A Little Knowledge Is a Good Thing: Empirical Evidence of the Effectiveness of Pre-Purchase Homeownership Counseling

May 22, 2001

Abdighani Hirad
Voice: (703) 903-2223
abdi_hirad@freddiemac.com

Peter M. Zorn
(corresponding author)
Freddie Mac
8200 Jones Branch Drive, MS# 484
McLean, VA 22102-3110
Voice: (703) 903-2898
FAX: (703) 903-4045
peter_zorn@freddiemac.com

We are deeply indebted to Jim Carey for providing us with the opportunity to do this research and for sharing his knowledge about counseling, to Oliver Zeng for his outstanding work in developing the loan matching routine, and to Jim Berkovec for his econometric insights and consultation. The views expressed in this paper are ours alone, and do not necessarily represent those of Freddie Mac or its Board of Directors.

Abstract

For the past three decades, homeownership counseling has been an integral part of affordable lending in the United States. Counseling's popularity has been based in large part on the belief that borrowers receiving counseling are better able to handle the responsibilities of homeownership. To this point, however, there has been no convincing empirical evidence to support this view.

This study uses data on almost 40,000 mortgages were originated under Freddie Mac's Affordable Gold program to pose three questions: Does pre-purchase homeownership counseling demonstrably reduce 90-day delinquency rates? Do the different types of pre-purchase homeownership counseling programs vary in their effectiveness at reducing delinquency rates? Are any counseling providers more or less effective in administering their programs?

We find that counseling can be effective in reducing mortgage delinquency. In our data, borrowers receiving counseling have, on average, a 19 percent lower 90-day delinquency rate. We find, moreover, that different counseling programs vary in their effectiveness. In particular, borrowers receiving counseling through individual programs experience a 34 percent reduction in delinquency rates, all things equal, while borrowers receiving classroom and home study counseling obtain 26 percent and 21 percent reductions, respectively. We find no evidence that telephone counseling mitigates credit risk. Nor, after controlling for the mix of counseling programs, do we find that counseling providers vary in their effectiveness in reducing delinquency rates.

Finally, we also attempt to determine whether our estimated impacts capture only the effect of counseling itself, or whether they also are driven by possible endogeniety of borrower assignment/selection into the counseling programs. We find that counseling itself has a significant impact on delinquency rates, and that this impact varies across the types of counseling programs. We also confirm the specific impact of classroom counseling. However, although borrowers receiving individual or home study counseling have lower delinquency rates, we are unable reliably to confirm that this reduction comes

from the counseling itself rather than the assignment/selection of borrowers into these programs.

I. Introduction and Overview

For the past three decades, homeownership counseling has been an integral part of affordable lending in the United States and has been credited with myriad benefits. Its advocates believe, for example, that counseling better prepares borrowers to recognize and accept the responsibilities of owning a home. By helping to get households into homes they can afford, and can afford to keep, homeownership counseling has been credited with stabilizing families and neighborhoods and reducing default risk to lenders.

This study uses data on almost 40,000 mortgages originated under Freddie Mac's Affordable Gold program to assess the claim that pre-purchase homeownership counseling programs lower mortgage delinquency rates. We find statistical evidence that counseling does, in fact, mitigate credit risk. Borrowers who receive pre-purchase homeownership counseling under the Affordable Gold program are, on average, 19 percent less likely to become 90 days delinquent on their mortgages than borrowers with equivalent observable characteristics who do not undergo counseling.

We also find significant variation in effectiveness across classroom, home study, individual, and telephone counseling. Our data clearly indicate that borrowers receiving individual counseling have the greatest mitigation in credit risk. All things equal, borrowers receiving individual counseling experience a 34 percent reduction in 90-day delinquency rates, an outcome that is superior to and statistically different from that obtained from either home study or telephone counseling. Classroom and home study counseling reduce delinquency rates at 26 percent and 21 percent, respectively, and are superior to telephone counseling, which has no statistically significant impact on borrower delinquency.

