<td>2.0</td>
<td>5.5</td>
</tr>
<tr>
<td>Total</td>
<td>2.6</td>
<td>1.0</td>
<td>0.5</td>
<td>5.5</td>
</tr>
</tbody>
</table>

\( n=108 \)

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

Significance measured through t-tests comparing each coach with the average metrics for all other coaches.

Table 4.8: Average Financial Goals Per Session

Interestingly, despite having the shortest sessions, Tasha has the highest average number of goals set per session with her clients (t=3.36; p<0.01), as can be seen in Table 4.8. Also inverting what might be expected, Beverly (who had the longest average session length) had significantly fewer goals recorded per client (t=-2.43; p<0.05). From a qualitative perspective, this gives the impression that Beverly (as well as Diana and Katherine) may be spending substantially more time per goal than Tasha.\(^79\)

An explanation for this might be the way coaches develop “action plans,” or the concrete steps clients are to take in order to accomplish their goals, with their clients. Quantifying action plans in this research is difficult to do in the same way that other elements of the coaching sessions have been quantified, as oftentimes the establishment of a goal itself can contain within it an assumed action plan (e.g. “Goal #1 - Write all bills' due dates on calendar to

\(^79\) An alternate explanation might be that coaches with longer session lengths may simply be engaging in “small talk” or other conversations not directly tied to the coaching itself. While this cannot be explicitly ruled out in the absence of actual recordings of the sessions, one way of assessing this is by looking at the number of personal comments made in the session notes. Figure 4.8 below measures this and finds that only one coach (Katherine) has a higher-than-average propensity to make personal comments and overall there does not look to be an obvious correlation between personal comments and session length; the coach with the longest session time (Beverly) was also the coach with the second fewest personal comments.
keep from forgetting to pay and being charged late fees,” which contains within it both a goal to avoid missing payments and an action of tracking payments on calendars). Further, in the context of this work the “depth” or detail of an action plan is something that can only be judged qualitatively. To do this, typical action plan recommendations will be illustrated here for each coach.80

**Tasha:** “Goal #1: Open savings account at bank with $25 per month direct deposited. Goal #2: Write a budget this week. E-mail financial coach when completed. Goal #3: Track spending daily. Goal #4: Review budget bi-weekly and use tracking info to adjust budget.”

Tasha does not typically spend much time developing detailed plans with her clients and what plans emerge generally involve deadlines or non-specific plans (“use tracking info to adjust budget”). In comparing this approach with Diana, Beverly, and Katherine, the differences are apparent.

**Diana:** “Short term Goal: try to bring the credit card balances down by paying more than minimum payment

Action plan: Mary is paying $80 a month towards vacation club (time share) and just has 4 more payments. After the 4 month she will put the $80 each month into her savings acnt. Mary has a credit card with the balance of $7500 and paying 19% interest. She wants to pay more than minimum payment. She will cut back on eating out (as she eats out a lot) and also her shopping. Mary will start going out to stores with the shopping lists and she also will go to stores once a week and not few times a week. Mary works in a bank and is very well familiar with the online budgeting tools.”

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80 This section includes direct quotations from the coaching session notes. These notes have been copied verbatim (though client names have been changed when necessary) and thus include shorthand abbreviations made by the coaches, though any spelling errors have been corrected.
**Beverly:** “Goal) Save $600 monthly. Strategy: Amanda to put 40% of her pay into a joint household account & boyfriend to put 65% of his - this will allow for extra money to go toward savings. Goal) Cut back on winter heat bills. Strategy: Keep thermostat at 68 degrees & have relatives (grandpa & father) help with weatherizing since they are more knowledgeable & very willing to help out. Goal) Have chairs & tv paid off before the 0% promotion ends. Strategy: Pay extra on the monthly payment.”

**Katherine:** “Kayla has 3 goals she is wanting to focus on at this time. Change her mortgage payments to bi-weekly, look at getting lowered interest rate on vehicle, and get student loan payment lowered. Goal #1) change mortgage payment schedule: Call US Bank, your mortgage company, and discuss with them the option of paying your mortgage in bi-weekly increments, and what that payment would look like and what these types of repayments entail. Goal #2) Lower interest rate on car loan: Research different lending institutions in your area to see what they are currently offering for interest rates on vehicle refinancing. You can also look beyond your local institutions for refinancing by going to www.lendingtree.com. Goal #3) lower your student loan payment: Call Great Lakes Higher Education, and talk to them about your current situation, request that they review your loan(s) for a lowered payment option, discuss with them different programs that are available regarding payout time, interest rates, payment schedules.”

These coaches tend to record a couple goals in their session notes and devote much more attention to developing a plan to achieve those goals with the client. Though not universally true in their session notes, these coaches tend to be very detail-oriented around the client plans and
provide concrete timelines for completion, specify amounts to deposit or pay (where relevant), and provide detailed paths for the clients to follow.\textsuperscript{81}

This variation in action plan development is interesting because the framework for generating strong action plans is defined explicitly in the guidebook given to coaches. Based on their training, coaches are expected to first help clients break down larger goals into a series of smaller, more manageable goals and then help clients develop specific action steps to achieve these manageable goals. Coaches are told that good action steps are specific, measurable, attainable, realistic, and time-bound (which form the acronym “SMART”), and examples of these types of action steps are provided (see Appendix G for the training coaches received on forming action steps). Given this framework, it seems relatively clear that Katherine, Beverly, and Diana are more committed to developing the type of action steps recommended by the program, thus demonstrating a strong commitment to the program technology, while Tasha’s action steps are much more basic and less in-line with the approach advocated by the program.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diana</td>
<td>126.1***</td>
<td>27.11</td>
<td>63.0</td>
<td>188.0</td>
</tr>
<tr>
<td>Katherine</td>
<td>155.3***</td>
<td>34.41</td>
<td>80.0</td>
<td>229.0</td>
</tr>
<tr>
<td>Beverly</td>
<td>74.4***</td>
<td>20.38</td>
<td>34.0</td>
<td>129.0</td>
</tr>
<tr>
<td>Tasha</td>
<td>79.0***</td>
<td>23.37</td>
<td>38.0</td>
<td>130.0</td>
</tr>
<tr>
<td>Total</td>
<td>100.0</td>
<td>41.0</td>
<td>34.0</td>
<td>229.0</td>
</tr>
</tbody>
</table>

\textit{n=108}

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

Significance measured through t-tests comparing each coach with the average metrics for all other coaches.

Table 4.9: Session Note Detail (Word Count per Session)

\textsuperscript{81} One aspect of these sessions that is not recorded is whether clients are taking notes on the action plans, or if these plans are just being established verbally. Credit counseling programs typically generate a concrete, written action plan for clients to follow, but financial coaching tends to be less formal than these counseling sessions. As such, the decision to write down action plans is likely left to the client’s discretion.
Table 4.9 and Figure 4.4 focus on the nature of the session notes themselves; here too there are major differences among coaches. In terms of the details around the sessions, as measured by an average of the word count in the notes for each session, Katherine and Diana include substantially more detail than their counterparts, with respective averages of 155.3 and 126.1 words per session recorded as compared to 74.4 and 79 words per session for Beverly and Tasha. All of these differences are significant below the one percent level. While some of this difference may be attributable to differences in writing styles among the coaches (for example, relying on full sentences instead of shorthand), a review of the notes indicates that this is only a partial and minor explanation at best. Diana and Katherine typically record some introductory details, then provide a fair amount of detail around the goals and the action plans they formulate with the client to help achieve that goal. Beverly is much briefer, often forgoing much introductory detail and focusing instead on succinctly listing goals and then outlining the strategy. Tasha is similarly brief and often (though not always) does not outline detailed goals and action plans; opting instead to list a relatively large number of client goals (a point
reinforced by Table 4.8). While the content of the coaches’ notes may differ along these lines, it
does not appear that differences in writing styles (e.g. using shorthand) is driving these
differences.

A similar pattern emerges when exploring the percentage of clients who have personal
details recorded about them by the coach, shown in Figure 4.4. Personal comments include any
personal detail about the client outside of the establishment of their goals or standard
demographic information, including major life events or fears and concerns held by the client.
Katherine records some personal note for about 80 percent of her clients ($\chi^2=6.82; p<0.01$),
which is dramatically higher than the other workers are. Tasha, by contrast, records personal
comments at slightly over half that rate ($\chi^2=3.14; p<0.1$). Diana and Beverly record personal
comments at slightly above and below the average of 54 percent, respectively.

Client Evaluations of Coaches

Another element of the coach/client relationship explored here is the client evaluations
of the coaching program itself. Unlike the previous data about the coaching sessions, which were
collected contemporaneously with the implementation of the program, these data were collected
from a follow-up survey conducted approximately one year after enrollment into the program.
This survey covered a wide array of financial topics and also contained a module asking the
clients who received coaching about their impressions of the program, asking on a scale of one
to five (from “strongly disagree” to “strongly agree”) if they enjoyed coaching, understood
coaching, had help setting and reaching goals from coaching, would recommend coaching, and
would do coaching again. Of the 108 clients who went through actual coaching sessions, 69
were able to be recontacted and completed the survey. As a note, overall client impressions of
the program were rather favorable, with majorities agreeing or strongly agreeing on every
metric. Given this, it was decided that the percentage of respondents who “strongly agree” with
each metric would be presented here to tease out a more detailed client perception of coach performance.