Affordable Gold borrowers receive counseling from a variety of sources, including government agencies, lenders, mortgage insurers, and non-profit organizations. Our basic analysis, however, offers no statistical evidence that any provider administers counseling in a manner that is either more or less effective in reducing credit risk. Borrowers receiving counseling from non-profit organizations and lenders do, on average, have lower 90-day delinquency rates than borrowers counseled by other providers. This, though, primarily appears to reflect the more effective mix of counseling these groups provide.

Our data are not collected as part of a controlled experiment. We therefore also consider the possibility that the effects we attribute to counseling are, in fact, due to unobserved characteristics associated with borrowers' assignment/selection into counseling programs. Statistical tests strongly reject the hypothesis that counseling's estimated effectiveness results entirely from such unobserved characteristics. Moreover, our best estimate, after accounting for these unobserved characteristics, is that counseling is more — rather than less — effective. We also statistically confirm the previously identified differences in effectiveness across alternative counseling programs, as well as differences across providers. We are unable, however, to confirm statistically that the effectiveness of individual and home study counseling is not the result of borrower assignment/selection.

This study is the first to provide significant empirical evidence that pre-purchase homeownership counseling can effectively reduce borrower delinquency rates.[1] Not withstanding some unresolved issues, any evidence of homeownership counseling's risk mitigation effectiveness is welcome news. Affordable lending programs historically have pushed the limits of underwriting in an effort to offer the benefits of homeownership to the greatest number of families. Pre-purchase counseling by no means eliminates the greater credit risk of these programs — even with counseling, affordable lending programs' loans probably will be among the riskiest of mortgages originated by most prime lenders. The empirical evidence presented in this paper does demonstrate, however, that pre-purchase homeownership counseling can increase the success of affordable lending programs by helping families keep their homes, a substantial benefit to both borrowers and lenders.

II. Overview of Homeownership Education and Counseling

Counseling generally is conducted as part of a broader initiative to extend homeownership opportunities. As a consequence, counseling programs are geared mostly toward first-time homebuyers and specifically toward minority families, immigrants, city dwellers, and others who have yet to attain homeownership at the national average rate.[2] Homeownership education and counseling began in earnest about 30 years ago, primarily in response to the high incidence of defaults and foreclosures among HUD section 235 participants. Today, homeownership education and counseling programs in the United States take an almost bewildering variety of forms. Lenders, non-profit organizations, government agencies, and others separately administer programs. The program themselves are delivered through many different avenues, including classroom, home study, individual counseling, and the telephone. The content of programs also varies significantly across each of these administrative and delivery mechanisms, as does the timing of the counseling — pre- or post-purchase.

Timing is a key distinction in counseling. Pre-purchase counseling and education are designed to better prepare families for the responsibilities of homeownership by explaining the home buying and financing process, encouraging financial planning and money management, and going over home maintenance and repair issues and concerns. Post-purchase counseling shares much of this focus but generally spends more time on individual budgeting and maintenance and repair issues. This study focuses entirely on pre-purchase counseling.

Another important distinction is that drawn between counseling and education. Counseling is specific and is tailored to the particular needs of the individual, while education typically is administered in a generic program. Although this distinction is independent of the format, an individual format generally implies counseling because it is a one-to-one session where borrowers can discuss their individual situations and concerns. Classroom counseling also can fall into this category because, although it is administered to a group of borrowers, it too can provide personal attention, can break sessions into several units, and often covers more subjects than the typical individual format. Home study and telephone formats, however, generally are considered education rather than counseling. In these formats, borrowers engage in self-study by following a generic program. They sometimes have an opportunity to interact with a counselor, but generally this is restricted to the administration of an exam.

While recognizing and acknowledging this distinction, we use the terms counseling and education interchangeably. This reflects the fact that it is impossible in our data to distinguish accurately between borrowers receiving homeownership counseling or education, as well as a preference for parsimony in prose.

There are manifold motivations for supporting homeownership counseling. Counseling can, for example, provide consumer outreach in nontraditional markets, build trust in the mortgage lending process, and provide lenders with mortgage-ready applicants. A central premise, however, is that effective counseling significantly reduces borrower delinquency rates. Despite any clear empirical evidence supporting this claim, or, perhaps more accurately, because of its belief in counseling's not-yet-demonstrated benefits, in 1993 Freddie Mac required all Affordable Gold borrowers to receive pre-purchase homeownership counseling.

Counseling in 1993 was supplied predominantly in a classroom or one-on-one setting. Freddie Mac's policy change — and an equivalent decision by Fannie Mae — significantly increased the demand for counseling in the mid-1990s. The current prominence of home study and telephone counseling is largely the result of this pressure on supply. Both home study and telephone counseling have the advantages that they can be put into place relatively quickly, can be accomplished with less time commitment from either the borrower or the provider, and are far less expensive to administer than either individual or classroom counseling. Telephone counseling is the more recently adopted of these two. Its advocates view it as an improvement over home study because it provides at least some personal contact with a third party.

III. Data on Freddie Mac's Affordable Gold Loans

The data used in this study are loans purchased by Freddie Mac under its Affordable Gold program, which was designed specifically to help open the doors of homeownership to borrowers who earn 100 percent or less of area median income.[3] Starting in 1993, Freddie Mac has required every Affordable Gold loan it purchases to have at least one qualifying borrower who receives pre-purchase homeownership counseling. Lenders are free to determine the characteristics of the counseling borrowers receive, but loans submitted for Freddie Mac's purchase must record the organization that provides the counseling (lender, non-profit, government agency, or "other") and the type of counseling delivered (classroom, home study, individual counseling, or "other").[4]

Fortunately for our study, a natural quasi-control group is formed by the fact that roughly 3 percent of Affordable Gold loans are exempted from Freddie Mac's homeownership counseling requirements. Mortgages qualify for this exemption on the basis of their perceived lower risk, specifically if: (1) at least one co-borrower has previously owned a home, (2) the loan-to-value ratio of the mortgage is 95 percent or less, or (3) borrowers have cash reserves after closing equal to at least two monthly mortgage payments. Not all borrowers meeting these criteria are exempted from counseling, but for those who are exempted, lenders record "education not required" in the administration and delivery fields described above.

Regardless of whether Affordable Gold borrowers do or do not receive counseling, we append servicing records to each loan in our data. Servicing records are available through 2000:IIQ, so to ensure that there is a minimum of 18 months of performance history for every loan, our analysis includes only loans originated from 1993:IV through 1998:IVQ. Borrowers are classified as experiencing repayment difficulties if, over the observation period, their servicing record shows that they have ever been 90 days or more late on scheduled mortgage payments.[5]

In addition, Freddie Mac maintains a variety of data on each loan in its portfolio, including many of the variables typically incorporated into standard underwriting models, such as loan-to-value ratio, FICO score, and total-debt-to-income ratio. These and other variables are used in running each Affordable Gold loan through an "emulated" version of Loan Prospector®, Freddie Mac's automated underwriting service.[6]

Freddie Mac's customers use Loan Prospector to get an immediate, accurate assessment of whether applications meet Freddie Mac's "investment quality" purchase standards. Loan Prospector, consequently, delivers a value of "accept" to applications that meet this standard, and a value of "caution" to those that appear not to. For the purposes of this study, however, we need a measure that captures more subtle variations in risk. For this reason we use an intermediate product from Loan Prospector, AUS score, a variable that measures the probability that a loan will go into foreclosure. Low values of AUS scores indicate a high probability of foreclosure (the minimum is roughly 500), high values indicate a low probability of foreclosure (the maximum is roughly 1,500), and a decrease of 60 points in AUS scores doubles the odds of foreclosure.