Figure 4.5: Client Responses to Coaching (% “Strongly Agree”)

Likely due in part to the relatively low base size for these questions, there were not many responses that came through as statistically significant when segmented by coach, so instead the examination of these data will be more descriptive in nature. Figure 4.5 shows the results for the client evaluations by coach. What is immediately clear from this analysis is that the two coaches who had the highest takeup rates, Beverly and Tasha, also seem to have the most favorable client perceptions in terms of their coaching performance. Interestingly, Beverly
appears to be the most engaging coach (over 60 percent of respondents strongly agreed that they enjoyed coaching sessions with her, which was the only significant difference ($\chi^2=4.6; p<0.05$) in this portion of the analysis), and she also had the highest takeup rates at 55 percent. Similarly, she also performs the highest concerning the percent of clients who would do coaching again, followed closely by Tasha. The coaches, who received the lowest percent of responses strongly agreeing they would do coaching again, Diana and Katherine, also had substantially lower takeup rates than their counterparts. As an additional point, Katherine (who performed the worst on this metric with only 14 percent of clients saying they would do coaching again) also had by far the fewest repeat coaching sessions with an average of 1.35 sessions per client. This, along with her performance in the client evaluations, low takeup rates, and difficulty in making voice contact with clients, indicates that she may have substantial difficulties in engaging potential clients.

The other interesting point to note here is that, qualitatively speaking, these client evaluations appear to be uncorrelated with client outcomes. This is to say that two of the coaches who performed on par with the program average in terms of delinquencies (Diana and Katherine) do not perform particularly favorably in their clients’ estimation relative to the average rating, while Tasha (who had double the rate of payment delinquencies as her counterparts) seems to have been perceived relatively favorably by comparison.

*Implementation Approaches and Outcomes*

Having gone through a wide array of different metrics capturing variation in individual workers’ approaches to implementing the coaching program, the next step is to attempt to synthesize these results to validate Assumptions 2a and 2b. For reference, Table 4.10 broadly summarizes the findings from the analysis of the various metrics in frontline implementation approaches.
From the prior examination of the data, at least three possible ways of categorizing implementation approaches emerge: Technology-oriented implementation, identity-oriented implementation, and promotion-oriented implementation.

The technology-oriented approach is an implementation approach that demonstrates a commitment to the mechanisms of client change underlying the coaching program. In coaching programs, these mechanisms include spending time with clients to get a sense of what their financial needs are, helping them generate goals, and developing action plans to guide the clients in pursuing those goals. From these data, technology-oriented implementation can be summarized in part by examining the amount of time clients spend in coaching sessions and the number of goals explored in those sessions. Diana, Katherine, and Beverly all have an average session length of over 20 minutes and Katherine and Beverly have average session lengths
significantly longer than average. Tasha, by contrast, is much briefer in the delivery of coaching sessions—almost five minutes shorter than the next briefest coach and over ten minutes shorter than Beverly. While time in a session itself is not necessarily indicative of a dedicated or high-quality coaching session, when compounded with the fact that Tasha also has the highest number of goals per session, this indicates that Diana, Katherine, and Beverly are spending more time on specific goals with their clients than Tasha. This is further supported by the qualitative exploration of how the individual coaches handle the development of action plans with their clients. Within the context of the existing research on frontline implementation, this implementation approach can be seen as representative of a frontline worker’s engagement with the program technology: They are more willing to spend longer times in coaching sessions and are more dedicated to guiding clients through the specifics of the behavioral changes necessary to reach their financial goals.

The promotion-oriented approach is exemplified by an ability to drive interest in the program and thus deliver the program at high rates, in line with Hypothesis 1. This is best seen in Tasha and Beverly, who not only had dramatically higher takeup rates than their counterparts but also were able to recruit clients for multiple coaching sessions at higher rates than Diana and Katherine. Similarly, Beverly and Tasha were the coaches who were the most engaging in the clients’ own estimations, based on their responses to the follow-up survey where they indicated that the sessions with these coaches were more enjoyable and that they would be relatively more willing to repeat coaching with Beverly and Tasha. This approach is in line with the approaches documented in the work on the importance of client-worker interactions in frontline implementation and the need to have workers with the skills (or willingness) to effectively communicate with clients and drive interest in the program being offered.

The identity-oriented approach is seen in the coaches who have relatively more focus on their client’s identity and the detail around their life outside of the establishment of financial
goals. This is what is explored in Table 4.9 and Figure 4.8 above, which outline the prevalence of personal comments about the clients in the session notes, as well as the detail of the session notes (using length of the notes as a proxy). This approach is characterized by Diana and Katherine, who (despite their low takeup rates) appear very focused on client details when they have coaching sessions. This approach, too, is in-line with the research on client-worker engagement, yet the frontline workers who best exemplify this approach notably fail to adequately promote the program to clients and drive program takeup.

A simple examination of Figure 4.1 shows that the coaches who practice a more technology-oriented implementation approach (Diana, Beverly, and Katherine) are also the coaches whose clients exhibit the best outcomes, which supports Hypothesis 2. When these coaches were pooled and a chi-squared test was run on the full sample of clients, their approach was significantly and negatively correlated with mortgage delinquency ($\chi^2=3.56; p<0.05$). Neither of the other approaches came through as statistically significant. As a confirmatory exercise that will also help quantify the impact of this approach, a series of probit regressions examining the relationship between implementation styles (in which each client was coded as ‘1’ if they had a coach practicing a given implementation approach and ‘0’ otherwise) and mortgage payment delinquencies are presented in Table 4.11.
This table presents a series of probit regressions measuring the impact that different implementation approaches have on the probability that a client will experience a severe mortgage delinquency. Standard errors are in parentheses.

\( n=295 \)

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

Table 4.11: Implementation Approach and Program Outcomes

Of the three implementation approaches specified, only the technology-oriented implementation approach significantly impacts the probability of a client having a serious mortgage delinquency in the first year after purchasing a home. This impact is robust to the inclusion of an indicator variable controlling for those clients who have credit scores characterized as “subprime” (below 640), indicating that the impact of technology-oriented implementation holds regardless of whether a client is relatively low-risk or high-risk in terms of their credit. Indeed, converting the probit coefficients into probabilities reveals that a client assigned to these coaches is less than half as likely to have a serious mortgage delinquency in the first year, even when controlling for subprime credit scores (7.2 percent versus 14.6 percent).
Discussion

This analysis has revealed several interesting insights into how client-worker interactions impact program success. Links between frontline dynamics and client outcomes (as opposed to outputs) are relatively rare in frontline implementation studies within the field of public administration (Domitrovich & Greenberg, 2000; Durlak & DuPre, 2008; Dusenbury et al., 2003). This analysis explicitly links frontline dynamics to client outcomes and does so in the context of a randomized, controlled trial, which is rarer still in implementation research.

The first key insight of this chapter is that implementation approaches differ substantially and appear to be more complicated than simple characterizations of “good” or “bad” program implementation. This is perhaps most obvious when considering the case of Tasha. In terms of making direct contacts with clients, getting them to enroll in the program, and engaging them in multiple instances of coaching, she was among the best. These attributes, combined with her relatively brief coaching sessions and focus on goal-setting for clients, give the impression of a frontline worker focused on efficiency. However, this efficiency may come with a price, as despite her relatively high program enrollment her clients had mortgage delinquency rates twice as high as other coaches’ client despite her clients having similar pre-treatment credit profiles to the other coaches’ clients. In terms of the theoretical framework underpinning this chapter, Tasha excels at client engagement but does not appear to fully engage with the program technology; she is less willing to dedicate the time required to really drive the people-changing processes in the program.

By contrast, Diana and Katherine performed comparatively well in improving client outcomes but struggled in actually enrolling clients into the program and the analysis in this chapter strongly implies that this is because they had difficulty “selling” the program to clients, even as they appear more qualified to transmit the program’s value than Tasha. It is entirely possible that this inability to convince clients to enroll in the program stems from clients feeling
disengaged with them, as is implied in the client survey responses on the coaches’ performance. In these two cases, the frontline workers appear committed to the change processes of the program technology but lack the skills (or traits) necessary to drive client engagement. From this, it can be argued that simply being concerned with clients and their identities may not be sufficient to “engage” clients; if clients cannot be convinced up-front to engage with coaches (i.e. if coaches cannot promote the program successfully), then focusing on the details of clients’ lives once they are in the program may be less relevant to overall program success.

Only Beverly seemed to perform in a way that might be considered “optimal,” combining the promotional abilities of Tasha with the program commitment of Diana and Katherine. Thus clients assigned to Beverly exhibited the highest take-up rates and among the best outcomes of all the coaches. Her ability to directly engage clients over the phone, the very favorable impressions of her held by clients (shown in the survey responses) and the length and apparent depth of her coaching sessions all appear from this exploratory review to be substantial contributors to the success of her implementation approach in terms of both program outputs and outcomes. In this case, she demonstrates an ability to quickly form productive relationships with clients as well as a commitment to engaging with the program technology; the length and depth of her sessions indicate that she is committed to the people-changing processes (the program technology) of this program.

It would be tempting to simply map these behaviors onto the established “people-processing” versus “people-changing” dynamic commonly occurring in the literature on frontline implementation (e.g. Hasenfeld, 1983, 2010). However, the underlying approaches appear more complicated. What separates implementers in this particular program is not a propensity to move through clients rapidly or take time with clients in order to improve their outcomes. Instead, what separates them appears to be an ability to have multiple competencies in
their implementation approach.\footnote{This finding provides a social service analogue to Sharma and Patterson’s (1999) work on financial advising relationships, which showed that both the ability to effectively communicate with clients and to provide high levels of service quality drove commitment levels in clients.} Tasha is very good at engaging clients and driving interest in program participation but is apparently unable to then take the required time to really focus on client needs and develop action plans that may enhance the program’s benefit for clients. Diana and Katherine fail to engage clients at levels comparable (or even close) to their counterparts but those who do choose to receive coaching from them receive in-depth sessions with more time spent on each goal and the development of action plans to achieve these goals. Beverly exhibits both competencies in that she is able to drive program take-up and program results and though she does not appear to focus as much on the relationship-building element of frontline implementation in this context, the client survey responses to her performance indicate that this is not necessarily a detriment.

The reason this may not map onto people-processing and people-changing behavior potentially stems from the nature of the program itself. As opposed to the public services that are the focus of much of the frontline implementation literature (e.g. police work, social work, welfare work, etc.) this program was voluntary, like an increasing number of government or government-sponsored services (Maynard-Moody & Portillo, 2010; Milward & Provan, 2000; Moe, 1987). When clients have a choice in their interaction with workers, people-processing becomes a much less viable strategy for workers as one of their core functions becomes to engage clients. This may be especially true when, in programs like this one, the funding received by the implementing agency is directly tied to the take-up rate and number of sessions delivered to clients. Given that relatively little of the frontline implementation literature focuses on more “customer-oriented” public service programs like the coaching program under study in this chapter and instead focuses on more traditional public programs and settings like welfare programs and police departments, the examination of frontline dynamics in this setting provides
one of the chief contributions of this work toward extending the frontline implementation literature. Developing the literature on implementation dynamics outside of traditional public service settings is important in advancing the implementation literature, as public services are increasingly being delivered outside of these contexts (Maynard-Moody & Portillo, 2010).

Another key finding of this analysis is the link between a specific implementation approach and client outcomes. Through what could best be described as triangulation, this work has qualitatively and quantitatively explored the commonalities and differences in a large array of program implementation attributes, the result of which is the finding that a technology-oriented approach where the coach spends a relatively large amount of time in sessions with the client to develop concrete action plans (and demonstrates a commitment to the program’s change process) is a primary driver of improved client outcomes. It is worth noting here that, given the findings of related research, this was not a foregone conclusion. Other implementation research has found that, for example, relationship building skills in frontline workers is a key driver of client improvements (Clark et al., 2002; Hall et al., 2012; Tout et al., 2012). This would imply that the approaches of Diana and Katherine, with their focus on the details of their sessions with the clients and their ability and willingness to elicit and record personal details about these clients, might be more successful than the approach of Beverly and Tasha, who are relatively sparse in their session details and do not track the personal details of their clients at the same rate. Additionally, the literature on how focusing can affect individual choices (e.g. Koszegi & Szeidl, 2012; Masatlioglu, Nakajima, & Ozbay, 2012; Sims, 2003) might imply that a promotion-oriented approach to coaching, with its high takeup rates and its encouragement of repeated sessions, would disproportionately help clients due to the fact that each session would provide focus on individual financial goals and financial obligations; this impact would be present regardless of the length or depth of the coaching session itself. Yet neither the relationship-oriented or promotion-oriented approaches appear to have strong links with the
improvements in client outcomes; only the implementation approach embracing the program technology and its change process that is clearly associated with stronger client outcomes.

**Limitations**

While this chapter has taken important steps toward delineating the relationship between implementation approaches, client engagement, and outcomes, and has done so in a program setting of increasing relevance to public administration scholars, it is necessary to point out several limitations to this analysis. The first is the small number of frontline workers under study in this chapter. The random assignment of clients to coaches strengthens the ability of this analysis to make inferences about the relationship between commonalities in implementation approaches and outcomes but the fact that there were only four frontline workers in this study nevertheless limits the ability to generalize to other settings. The program setting of this study, in which participation is voluntary, conducted over the phone, and focused on personal financial choices, also limits the ability of this chapter to generalize to other types of programs. Further, several of the measures employed in this chapter are likely impacted to a certain degree by instrumentation problems. Certain measures rely on the coaches’ accuracy in recording time, key events, and details of the sessions. Though reviews of the session notes indicate that there are no systemic problems in recording any of the metrics employed in this analysis, as the sessions and contacts attempts were not observed by an impartial recorder it is possible that there are still issues with these data. Finally, this chapter only examines one outcome variable. While the avoidance of mortgage delinquency is the chief outcome of interest for this program (which has the longer-term aim of avoiding mortgage default), it is possible that other outcomes may also be impacted by the frontline dynamics in this program. However, given that client financial profiles are likely in a high degree of flux around the time they buy a new home (for example, they may take on additional debt or spend down savings to make home repairs or improvements), it was
decided to focus on mortgage payment delinquencies, as these delinquencies present a concrete sign of financial distress in a way that other changes in financial profiles might not.

Implications and Future Research

Though this analysis is not without limitations, there are several policy implications that can be derived from this chapter. Most generally, through linking frontline implementation dynamics to program outputs and outcomes, this chapter underscores the importance of the frontlines of program and policy implementation to program success. Based on the discretionary choices of frontline workers, major differences in takeup rates and the key program outcome (avoidance of mortgage delinquency) were observed. This chapter has also revealed that different program contexts may require a different understanding of the relationship between program implementation and program success. In traditional public sector contexts where clients have little to no choice in interacting with frontline workers, the “promotion-oriented” implementation approach seen here is likely of limited utility; frontline workers do not need to convince potential clients to enroll in a food stamp program, for example. However, in voluntary programs like the financial coaching program under study, as well as many other nonprofit and public programs, being able to quickly engage clients and effectively promote the program is essential to driving program enrollment and program success.

Finally, this chapter has also revealed the importance of having multiple competencies among frontline workers. Being able to promote the program and drive enrollment is not the same as being able to effectively deliver the program and being able to effectively deliver the program is not sufficient to drive interest in the program. This finding leads to the conclusion that agencies should either provide training to develop both skillsets, or alternately to structure program implementation in such a way as to maximize the different skills of frontline workers: Those who have demonstrated an ability to engage clients and quickly form relationships with them can be used to make first contacts and drive enrollment, while those who show more
commitment or competence with the program technology itself can focus more on actual program delivery than client contact and enrollment. It should also be noted that the frontline workers demonstrating more commitment to the program technology by spending more time working with clients and developing more actionable plans were by some measures less efficient. They tended to enroll fewer clients in the program and spent more time on the clients they did enroll. As many social service agencies face budget and capacity constraints for their programs, there may be a limit to how much commitment to a program technology is “desirable.”

By demonstrating the role that specific competencies can play in driving the key metrics of program success, this chapter has also opened avenues for future research. Of particular interest is research that incorporates the understandings of worker behaviors from the private sector literature and investigates how different behaviors can drive client outcomes in the social services sector. For example, adapting behavioral scales such as those used in Hurley (1998) and explicitly measuring worker behaviors in the context of experimental program implementation (assuming the client assignment to a frontline worker was random) and linking those behaviors to variations in both program outputs and outcomes would provide a more rigorous link between frontline worker behaviors and program success criteria than simply exploiting available data within an experimental context to triangulate on a link between worker behavior and program success, as this chapter has done. Other studies might also investigate the benefits of structuring program implementation in such a way that capitalizes on worker competencies; for example by having more promotion-oriented workers drive take-up into the program while workers with a demonstrated ability to deliver the program successfully actually provide the treatment itself to clients.
Chapter 5: Conclusion

This dissertation set out to enhance the understanding of credit counseling programs, their clients, and their potential to improve client outcomes. Given the continuing prominence of consumer issues relating to financial management, debt, and credit, there is an important need to develop both theory and robust evaluations for credit counseling programs, which serve millions of people a year and have the potential to improve the welfare of people experiencing financial distress. The preceding chapters of this dissertation provide important research that enhances both the theoretical and empirical underpinnings of the credit counseling field.

The primary contributions of this work are (1) The framework providing concrete links between the target population characteristics, the level of service provided by agencies, the mechanisms embedded within these services, and the behaviors and outcomes potentially driven by these mechanisms; (2) The exploration of the financial, demographic, and behavioral profile of credit counseling clients, and how key indicators for these clients compare to the general U.S. population; (3) The impact analysis of a nationwide credit counseling initiative, which tracked client outcomes over time relative to a matched comparison group; and (4) The exploration of the dynamics at the frontlines of a financial coaching program embedded within a credit counseling agency. As such, this dissertation contributes to both theory and practice and does so in part through the use of control groups (both random and matched) to explore client impacts, a rarity in both the credit counseling literature and the social service program implementation literatures underpinning this dissertation.

Perhaps most importantly, this dissertation speaks to the potential for interventions to make concrete, positive impacts in financially-distressed or financially-vulnerable target
populations. With credit usage continuing to grow, savings levels remaining anemic, and an economy that continues to be volatile particularly for those on the lower end of the income spectrum, understanding whether certain interventions can improve outcomes is essential for policymakers, as is understanding the specific drivers of change in these programs. While this dissertation only presents analyses of two such interventions, through this work it provides evidence that these programs have the potential to assist financially-distressed populations and thus helps illuminate possible levers for policymakers to utilize in addressing the needs of these populations.