We also include three additional sets of variables to account for observable differences that may affect the risk characteristics of borrowers. First, we include characteristics of the mortgage and the property — loan origination amount, loan purpose, number of units, and property type. Second, we include demographic variables of the borrower — borrower race/ethnicity, minority population in the Census tract, family income, median income in the Census tract, and whether the borrower is a first-time homebuyer. Third, we include variables to account for different economic environments experienced by borrowers — whether the property is located in an MSA, the quarter when the loan was originated, and the state in which the property is located.

IV. Methodology

This study poses three questions: Does homeownership counseling demonstrably reduce 90-day delinquency rates? Do the different types of counseling programs vary in their effectiveness? Are any of the counseling providers more or less effective in administering their programs? We answer these questions using a logit model estimating the probability that borrowers ever become 90 days or more delinquent.[7] Specifically, we estimate the following equation

$$(1) \qquad P(delinquent) = \frac{\exp\left(X^1\beta^1 + X^2\beta^2 + \varepsilon\right)}{1 + \exp\left(X^1\beta^1 + X^2\beta^2 + \varepsilon\right)}$$

where, X^1 is a matrix composed of columns of dummy variables, one for each type of counseling/counseling provider combination (a total of 16 mutually exclusive columns, where borrowers exempted from counseling are the omitted category), X^2 is a matrix composed of columns of observable independent variables thought to be associated with mortgage delinquency, β^1 and β^2 are column vectors of estimated coefficients, and ε is a column vector of error terms assumed to be independently and identically distributed extreme value.

The β^1 can be interpreted as estimates of the marginal impact of alternative counseling programs on 90-day delinquency rates. We can, therefore, express our research questions in terms of restrictions on the β^1. Specifically, if counseling has no effect on delinquency rates, then β^1 will be zero. This leads to a test of the null hypothesis

(2) $$H_0^1 : \beta^1 = 0 .$$

Likewise, if the different types of counseling are equally effective in reducing delinquency rates, then every provider's estimated coefficients will be the same across all counseling types. This leads to the null hypothesis

(3) $$H_0^2 : \beta_{ik}^1 = \beta_{jk}^1 \quad \forall i, j \in T, \forall k \in P$$

where, T is the set of all types of counseling and P is the set of all counseling providers. Finally, if counseling providers are equally effective in administering their programs then each counseling type's estimated coefficients will be the same across all providers. This yields the null hypothesis

(4) $$H_0^3 : \beta_{ij}^1 = \beta_{ik}^1 \quad \forall j, k \in P, \forall i \in T .$$

In addition to this basic analysis, we also attempt to address the fact that borrowers in our data are not randomly assigned to counseling programs. More specifically, counseling programs likely are endogenously assigned/selected. If the error term of the underlying counseling program assignment/selection model is correlated with ε, then estimates of β^1 in equation (1) will be biased and inconsistent. As an example, disproportionately more "motivated" lower-risk borrowers may choose to receive the more intensive classroom and individual counseling, resulting in an overestimate of these programs' benefits.

We address this concern with a two-stage estimation procedure designed to purge any correlation between the error terms in these two models.[8] We first estimate a model of borrower assignment/selection into counseling programs. We then incorporate these probability estimates into an alternative version of equation (1). Specifically, we estimate the logit model

$$(5) \qquad P(delinquent) = \frac{\exp\left(\hat{P}(X^1)\gamma^1 + X^2\gamma^2 + \eta\right)}{1 + \exp\left(\hat{P}(X^1)\gamma^1 + X^2\gamma^2 + \eta\right)}$$

where, $\hat{P}(X^1)$ is a matrix of predicted probabilities that borrowers are assigned to/select alternative counseling programs, γ^1 and γ^2 are column vectors of estimated coefficients, and η is a column vector of error terms assumed to be independently and identically distributed extreme value.[9] Finally, we retest the null hypotheses in equations (2) through (4), after first substituting γ^1 for β^1.