This research also contributes to the broader literature combining behavioral economics with public policy issues. Through enhancing the understanding of credit counseling and financial coaching programs, which contain change mechanisms that seek to correct fundamental behavioral deficits (such as an inability to regulate consumption, manage debt payments, and pursue financial goals), this dissertation speaks to the use of behaviorally-oriented programs to address public concerns. As interest in how understanding individual behaviors and biases continues to increase amongst both practitioners and researchers in the field of public policy (Shafir, 2013), documenting behaviorally-oriented programs that lead to positive client changes is a necessary step in both establishing the legitimacy of the behavioral approach to policy research and raising awareness of the behavioral tools available to policymakers. In providing empirical analyses assessing both credit counseling and financial coaching programs, this dissertation contributes to the growing literature on behavioral interventions. With respect to consumer finance initiatives alone, these interventions have included (among other things) retirement savings initiatives (Madrian & Shea, 2001; Thaler & Benartzi, 2004), using accountability mechanisms to drive commitments to financial goals (Ashraf et al., 2006), coaching initiatives for new homebuyers (Moulton et al., 2015), using goal commitments and implementation plans to drive savings behaviors (Loibl & Scharff, 2010), and policies raising awareness of debt
repayment schedules (Soll et al., 2013). In a sense, research on credit counseling initiatives like that found in this dissertation is uniquely suited to enhancing the behaviorally-oriented policy research in this vein, as credit counseling services provide a platform for addressing many of these policy concerns through a variety of behavioral tools. Credit counseling agencies can employ commitment devices like action plans, automatic reminders to resolve inattention problems, coaching models to provide accountability (in line with Lerner & Tetlock, 1999), and debt restructuring to improve the likelihood of repayment (Amar et al., 2011). This research, in providing an empirical base for understanding credit counseling programs, their clients, and their impact, also illuminates a class of interventions that are amenable to many previously-explored behaviorally-oriented program augmentations even as it speaks to the broader issues of employing behavioral approaches to solve public problems.

**Key Findings**

Each of the preceding chapters seeks to address a different set of issues or research questions; this section summarizes the approach and key findings of each chapter. To provide a theoretical lens to understand the role counseling can play in driving client outcomes and to address a relative dearth of theory development in this field, Chapter One of this dissertation developed a theoretical framework for credit counseling initiatives. In this framework, the decision to seek out credit counseling services is explained by non-financial client characteristics such as demography and individual motivation, as well as client financial characteristics such as their credit profiles (particularly their debt levels, payment histories, and credit scores), their income and expense levels, and the volatility of their income and expenses. Once clients decide to engage credit counseling services, they receive service outputs contingent on their financial profiles and the characteristics of the credit counseling organization. Client income and expense levels can determine their eligibility for a DMP, while organizational factors govern the emphasis put on DMPs, educational/counseling interventions, and supplemental services (like financial
coaching) offered to clients by the agency. Each of the core counseling services, which include financial education, budget counseling, and debt management programs, affect changes in client behaviors and outcomes through different programmatic mechanisms, broadly defined as “Information/Awareness,” “Planning/Intentions,” Monitoring/Support,” and “Altered Conditions.” Financial education, for example, uses information to convey the risks of high cost lenders, leading to the selection of lower cost lenders and subsequently to lower debt levels in the long run. Budget counseling can increase client awareness of sub-optimal financial behaviors (i.e. spending more money than they would like on eating out), which leads to their reducing unnecessary expenses and possibly leading to a growth in the client’s ability to save money. Budget counseling may also assist financial planning through the development of action plans and counselors may provide regular check-ins after credit counseling to monitor client progress towards their financial goals and provide additional support to clients. Debt management programs directly alter client financial conditions through, for example, consolidating payments for clients, enabling them to pay debts more consistently, and having less propensity to fall delinquent on their payments, thus improving their credit score in the long-run and providing them with access to debt products on more favorable terms. Each of these mechanisms is in turn influenced by the frontline workers interacting with the client; as their engagement with both the client and their “buy-in” to the programs, as well as their training, workload, and other factors govern the ways in which they deliver these services. The subsequent chapters of this dissertation explore different aspects of this framework.

Chapter Two uses four datasets to examine the demographic, financial, and behavioral profile of participants in the Sharpen Your Financial Focus credit counseling initiative and leverages the American Community Survey and the Survey of Consumer Finances to compare credit counseling clients to the general U.S. population across many of these indicators. This chapter also measures the self-reported financial behaviors and indicators of financial well-being
for these clients and how key credit indicators evolve for these clients from the period prior to credit counseling to a year and a half after counseling. The analysis shows that credit counseling clients are often driven to seek credit counseling because they are facing some unforeseen income or expense shock, either from the loss of a job or increased expenses. These shocks appear to manifest themselves in the credit outcomes for clients around the time they seeking credit counseling: On average clients experience a spike in payment delinquencies and a drop in their credit score between the pre-counseling period and the first post-counseling period and these metrics recover about a year after credit counseling. Credit counseling clients also have relatively low incomes and report extremely low levels of liquid savings at the time of counseling and these levels are well below those of the general U.S. population. Additionally, credit counseling clients also have substantially lower incomes, lower credit scores, higher levels of revolving debt, and higher reported rates of credit card usage than the average American. After credit counseling, clients see reductions in a variety of debt indicators and over two-thirds report that they are better managing their money, paying their debt more consistently, setting financial goals, and seeing improvements in their overall confidence.

Chapter Three presents an impact analysis of the nationwide Sharpen Your Financial Focus credit counseling initiative. This chapter uses Coarsened Exact Matching to create a non-counseled comparison group for clients in the Sharpen Your Financial Focus initiative and then assesses client outcomes relative to the comparison group (a differences-in-differences approach) through a series of fixed effects panel regressions. Compared to the counterfactual outcomes, Sharpen clients make significant reductions in their debt balances after credit 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, and are more pronounced when examining only those individuals who held debt in the baseline period. Clients
participating in agency-sponsored DMPs experience even greater reductions in debt balances relative to the comparison group than those not enrolled in DMPs. 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.

Chapter Four moves from the broad examination of credit counseling clients and program impacts to examine the frontline implementation dynamics in a single financial coaching program implemented experimentally within a credit counseling agency. Using a multi-method approach that includes the coding of session notes and statistical analyses of variations in implementation approaches and their relationship to program success, the analysis shows that the key program output (client take-up of coaching services) and the key target group outcome (the avoidance of severe mortgage delinquency) vary by the frontline worker implementing the program. This chapter also demonstrates that differences in outputs and outcomes are associated with differing approaches to client engagement, as well as different levels of worker engagement with the mechanisms the coaching program uses to drive change in a target population, also known as the “program technology.” Workers who are capable of successfully engaging clients are significantly more capable of driving program take-up rates and promoting the program, while workers who are more engaged with the change process of the program are significantly more capable of driving improved client outcomes.

Overall, this research demonstrates that while credit counseling initiatives can improve client outcomes, they are not a panacea. Credit counseling clients, generally speaking, are experiencing large degrees of financial distress and while their debt outcomes do show substantial improvement over a non-counseled comparison group, their credit scores are significantly lower than the comparison group’s a year and a half after counseling due drops in credit scores (and
increases in payment delinquencies) around the time clients are seeking credit counseling. This finding demonstrates both that credit counseling can serve as a tool for policymakers to leverage in addressing the persistent consumer credit and financial management issues faced by many U.S. households and that counseling agencies should seek to augment or supplement their core services in such a way as to offset these shocks (or limit their impact on client credit profiles).

Policymakers and practitioners should also seek to find ways to guide people into credit counseling services at the first signs of an unsustainable economic shock; pairing credit counseling services with the provision of unemployment benefits, for example, would give distressed households access to these services at the start of a crisis and help ensure that newly-unemployed individuals do not only seek credit counseling once their credit profiles have begun to deteriorate. This dissertation has also shown that the programs themselves may not be sufficient in driving outcomes but that dynamics at the frontlines of these agencies may contribute substantially to the success of these programs. In light of this finding, this dissertation encourages both practitioners and researchers to incorporate an understanding of implementation dynamics into their assessments of credit counseling and related interventions.

Limitations

The specific limitations of the research presented in this dissertation are discussed in each chapter, but broadly speaking the central limitation of this work is the inability to isolate specific drivers of client change. The marginal contributions to client outcomes of each core service offered by credit counseling programs (financial education, budget counseling, and debt management) were not explicitly examined in this research, although Chapter Three takes steps to tease out the marginal contribution of debt management plans to debt and credit outcomes. However, while specifying the contributions that each mechanism involved in credit counseling makes in improving client outcomes may provide value to both researchers and practitioners in this field, understanding the impact of the total bundle of counseling services on client outcomes
is still of substantial relevance to policymakers and practitioners given the relative lack of research rigorously examining credit counseling’s relationship to client outcomes. Additionally, though Chapter Four seeks to triangulate on the frontline dynamics driving variations in programs outputs and outcomes in a financial coaching program, the study was not explicitly constructed to experimentally isolate different implementation approaches. The random assignment of clients to coaches in Chapter Four allows for the isolation of coaching approaches as a driver of differences in program outcomes among workers but the fact that there were only four frontline workers in this study nevertheless limits the chapter’s ability to make categorical claims about the nature of these relationships.