$$(6) \qquad H_0^4 : \gamma^1 = 0 .$$

$$(7) \qquad H_0^5 : \gamma_{ik}^1 = \gamma_{jk}^1 \quad \forall i, j \in T, \forall k \in P$$

$$(8) \qquad H_0^6 : \gamma_{ij}^1 = \gamma_{ik}^1 \quad \forall j, k \in P, \forall i \in T$$

V. Empirical Results

Exhibit 1 provides the distribution of the loans used in the study across the various homeownership counseling programs. A total of 39,318 Affordable Gold loans are originated between 1993:IQ and 1998:IVQ. Of this number 1,238 loans (roughly 3 percent of the total) are exempted from counseling.

The 38,080 loans receiving counseling are far from uniformly distributed across counseling types and providers. The distribution across types of counseling, for example, is quite skewed — 43 percent of counseling is delivered through home study, 34 percent is delivered through telephone, and just 10 percent and 9 percent of borrowers receive individual and classroom counseling, respectively. All told, lenders provide 50 percent of the counseling, mortgage insurers provide 44 percent, non-profit organizations provide 3 percent, and government agencies administer counseling to only 2 percent of borrowers.

The uneven distribution of Affordable Gold loans across these categories is less than ideal from an experimental design perspective. In particular, rates of loans that have ever been 90 days delinquent will be measured with greatest precision for the counseling types and providers having the greatest number of observations, and with least precision for those having the fewest observations. We are, consequently, most likely to find that counseling generates statistically significant risk-mitigating benefits when it is home study provided by lenders or telephone counseling administered by mortgage insurers. This concern notwithstanding, exhibit 1 illustrates that there are sufficient data to assess the efficacy of counseling across types and providers, with, perhaps, the small exception of "other" counseling provided by government agencies and non-profit organizations.

Delinquency rates of Affordable Gold loans also are shown in exhibit 1 under the far right-hand column labeled "Percent ever 90 days delinquent." Looking first at the bottom of that column, Affordable Gold loans taken as a group clearly are higher risk than the average non–Affordable Gold loan in Freddie Mac's portfolio — the rate of those who were ever 90 days delinquent on Affordable Gold loans is 6.9 percent, relative to a portfolio average of 1.8 percent.[10] Nor do Affordable Gold borrowers receiving pre-purchase homeownership counseling outperform those that do not — 6.9 percent of Affordable Gold borrowers receiving counseling end up going into 90-day delinquency while only 5.7 percent of the Affordable Gold borrowers who do not receive counseling perform as poorly. There is, however, substantial variation in ever-90-days delinquency rates across alternative counseling delivery mechanisms, with values ranging from a low of 3.0 percent (individual counseling administered by mortgage insurers) to a high of 9.8 percent ("other" counseling provided by government agencies).

Finally, exhibit 1 shows that there are significant differences in the risk characteristics of borrowers across the various counseling programs. For example, the column labeled "Mean AUS Score" shows that average AUS score values range from as low as 867 for individual counseling provided by non-profit organizations to as high as 941 for "other" counseling provided by lenders.

Each type of counseling, moreover, has lower mean AUS scores (*i.e.*, higher risk characteristics) than loans without counseling. As a result, Affordable Gold borrowers receiving counseling have an average AUS score of 900, compared to an average AUS score of 943 for Affordable Gold borrowers receiving counseling. This offers an explanation for the observed higher 90-day delinquency rates of borrowers receiving counseling; as well as the suggestion that counseling does indeed mitigate risk. If a 60-point reduction in AUS score roughly doubles the odds of 90-day delinquency in our data, borrowers receiving counseling should have $2^{43/60} = 2^{0.7} = 1.6$ times greater odds of becoming delinquent than those not receiving counseling. In fact, the odds of delinquency are $\frac{6.9/93.1}{5.7/94.3} = 1.2$ times greater, suggesting that, on average, counseling reduces 90-day delinquency rates by roughly 25 percent.

A. Basic Analysis

Our strategy, as noted above, is to improve on this crude estimate by using a logit model to control for AUS scores and other factors that may influence 90-day delinquency rates. Exhibit 2 provides summary statistics of the independent variables used in this logit estimation. No characteristics of the data particularly stand out. As expected from exhibit 1, there is significant variation in AUS scores across Affordable Gold borrowers — the distribution of AUS scores has a standard deviation of 104. The mean loan origination amount is \$94,000. On average Affordable Gold borrowers have family incomes that are 83 percent of area median, and reside in Census tracts with 20 percent minority populations and median family incomes that are 86 percent of area median.[11] Most of the loans in our analysis are taken out for the purpose of purchasing single-family, one-unit properties. About 56 percent of Affordable Gold borrowers are first-time homebuyers and about 93 percent of them reside in an MSA. A little over 70 percent of the borrowers are white, 26.5 percent are minority and 3.2 have unknown race/ethnicity.

Exhibit 3 provides the results from our logit estimation of loans becoming 90 days delinquent. Looking first at the estimated coefficients on the counseling variables, we see clear evidence that pre-purchase homeownership counseling can significantly reduce 90-day delinquency rates. Among the 16 estimated coefficients there are seven that are statistically significant at the 10 percent level — classroom counseling by lenders and non-profit organizations, home study counseling by government agencies and lenders, individual counseling by lenders and mortgage insurers, and "other" counseling by lenders. All seven of these coefficients are negative in value, implying that borrowers receiving these types of counseling have significantly lower delinquency rates than borrowers with similar observable characteristics who receive no counseling.

Not surprisingly, it is the counseling types with the greatest number of observations that generally are statistically significant. An interesting exception to this trend is telephone counseling by mortgage insurers; received by over one-third of Affordable Gold borrowers, telephone counseling has no statistically significant effect on 90-day delinquency rates. Before we explore these coefficients in greater detail, however, we briefly turn to the other variables in the model.

Most of estimated coefficients on the control variables have the expected signs and are statistically significant. The estimated coefficients on the AUS score groupings, for instance, are monotonically decreasing as the risk of the loan decreases (*i.e.*, as AUS scores increase) and almost all are statistically significant. They do suggest, however, that a 60-point AUS score reduction less than doubles the odds of 90-day delinquency — on average, estimated coefficients increase by 0.44 with each 50-point reduction in AUS score, implying that the odds of delinquency increase by $\exp(0.44) = 1.5$, somewhat less than the assumed $2^{50/60} = 2^{0.8} = 1.8$ increase required to double the odds.[12]

We also find that delinquency rates decrease as loan origination amounts increase, and, somewhat surprisingly, for borrowers who take out mortgages on condominiums (relative to single-family units). Purchase money mortgages, as usually is the case, are less likely to ever be 90 days delinquent. First-time homebuyers are no more or less likely than repeat-home buyers to become delinquent. As is typically found in these types of estimations, African-American borrowers are more likely to experience repayment difficulties than non-minority borrowers, and the higher the ratio of minority population in the Census tract the more likely borrowers are to become delinquent. We find no statistically significant association between delinquency and median tract income, although borrowers living in an MSA are more likely to become delinquent, as are borrowers with lower family income. Finally, we include loan origination data and state fixed-effects, neither of which are reported here but both of which are statistically significant as a group.

Exhibit 4 provides goodness-of-fit measures for the logit estimation. The graph in the top panel of the exhibit depicts the distribution of delinquent loans across predicted probability deciles. If our model perfectly fit the data 100 percent of the delinquent loans would be distributed into the (high risk) 10th probability decile. Our estimation, obviously, does not achieve this standard. Nonetheless the graph illustrates that our model does a reasonably good job of distinguishing between loans that will and will not become 90 days delinquent. For example, only 1 percent of delinquent loans are found in the (low risk) 1st probability decile, while 37 percent of delinquent loans are in the (high risk) 10th probability decile.