There are also limitations in the generalizability of the work in this dissertation. While the program examined in Chapters Two and Three of this dissertation is fairly similar to other nonprofit credit counseling initiatives (particularly the counseling undertaken by NFCC member agencies), the clients in the impact analysis in Chapter Three only come from a subset of 13 credit counseling agencies and of these clients only the subset with a matched comparison individual are retained. Appendixes C and E of this dissertation explore client differences based on whether their agency participated in the credit analysis and whether they had a matched comparison individual in the impact analysis (conditional on their being in a participating agency). These analyses indicate that there are not many substantial differences based on the agencies in which clients were counseled, but did find that clients excluded from the matching analysis appear to be in relatively extreme financial distress and in particular are experiencing housing-related issues. While the impact analysis in Chapter Three does examine outcomes for extremely distressed clients specifically (defined by their credit risk profile at baseline), it may be that the generalizability of this work does not extend to clients who are experiencing financial troubles well above the average credit counseling client.
Additionally, credit counseling services are just one of many potential services that may benefit financially-distressed individuals. Within credit counseling agencies alone there are bankruptcy counseling and homeownership counseling programs that have some similarity with credit counseling, but the analysis of credit counseling in this dissertation likely only has limited generalizability to those programs as they target different client bases for different purposes. Outside of credit counseling agencies, there are debt settlement programs, financial empowerment programs (which can combine financial education with access to financial services), financial coaching programs, IDAs, and a variety of other programs that bear some similarity to credit counseling but ultimately the findings in this dissertation likely cannot be generalized among any of these programs.

The work on financial coaching and frontline dynamics in Chapter Four may also suffer from limited generalizability, as this work is based on a relatively small coaching pilot program implemented experimentally using only four frontline workers. This program was also housed in a credit counseling agency, which is not true of many financial coaching programs. Given this, the ability to generalize these results to the implementation of other financial coaching programs and to social service programs more generally may be limited.

Future Research

Credit counseling agencies are rich sources of potential research. With their access to a target population of distinct policy interest and their focus on an extremely complex issue, these agencies can serve as platforms for introducing program innovations to a wide variety of clients in an effort to help improve their financial outcomes. Future research in this area will focus on these programs; at the time of this writing several additional program innovations are currently being rolled out or developed by the NFCC and its member agencies. These innovations include tailored programs targeting key populations who can benefit from credit counseling (such as student loan borrowers) and a randomized, controlled trial of an automated reminder program that
uses text- and email-based messages to help clients keep track of their financial obligations and to remind them of the financial goals they set during their credit counseling sessions.

Beyond testing the impact of these supplemental or targeted innovations, future research should also experimentally examine variations in credit counseling’s core services. While it is somewhat infeasible to experimentally assess counseling itself (which would likely require turning away services from clients in need), it is possible to experimentally test augmentations of the financial education, budget counseling, or debt management services provided by credit counseling agencies. Conscientiously designing variations in these core services and testing them experimentally will allow for agencies to potentially optimize the design of their services and drive improvements in client outcomes beyond what has been observed in this dissertation.

One area where credit counseling could be evaluated experimentally may be in using counseling to supplement other existing interventions. In Chapter Two of this dissertation, the level of financial distress faced by credit counseling clients is illustrated by the volatility in their credit indicators around the time they are seeking credit counseling, and that chapter closed with a suggestion that credit counseling services could be tied to other interventions that also target financially-distressed households, such as unemployment benefit programs or disability insurance programs. Offering credit counseling as a supplemental intervention to already distressed or potentially distressed households could be done in an experimental fashion and provide an additional read on the benefits of credit counseling, even as generalizability would likely be limited due to the unique nature of the target populations. Other avenues for experimental analysis of credit counseling include offering student loan-specific counseling to new student loan borrowers (with the offer of counseling made randomly), or through randomized offers of credit counseling for individuals in other programs such as financial education or financial coaching initiatives.
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219


220


Readiness and Greater Twin Cities United Way.


Appendix A: The Three-Month Post Counseling Survey

The survey was offered to all Sharpen clients via email three months after they received credit counseling. The survey results are analyzed in Chapter Two and this Appendix includes the full text for the survey:

Since taking advantage of the Program three months ago,

1. Has your employment situation in your household: (Improved/Stayed the same/Worsened)

2. Has the number of household members: (Increased/Stayed the same/Decreased)

3. Has the available income: (Increased/Stayed the same/Decreased)

4. Have large, unexpected expenses: (Occurred/Not Occurred)

5. Have you moved? (Yes/No)

6. Have you or anyone in your household put in place any changes to better manage your money, such as a establishing a written budget or purchased financial software that allows you to better monitor your expenses? (Yes/No/Don’t know)

7. Have you ordered or received a copy of your credit report? (Yes/No/Don’t know)

8. Would you say that the total amount of credit card debt that your household carries has: (Increased/Decreased/Stayed the same/Don’t know)

9. Are you currently saving money? (Yes/No/Don’t know)

10. Would you say that the total amount of money you are able to save on a regular basis has: (Increased/Stayed the same/Decreased/Don’t know)

11. Have you opened or acquired any traditional financial products that you did not use before, such as a checking account, savings account, a debit card or a credit card? (Yes/No/Don’t
12. Have you paid late fees on any of your accounts or used overdraft protection (if applicable)? (Yes/No/Don’t know)

13. Have you taken out payday loans in the past 3 months? (Yes/No/Don’t know)

14. Would you say that you now pay your debt and monthly obligations more consistently that you did six months ago? (Yes/No/Don’t know)

15. How confident do you feel doing each of the following (please rank from 1-5, 5 being very confident):
   a. Taking care of my day-to-day finances
   b. Planning for future expenses like vacations, big purchases and emergencies
   c. Planning for my retirement
   d. Making my monthly mortgage/rent payment
   e. Paying off my loans and credit cards

16. Overall, how confident are you that your ability to manage your personal finances has improved? (Not at all confident/Confident/Extremely confident/Don’t know)

17. Do you set financial goals for the next one to two months for what you want to achieve with your money? (Yes/No)

18. Thinking of your relationship with financial institutions (such as your bank, car loan company or mortgage lender), do you feel that your level of trust in their ability to serve you well (i.e. advise and provide suitable products that meet your personal goals and lifestyle) has increased over the past six months? (Yes/No/Stayed the same/Don’t know)

19. Thinking of your relationship with financial institutions (such as your bank, car loan company or mortgage lender), do you feel that the quality of their customer service and responsiveness in general have increased over the past six months? (Yes/No/Stayed the same/Don’t know)

226
20. Which of the following financial institutions do you do the most business with? (List of major financial institutions)
Appendix B: Sample Comparisons: MMCU and Client Survey

This appendix compares the characteristics of clients (1) with linked MMCU data and (2) responding to the three-month follow-up survey, to the broader sample population. Only clients with MMCU data that could be linked to Sharpen administrative data were included in the analysis. MMCU linking was done via email address (the only unique identifier available in both datasets). In many cases, email addresses were missing or did not match.\(^83\) The three-month follow-up survey was administered via email and was completely voluntary and thus it is expected that there may be differences between clients who responded and did not respond to the survey. Using the Sharpen administrative data (available for all clients), the characteristics of clients with and without MMCU data, and who completed and did not complete the survey, can be compared.

Table B.1 presents the results of the comparisons. Overall, clients with linked MMCU data do not differ much from clients without linked MMCU data. While some characteristics are statistically different, the magnitude of the differences is relatively small. Specifically, there are relatively fewer black clients in the linked MMCU data and slightly higher baseline savings amounts and lower liabilities for linked clients.

Clients who completed the post-counseling survey, on the other hand, do have some notable differences from non-completers: They are more likely to be white, less likely to be male, and are slightly older, more educated, and have more savings and assets than non-completers. However, while these differences are statistically significant, they are not large in magnitude and

\(^83\) This was partially addressed by using a procedure known as “fuzzy matching” to link similar email addresses that may have had slight discrepancies (such as a missing letter) but this process could not fully overcome the issue of using multiple, substantially different email addresses.
overall the two groups look reasonably similar (particularly in terms of their income and expenses).

<table>
<thead>
<tr>
<th>Client Characteristics</th>
<th>MyMoneyCheckUp MMCU Data Linked</th>
<th>MyMoneyCheckUp MMCU Data Not Linked</th>
<th>Post-Counseling Survey Completed†</th>
<th>Post-Counseling Survey Did Not Complete</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Age</td>
<td>43.6**</td>
<td>43.3</td>
<td>44.6**</td>
<td>43.4</td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>18%***</td>
<td>23%</td>
<td>17%***</td>
<td>21%</td>
</tr>
<tr>
<td>White</td>
<td>66%</td>
<td>67%</td>
<td>76%***</td>
<td>66%</td>
</tr>
<tr>
<td>Male</td>
<td>35%***</td>
<td>33%</td>
<td>30%**</td>
<td>34%</td>
</tr>
<tr>
<td>Marital Status</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Married/Living with a Partner</td>
<td>41%</td>
<td>42%</td>
<td>43%</td>
<td>42%</td>
</tr>
<tr>
<td>Single</td>
<td>35%</td>
<td>35%</td>
<td>32%*</td>
<td>35%</td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High School Diploma</td>
<td>33%***</td>
<td>35%</td>
<td>27%***</td>
<td>34%</td>
</tr>
<tr>
<td>Four Year Degree</td>
<td>30%**</td>
<td>29%</td>
<td>38%***</td>
<td>30%</td>
</tr>
<tr>
<td>Financials</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Monthly Income</td>
<td>$3,384</td>
<td>$3,420</td>
<td>$3,495</td>
<td>$3,405</td>
</tr>
<tr>
<td>Monthly Housing Expenses</td>
<td>$1,076</td>
<td>$1,082</td>
<td>$1,110</td>
<td>$1,079</td>
</tr>
<tr>
<td>Monthly Debt-Related Expenses</td>
<td>$1,408***</td>
<td>$1,306</td>
<td>$1,384</td>
<td>$1,345</td>
</tr>
<tr>
<td>Tangible Assets</td>
<td>$77,054</td>
<td>$76,235</td>
<td>$88,634**</td>
<td>$76,329</td>
</tr>
<tr>
<td>Savings</td>
<td>$1,328***</td>
<td>$1,102</td>
<td>$2,076**</td>
<td>$1,173</td>
</tr>
<tr>
<td>Liabilities</td>
<td>$71,676***</td>
<td>$74,450</td>
<td>$78,178</td>
<td>$73,294</td>
</tr>
<tr>
<td>Observations</td>
<td>16,227</td>
<td>26,845</td>
<td>730</td>
<td>42,342</td>
</tr>
</tbody>
</table>

This table compares client characteristics based on clients for whom MMCU data is linked to portal data compared to those for whom it is not and for those who completed the post-counseling survey and those who did not. Significant differences are measured through t-tests (for continuous variables) and logistic regression (for binary variables such as race or marital status).

*Source: NFCC Administrative, MyMoneyCheckup, and Post-Counseling Survey Data*

†While 777 surveys were completed, only 730 of those were able to be linked to administrative data. This means that 47 of the respondents are contained within the set of 42,342 survey non-completers as the data required to link their surveys with the administrative data are not available. By definition, any individual completing the post-counseling survey was a Sharpen client.

Table B.1: Demographic Comparisons by Data Availability
Appendix C: Client Characteristics by Agency Evaluation Participation

This portion of the analysis assesses the degree to which clients from agencies participating in the credit analysis (Chapters 2 and 3 of this dissertation) are similar to clients participating in Sharpen Your Financial Focus generally. Here, administrative data are compared for 18,829 individuals\textsuperscript{84} in participating agencies and 24,243 in non-participating agencies. Table C.1 compares selected client characteristics between these agencies.

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.

\textsuperscript{84} This base size differs from the base size used in the credit analysis because it captures all the clients who enrolled in the study period, while the long-term credit analysis only includes clients who enrolled in the first quarter of the program; a decision made to facilitate the collection of at least a year and a half of post-counseling data on these clients. See Appendix D for a guide to the base sizes in this analysis.
### Table C.1: Client Characteristics by Agency Participation in the Long-Term Credit Analysis

<table>
<thead>
<tr>
<th>Client Characteristics</th>
<th>Participating Agencies</th>
<th>Non-Participating Agencies</th>
<th>Significance†</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (Years)</td>
<td>42.4</td>
<td>44.3</td>
<td>***</td>
</tr>
<tr>
<td>Male (%)</td>
<td>34%</td>
<td>33%</td>
<td>**</td>
</tr>
<tr>
<td>Marital Status</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Married or Living with a Partner (%)</td>
<td>43%</td>
<td>40%</td>
<td>***</td>
</tr>
<tr>
<td>Single (%)</td>
<td>36%</td>
<td>34%</td>
<td>***</td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black (%)</td>
<td>19%</td>
<td>22%</td>
<td>***</td>
</tr>
<tr>
<td>White (%)</td>
<td>69%</td>
<td>65%</td>
<td>***</td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Four-Year College Degree (%)</td>
<td>26%</td>
<td>33%</td>
<td>***</td>
</tr>
<tr>
<td>High School Graduate or GED (%)</td>
<td>32%</td>
<td>37%</td>
<td>***</td>
</tr>
<tr>
<td>Financials</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Monthly Income ($)</td>
<td>3,420</td>
<td>3,394</td>
<td></td>
</tr>
<tr>
<td>Monthly Housing Expenses ($)</td>
<td>1,162</td>
<td>1,010</td>
<td>***</td>
</tr>
<tr>
<td>Debt-Related Expenses ($)</td>
<td>1,132</td>
<td>1,527</td>
<td>***</td>
</tr>
<tr>
<td>Tangible Assets ($)</td>
<td>81,774</td>
<td>72,079</td>
<td>***</td>
</tr>
<tr>
<td>Savings ($)</td>
<td>940</td>
<td>1,402</td>
<td>***</td>
</tr>
<tr>
<td>Liabilities ($)</td>
<td>79,770</td>
<td>67,953</td>
<td>***</td>
</tr>
<tr>
<td>Total Clients</td>
<td>18,829</td>
<td>24,243</td>
<td></td>
</tr>
</tbody>
</table>

Source: NFCC Administrative Data

†Significance for continuous variables is measured by t-tests, significance for dichotomous variables is measured by chi-squared tests
Appendix D: Credit Evaluation Base Size Diagram

Figure D.1: Guide to Base Sizes at Different Stages of the Sharpen Evaluation
Appendix E: Comparing Matched and Unmatched Credit Counseling Clients

This appendix examines the differences between credit counseling clients for whom there was a matched comparison individual in Experian’s credit database with those clients for whom there was no match. Given the size of the potential pool of comparison individuals (a five percent random sample of all U.S. individuals Experian’s database), clients for whom no match could be found are likely to have relatively idiosyncratic credit profiles almost by definition and the analysis in this appendix bears that out. In total, there were 2,703 clients for whom no match was found. Nine were excluded because of incomplete data, leading to a final base size of 2,697.

Table E.1 shows the difference in baseline credit outcomes for matched and unmatched credit counseling clients. Though the matched clients are financially distressed (as demonstrated by the full analysis in this evaluation), clients for whom there was no match appear to be more distressed still. Credit scores for unmatched credit counseling clients are around 20 points lower than for matched clients and each debt measure explored is substantially higher for unmatched clients. Additionally, unmatched clients have over twice as many payments 60 days past due in the last year and over four times as many mortgage payments 90 days past due in the last two years.
### Table E.1: Credit Characteristics for Matched and Unmatched Counseling Clients

<table>
<thead>
<tr>
<th>Credit Indicators</th>
<th>Matched Counseling Clients</th>
<th>Unmatched Counseling Clients</th>
<th>Significance(^\d)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit Score</td>
<td>Mean(^\d) 592.7</td>
<td>Mean 572.5</td>
<td>***</td>
</tr>
<tr>
<td>Open Revolving Debt ($)</td>
<td>10,582</td>
<td>19,262</td>
<td>***</td>
</tr>
<tr>
<td>Total Installment Debt ($)</td>
<td>20,425</td>
<td>33,205</td>
<td>***</td>
</tr>
<tr>
<td>Mortgage Debt ($)</td>
<td>44,021</td>
<td>104,790</td>
<td>***</td>
</tr>
<tr>
<td>Number of Bankruptcies</td>
<td>0.30</td>
<td>0.36</td>
<td></td>
</tr>
<tr>
<td>Age of Oldest Account (Months)</td>
<td>182</td>
<td>214</td>
<td>***</td>
</tr>
<tr>
<td>Payments 60 Days Delinquent (Last 12 Months)</td>
<td>0.58</td>
<td>1.31</td>
<td>***</td>
</tr>
<tr>
<td>Mortgage Payments 90 Days Delinquent (Last 24 Months)</td>
<td>0.11</td>
<td>0.47</td>
<td>***</td>
</tr>
<tr>
<td>Balance to Credit Ratio on Revolving Debt</td>
<td>0.52</td>
<td>0.75</td>
<td>***</td>
</tr>
<tr>
<td>Total Clients</td>
<td>6,094</td>
<td>2,697</td>
<td></td>
</tr>
</tbody>
</table>

*Source: Credit Attributes Data*

\(^\d\)Significance measured by t-tests.

\(^\d\)Baseline measures for the counseling group differ slightly from earlier analyses in this evaluation because the observations in this supplemental analysis do not need to be weighted.

While this difference does not change the interpretation of the matching analysis, it does indicate that the matching analysis may be excluding clients in relatively extreme states of financial distress. The difference in mortgage debt levels and mortgage payment delinquencies in particular suggest that unmatched clients may be more prone to housing-related financial issues. This exclusion may raise concerns about the measurement of the overall treatment effect of Sharpen participation. However, this evaluation does track outcomes for exceptionally credit-distressed individuals in the matching analysis (defined by being in the 50\(^{th}\) or 25\(^{th}\) credit percentiles at baseline), so the question of Sharpen’s impact on distressed clients is at least partially addressed.

To assess the patterns in credit outcomes for unmatched clients, Table E.2 traces the credit score, total debt, and revolving debt for these clients over the evaluation period.
Interestingly, the overall change in credit scores for unmatched clients is similar to those in the matched group (as shown in Chapter Two). The debt indicators for these clients also drop over the study period at a similar rate to the matched group as well. The major difference between the matched and unmatched counseling clients on these metrics appears to be the baseline levels of the debt indicators, which are substantially higher for the unmatched group than the matched group. These debt reductions hold even when excluding any clients who had bankruptcies, charge-offs, or foreclosures over the study period: The full sample of unmatched clients reduce their revolving debt by 18 percent and their total debt by seven percent excluding these factors.
## Table E.2: Change in Credit Indicators Over the Evaluation Period For Unmatched Counseling Clients

<table>
<thead>
<tr>
<th>Credit Indicators</th>
<th>Pre-Counseling Quarter</th>
<th>First Quarter</th>
<th>Second Quarter</th>
<th>Third Quarter</th>
<th>Fourth Quarter</th>
<th>Fifth Quarter</th>
<th>Sixth Quarter</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Credit Score</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>25th Credit Percentile</td>
<td>503</td>
<td>504</td>
<td>515</td>
<td>536</td>
<td>549</td>
<td>559</td>
<td>567</td>
</tr>
<tr>
<td>All Clients</td>
<td>572</td>
<td>557</td>
<td>561</td>
<td>576</td>
<td>585</td>
<td>593</td>
<td>600</td>
</tr>
<tr>
<td><strong>Total Debt</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>25th Credit Percentile</td>
<td>$151,279</td>
<td>$144,528</td>
<td>$139,041</td>
<td>$130,908</td>
<td>$123,710</td>
<td>$115,486</td>
<td>$108,142</td>
</tr>
<tr>
<td>All Clients</td>
<td>$167,504</td>
<td>$162,064</td>
<td>$158,143</td>
<td>$148,603</td>
<td>$142,219</td>
<td>$136,669</td>
<td>$131,111</td>
</tr>
<tr>
<td><strong>Total Revolving Debt</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>25th Credit Percentile</td>
<td>$26,791</td>
<td>$24,383</td>
<td>$19,552</td>
<td>$15,327</td>
<td>$13,629</td>
<td>$11,869</td>
<td>$11,035</td>
</tr>
<tr>
<td>All Clients</td>
<td>$29,763</td>
<td>$28,411</td>
<td>$25,657</td>
<td>$21,650</td>
<td>$19,168</td>
<td>$17,510</td>
<td>$16,395</td>
</tr>
</tbody>
</table>

**n=2,697**

*Source: Credit Attributes Data*

Table E.2: Change in Credit Indicators Over the Evaluation Period For Unmatched Counseling Clients
Appendix F: Full Regression Output for Selected Models

Each of the following tables replicate key tables from the main analysis but provide the full output including quarterly impacts and treatment-quarter interactions. The coefficients on these time variables allow for the calculation of the relative trends in these indicators for the counseling and comparison groups.