The lower panel of exhibit 4 provides three additional measures of fit — the Hosmer–Lemeshow test statistic, mean predictions of the dependent variable, and the Kolmogrorov–Smirov (K–S) test statistic. All three measures show that the model does a good job in distinguishing loans that become 90 days delinquent. The Hosmer–Lemeshow test statistic shows that we cannot reject the null hypothesis that the model provides a good fit to the data.[13] Mean delinquency predictions also vary appreciably for loans that have and have not been 90 days delinquent; mean predictions are 17.7 percent for delinquent loans, compared to 6.2 percent for loans that never become delinquent. Finally, the K–S test statistic strongly rejects the null hypothesis that our model cannot distinguish between loans that will and will not become 90 days delinquent.[14]

We turn now to our specific research questions and tests of the associated null hypotheses. Our first research question is whether counseling has a statistically significant impact on 90-day delinquency rates. Our discussion of the logit results clearly suggests that it does, and this is confirmed by our strong rejection of H_0^1.[15] Similarly, we reject H_0^2, providing evidence that different types of counseling vary significantly in their effectiveness at reducing delinquency rates.[16] We are, however, unable to reject H_0^3, finding no evidence of counseling providers' differential effectiveness in administering their programs.[17]

We explore these research questions more fully using simulation results designed to estimate the reduction in 90-day delinquency rates provided by each of the counseling types. Reductions in delinquency rates are displayed in exhibit 5 in matrix format, where the rows represent the type of counseling borrowers receive and the columns represent the counseling provider. The far right column of the first five rows shows the marginal effect of each type of counseling, the first four columns of the last row show the marginal effect of each counseling provider, and the fifth column of the last row shows the average effect of counseling across all types and providers.

To construct each estimate in exhibit 5, we simulate the outcome of conceptual experiments that first create perfect matched-pairs for each of the 39,318 Affordable Gold loans in our data and then randomly assign one pair-member to a treatment group and the other pair-member to a control group. We create the control group by using our logit estimates to predict 90-day delinquency rates for each of the 39,318 Affordable Gold loans in the data, while assigning each loan the impact of receiving no counseling (*i.e.*, setting $\beta^1 = 0$). We create each "treatment" group by using our logit estimates to predict 90-day delinquency rates for each of the loans in the data, while assigning them the impact of receiving one of the counseling type/provider combinations (*i.e.*, setting $\beta^1 = \beta^1_{ij}$). The treatment effect from counseling is then estimated separately for each loan by calculating the ratio of "treatment" predicted delinquency rate to "control" predicted delinquency rate, and converting this to a percentage reduction. The values presented in exhibit 5 are the means of these percentage reductions across all 39,318 Affordable Gold loans in our data.[18]

The main portion of exhibit 5 (columns one through four and rows one through five) clearly shows that counseling can successfully decrease 90-day delinquency rates. All but two of the simulation point estimates are positive, and some imply quite substantial risk-mitigating effects. The simulations also show, however, that all counseling is not equally effective. Statistically significant reductions from pre-purchase homeownership counseling range from a low of 23 percent (home study counseling by lenders) to a high of 55 percent (individual counseling by mortgage insurers). Not all estimates, moreover, are statistically significant.