While interpreting the overall change for credit counseling clients relative to the comparison group over the full evaluation period is simple (it is the coefficient on the “Counseling Client” indicator), interpreting the period-by-period changes for both groups requires additional explanation. To do this, the coefficients for each group must be interpreted and added together correctly. For the comparison group, their quarterly change relative to the baseline period is simply the coefficient on the quarter indicators: In the first post-counseling quarter the revolving debt (Model 1) for the comparison group decreases by ~$494 relative to the baseline period and by the sixth post counseling quarter the comparison group has reduced their debt by ~$2,098 relative to the baseline.

To assess the quarterly change for credit counseling clients relative to the baseline, it is necessary to add the total counseling coefficient to a given quarterly indicator and to the treatment quarter interaction for that quarter. So assessing the counseling change in revolving debt (Model 1) for the first quarter relative to the baseline involves adding the coefficients on the counseling client indicator (-3,637), the coefficient on the first post-counseling quarter indicator (-494), and the coefficient on the counseling-quarter interaction (3,919). This indicates that, relative to the baseline, the counseling group saw a decrease in their debt of ~$212 between
baseline and the first post-counseling quarter. To assess the relative difference in each quarter between counseling and comparison groups, simply take the coefficient the counseling client indicator and add it to the counseling-quarter interaction term for a given quarter. To illustrate, the counseling group had a decrease in their debt of $212 in the first post-counseling quarter while the comparison group had a decrease of $494, a difference of $282. Similarly, if one adds the coefficient on counseling clients (-3,637) to the coefficient on the first post-counseling quarter interaction (3,919) it adds to $282. Generally speaking, one can get a sense of the relative trends between the two groups by looking at the quarterly indicators over time. For example, in Model 2 the total debt for the comparison group is generally increasing (looking at the quarter indicators) while the total debt for the counseling group is generally decreasing (the treatment-quarter interactions).
## Table F.1: Differences-in-Differences Analysis - Client Outcomes on Key Debt Indicators

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Total Revolving Debt</th>
<th>Total Debt</th>
<th>Open Credit Ratio</th>
<th>Total Balance-to-Credit Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Counseling Client</td>
<td>-3,637.18***</td>
<td>-11,341.00***</td>
<td>0.04***</td>
<td>-0.04***</td>
</tr>
<tr>
<td></td>
<td>(341.88)</td>
<td>(1,368.07)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
</tbody>
</table>

### Quarter Indicators (Baseline as Reference)

<table>
<thead>
<tr>
<th>Quarter</th>
<th>Total Revolving Debt</th>
<th>Total Debt</th>
<th>Open Credit Ratio</th>
<th>Total Balance-to-Credit Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>1Q Post Counseling</td>
<td>-493.93***</td>
<td>512.71</td>
<td>0.03***</td>
<td>-0.03***</td>
</tr>
<tr>
<td></td>
<td>(94.55)</td>
<td>(657.35)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>2Q</td>
<td>-1,031.38***</td>
<td>1,735.79***</td>
<td>0.05***</td>
<td>-0.05***</td>
</tr>
<tr>
<td></td>
<td>(198.23)</td>
<td>(694.10)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>3Q</td>
<td>-1,516.85***</td>
<td>1,288.81*</td>
<td>0.08***</td>
<td>-0.07***</td>
</tr>
<tr>
<td></td>
<td>(209.31)</td>
<td>(776.91)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>4Q</td>
<td>-1,791.68***</td>
<td>1,391.67*</td>
<td>0.09***</td>
<td>-0.08***</td>
</tr>
<tr>
<td></td>
<td>(220.78)</td>
<td>(836.38)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>5Q</td>
<td>-2,032.59***</td>
<td>2,420.78***</td>
<td>0.09***</td>
<td>-0.09***</td>
</tr>
<tr>
<td></td>
<td>(227.78)</td>
<td>(868.70)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>6Q</td>
<td>-2,098.07***</td>
<td>2,808.70***</td>
<td>0.10***</td>
<td>-0.10***</td>
</tr>
<tr>
<td></td>
<td>(239.86)</td>
<td>(968.64)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
</tbody>
</table>

### Treatment Quarter Interactions (Final Quarter as Reference)

<table>
<thead>
<tr>
<th>Interaction</th>
<th>Total Revolving Debt</th>
<th>Total Debt</th>
<th>Open Credit Ratio</th>
<th>Total Balance-to-Credit Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment*1Q Post-Counseling</td>
<td>3,918.54***</td>
<td>12,014.93***</td>
<td>-0.05***</td>
<td>0.05***</td>
</tr>
<tr>
<td></td>
<td>(329.36)</td>
<td>(1,266.27)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Treatment*2Q</td>
<td>3,378.52***</td>
<td>9,290.58***</td>
<td>-0.03***</td>
<td>0.03***</td>
</tr>
<tr>
<td></td>
<td>(252.74)</td>
<td>(1,167.90)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Treatment*3Q</td>
<td>2,074.04***</td>
<td>6,277.40***</td>
<td>-0.02***</td>
<td>0.02***</td>
</tr>
<tr>
<td></td>
<td>(226.10)</td>
<td>(1,047.73)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Treatment*4Q</td>
<td>1,059.97***</td>
<td>4,075.49***</td>
<td>-0.02***</td>
<td>0.01***</td>
</tr>
<tr>
<td></td>
<td>(177.01)</td>
<td>(864.83)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Treatment*5Q</td>
<td>456.61***</td>
<td>1,540.19**</td>
<td>-0.01*</td>
<td>0.01*</td>
</tr>
<tr>
<td></td>
<td>(122.36)</td>
<td>(700.31)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>Constant</td>
<td>16,532.97***</td>
<td>82,582.95***</td>
<td>0.49***</td>
<td>0.52***</td>
</tr>
<tr>
<td></td>
<td>(100.20)</td>
<td>(406.35)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
</tbody>
</table>

| 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 |

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
### Table F.2: Differences-in-Differences Analysis - Client Outcomes on Key Credit Indicators

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Credit Score</th>
<th>Payments 60 Days Delinquent (Past 6 Months)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Counseling Client</strong></td>
<td><strong>-6.76</strong>*</td>
<td><strong>-0.01</strong></td>
</tr>
<tr>
<td></td>
<td>(1.23)</td>
<td>(0.03)</td>
</tr>
<tr>
<td><strong>Quarter Indicators (Baseline as Reference)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1Q Post Counseling</td>
<td>3.78***</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>(0.49)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>2Q</td>
<td>6.24***</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>(0.61)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>3Q</td>
<td>10.67***</td>
<td>-0.04**</td>
</tr>
<tr>
<td></td>
<td>(0.67)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>4Q</td>
<td>11.45***</td>
<td>-0.05**</td>
</tr>
<tr>
<td></td>
<td>(0.73)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>5Q</td>
<td>12.95***</td>
<td>-0.07***</td>
</tr>
<tr>
<td></td>
<td>(0.79)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>6Q</td>
<td>14.64***</td>
<td>-0.07***</td>
</tr>
<tr>
<td></td>
<td>(0.83)</td>
<td>(0.02)</td>
</tr>
<tr>
<td><strong>Treatment Quarter Interactions (Final Quarter as Reference)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treatment*1Q Post-Counseling</td>
<td>-9.55***</td>
<td>0.22**</td>
</tr>
<tr>
<td></td>
<td>(1.19)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Treatment*2Q</td>
<td>-12.14***</td>
<td>0.45**</td>
</tr>
<tr>
<td></td>
<td>(1.10)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Treatment*3Q</td>
<td>-8.81***</td>
<td>0.31**</td>
</tr>
<tr>
<td></td>
<td>(1.01)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Treatment*4Q</td>
<td>-4.86***</td>
<td>0.15**</td>
</tr>
<tr>
<td></td>
<td>(0.86)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Treatment*5Q</td>
<td>-3.11***</td>
<td>0.08**</td>
</tr>
<tr>
<td></td>
<td>(0.66)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Constant</td>
<td>595.12***</td>
<td>0.46**</td>
</tr>
<tr>
<td></td>
<td>(0.39)</td>
<td>(0.01)</td>
</tr>
<tr>
<td><strong>R-squared</strong></td>
<td>0.03</td>
<td>0.01</td>
</tr>
<tr>
<td><strong>Observations (Individuals*Quarters)</strong></td>
<td>82,859</td>
<td>84,693</td>
</tr>
<tr>
<td><strong>Unique Individuals</strong></td>
<td>11,837</td>
<td>12,099</td>
</tr>
</tbody>
</table>

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
## Table F.3: Differences-in-Differences Analysis - Client Outcomes on Key Credit Indicators

(50th Credit Percentile at Baseline)

<table>
<thead>
<tr>
<th>Treatment Quarter Interactions (Final Quarter as Reference)</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment*1Q Post-Counseling</td>
<td>2,012.69***</td>
<td>-10.29***</td>
<td>0.34***</td>
</tr>
<tr>
<td></td>
<td>(381.00)</td>
<td>(1.78)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Treatment*2Q</td>
<td>1,552.82***</td>
<td>-10.89***</td>
<td>0.45***</td>
</tr>
<tr>
<td></td>
<td>(285.87)</td>
<td>(1.67)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Treatment*3Q</td>
<td>1,059.17***</td>
<td>-7.09***</td>
<td>0.27***</td>
</tr>
<tr>
<td></td>
<td>(276.14)</td>
<td>(1.55)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Treatment*4Q</td>
<td>519.33***</td>
<td>-4.30***</td>
<td>0.11**</td>
</tr>
<tr>
<td></td>
<td>(194.78)</td>
<td>(1.34)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Treatment*5Q</td>
<td>81.37</td>
<td>-2.22**</td>
<td>0.07**</td>
</tr>
<tr>
<td></td>
<td>(91.93)</td>
<td>(1.03)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Constant</td>
<td>7,195.09***</td>
<td>526.27***</td>
<td>0.96***</td>
</tr>
<tr>
<td></td>
<td>(115.89)</td>
<td>(0.55)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.03</td>
<td>0.08</td>
<td>0.02</td>
</tr>
</tbody>
</table>

**Observations (Individuals*Quarters)**

| 37,135 | 36,694 | 37,135 |

**Unique Individuals**

| 5,305 | 5,242 | 5,305 |

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
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

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Total Revolving Debt</th>
<th>Credit Score</th>
<th>Payments 60 Days Delinquent (Past 6 Months)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Counseling Client</td>
<td>-526.09</td>
<td>7.49***</td>
<td>-0.17</td>
</tr>
<tr>
<td></td>
<td>(355.70)</td>
<td>(2.57)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>Quarter Indicators (Baseline as Reference)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1Q Post Counseling</td>
<td>-578.28***</td>
<td>12.67***</td>
<td>-0.15***</td>
</tr>
<tr>
<td></td>
<td>(104.97)</td>
<td>(1.08)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>2Q</td>
<td>-1,211.23***</td>
<td>20.47***</td>
<td>-0.50***</td>
</tr>
<tr>
<td></td>
<td>(211.26)</td>
<td>(1.37)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>3Q</td>
<td>-1,480.31***</td>
<td>27.64***</td>
<td>-0.64***</td>
</tr>
<tr>
<td></td>
<td>(221.06)</td>
<td>(1.42)</td>
<td>(0.08)</td>
</tr>
<tr>
<td>4Q</td>
<td>-1,633.85***</td>
<td>30.66***</td>
<td>-0.68***</td>
</tr>
<tr>
<td></td>
<td>(230.59)</td>
<td>(1.65)</td>
<td>(0.08)</td>
</tr>
<tr>
<td>5Q</td>
<td>-1,708.34***</td>
<td>34.34***</td>
<td>-0.75***</td>
</tr>
<tr>
<td></td>
<td>(234.95)</td>
<td>(1.69)</td>
<td>(0.08)</td>
</tr>
<tr>
<td>6Q</td>
<td>-1,722.11***</td>
<td>40.27***</td>
<td>-0.80***</td>
</tr>
<tr>
<td></td>
<td>(236.28)</td>
<td>(1.87)</td>
<td>(0.08)</td>
</tr>
<tr>
<td>Treatment Quarter Interactions (Final Quarter as Reference)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treatment*1Q Post-Counseling</td>
<td>490.07*</td>
<td>-10.35***</td>
<td>0.32***</td>
</tr>
<tr>
<td></td>
<td>(265.22)</td>
<td>(2.54)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>Treatment*2Q</td>
<td>351.11***</td>
<td>-9.80***</td>
<td>0.29***</td>
</tr>
<tr>
<td></td>
<td>(133.14)</td>
<td>(2.39)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>Treatment*3Q</td>
<td>234.72**</td>
<td>-5.74**</td>
<td>0.19**</td>
</tr>
<tr>
<td></td>
<td>(92.17)</td>
<td>(2.29)</td>
<td>(0.08)</td>
</tr>
<tr>
<td>Treatment*4Q</td>
<td>148.41***</td>
<td>-3.05</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>(53.43)</td>
<td>(1.94)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Treatment*5Q</td>
<td>83.68***</td>
<td>-0.55</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>(30.15)</td>
<td>(1.54)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Constant</td>
<td>3,631.72***</td>
<td>487.04***</td>
<td>1.48***</td>
</tr>
<tr>
<td></td>
<td>(130.24)</td>
<td>(0.74)</td>
<td>(0.04)</td>
</tr>
</tbody>
</table>

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 F.4: Differences-in-Differences Analysis - Client Outcomes on Key Credit Indicators (25th Credit Percentile at Baseline)
Appendix G: Excerpt from the Financial Coaching Training Manual

This Appendix features an excerpt from the financial coaching training manual provided to coaches by the Ohio Housing Finance Agency. Specifically, this Appendix focuses on the guidance received by coaches in helping clients formulate action plans to achieve their goals, a key mechanism in the coaching process.

Fine-tune the Action Plan: Clearly define client’s goals

The MyMoneyPath Action Plan will help you during the next part of your coaching session.

After the client filled out the online Check-Up in which they listed small goals or “action steps,” they were given the following prompts to create their Action Plan

1. Prioritize your action steps
2. Plan how you will complete each action step
3. Plan when you will complete each action step

Here is a sample Action Plan:

**Borrowing**

Goal: Pay down debt by $102 each month
Step: Plan to pay extra on your credit cards each month
How: Sit down with my husband and figure out how we will do this
When: July 15, 2011

Here are a few places to look for help:

- [Tools: Use a credit card repayment calculator.](#)

Step: Review the interest rates on your credit cards
How: Look for your credit card interest rate on your next statement. Research other credit card options.
When: June 10, 2011

Here are a few places to look for help:

- [Tips: Learn about credit card interest rates.](#)
It is now your job to help the client tweak or re-define their goals, with a focus on 1) breaking down large goals into smaller goals and 2) clearly defining those actionable steps that you will help them achieve in the months ahead.

**Breaking down goals**

Oftentimes clients have a larger goal (establish a $5000 rainy day fund), nested inside of which are a number of smaller goals (learn where my money is currently going, change troubling spending patterns, find ways to bring in more revenue, establish a budget and stick to it. Then put $XX away every month for XX months and put away half of my tax returns too until I reach $5000).

While your client may not be able to reach the larger goal of saving $5000 over the course of our 12 month program, they may be able to figure out how they spend their money currently, change some patterns, seek out additional revenue sources, and create a realistic budget.

Without the larger goal, the client is not motivated to take the first step toward the smaller goal. Without the smaller goals, the client feels powerless to achieve the large goal.

Help your client break down large goals into smaller, more manageable goals that are action steps toward that large goal.

**TIP:** Your client will come up with their own goals and action steps, but you can prompt them with good questions to get them thinking.

**How many goals/action steps per coaching session?**

Only your client knows what is manageable for them in a 3-month period. It is not your job to define goals for the client. But you should ask them the right questions so that you get a feel for how much they want to do in the break between coaching sessions. Once you have an idea of how much time they have, you can help them create an action plan that will respect that time commitment.

Of course some clients are going to under-commit and some will over-commit. Many will have the best intentions and be hit with unexpected barriers over the coming months. Your job is to reflect the ambitions of the client at this point in time, encourage them to reach toward their aspirations, and be there to provide accountability down the road.

a. **Define S.M.A.R.T action steps**

Once you have some clear-cut action steps listed out, you will help the client define them in a **Specific, Measurable, Attainable, Realistic, and Time-bound (SMART)** way.

**Example**
Client says: I guess the first action step I want to accomplish is to see what I’m really spending my money on.

A SMARTly redefined action step might be:

- I will sit down with my spouse this weekend and make a list of all of the non-monthly but still regular expenses we can think of (e.g. annual insurance premium, holiday shopping, back-to-school shopping, vacation, vet bill, quarterly water bill)

- Then starting Monday I’ll save all of my receipts and track my spending in a handwritten log for one month

- At the end of the month I will make a spreadsheet of these, add in my online bill payments and a 1/12th portion of the annual expenses my spouse and I listed out

- I will categorize my expenses as “must-spend,” “could-spend-less,” or “could-cut”

**Showing the coach progress**

Throughout the process of defining action steps, plan together how the client will demonstrate their progress to you. It is this accountability that is the key to financial coaching success.

You need not pore over or evaluate detailed financial information nor provide the advice or counsel of a financial planner. Encourage the client to seek outside resources like their benefits office at work, nonprofit or professional experts, or reputable online tools.

But the client should present you with an affirmation that they have completed their action steps. This will likely come in the form of a phone call or email from the client telling you what they have done. By scheduling these affirmations to come at mutually-established dates in between coaching sessions, you can help keep the client on track to achieve all of their action steps over the three-month period.