Perhaps the simplest way to assess the differential impact of alternative types of counseling is by considering their marginal effects. The far-right column of exhibit 5 shows simulation results calculating the marginal effect of each counseling type. These marginal estimates confirm that there is a clear rank ordering in counseling's effectiveness. Individual counseling is the most effective and provides an estimated 34 percent reduction in 90-day delinquency rates. This is followed by classroom and home study that provide, respectively, 26 and 21 percent risk mitigation. Telephone counseling provides an estimated 8 percent reduction in delinquency rates, but this result is not statistically differentiable from zero.[19] Tests show, moreover, that individual counseling's superiority to both home study and telephone is statistically significant, as are both classroom and home study counseling's superiority to telephone.[20]

Looking at the marginal effects of counseling provider (*i.e.*, the last row of exhibit 5) we also see a clear rank ordering. As noted earlier, however, we find no statistical difference in the effectiveness of providers in administering counseling programs. The differentials we see in the marginal effects, therefore, come from the mix of counseling administered by each provider, not from statistically significant differences in administering any given type of counseling.

Finally the overall effect of counseling is shown in the lower right-hand corner of exhibit 5 in the cell labeled "All Types" and "All Providers." We find that borrowers who receive pre-purchase homeownership counseling are, on average, 19 percent less likely to become 90 days delinquent on their mortgages than borrowers with equivalent observable characteristics who do not undergo counseling.

B. Assignment/Selection Analysis

We now turn briefly to the results of our two-stage procedure for addressing potential endogeneity in counseling assignment/selection. Our first stage estimates a nested logit model of borrower assignment/selection into counseling programs. Estimated coefficients from this model are applied to each Affordable Gold borrower to predict the probabilities of receiving each type of counseling from each counseling provider, as well as being exempted entirely from counseling. Our second stage estimates the delinquency model of equation (5).

Details of these procedures are provided in the appendix. We note here, however, that our nested logit model is not particularly well fitting and that our second stage estimation of 90-day delinquency rates suffers from symptoms of multicollinearity. Notwithstanding these problems, the results of these and auxiliary estimations allow us to test the null hypotheses H_0^4, H_0^5, and H_0^6.

Our first null hypothesis assesses whether, after controlling for the endogeneity of assignment/selection, counseling has a statistically significant impact on 90-day delinquency rates. Once again we confirm that it does — we strongly reject the null hypothesis that the γ^1 in equation (5) all are equal to zero.[21] Counseling's estimated effectiveness, therefore, clearly is not due entirely to unobserved differences in borrower characteristics.

Despite rejection of H_0^4, however, our individual point estimates of counseling types and programs are estimated quite imprecisely and only the coefficients on classroom counseling are found to be statistically significant. This imprecision affects our estimate of counseling's average impact, and it too is not statistically significant. Nonetheless we note that an estimated 37 percent average reduction in 90-day delinquency rates from counseling suggests, albeit weakly, that accounting for endogeneity of assignment/selection tends to increase rather than decrease counseling's predictiveness effectiveness.

We also are able to reject H_0^5, finding that, even after accounting for borrower assignment/selection, there are statistically significant differences across types of counseling in their effectiveness at reducing 90-day delinquency rates.[22] The marginal impacts for each type of counseling suggest roughly the same rank ordering of effectiveness as our basic analysis although the point estimates generally are much larger than previously and classroom is not found to be more efficient than individual counseling. The standard errors also are quite large, however, and only classroom counseling shows statistical significance on average in reducing delinquency rates. Surprisingly, we also reject H_0^6, finding that providers do show differential effectiveness in administering counseling programs.[23] This last result is inconsistent with our earlier analysis.

In summary, our assignment/selection analysis provides mixed results. On one hand it supports the overall conclusion from our basic analysis that counseling can significantly reduce 90-day delinquency rates, and that different types of counseling vary in their effectiveness. Moreover, we are able to confirm classroom counseling's effectiveness in risk mitigation. On the other hand, however, our relatively poor success in predicting borrower assignment/selection prevents us from reliably demonstrating that individual's and home study's effectiveness is not due to borrower assignment/selection. Moreover, our point estimates suggest that, after accounting for assignment/selection, classroom may be more effective than individual counseling.

VI. Implications and Caveats

The results presented in this study provide the first empirical evidence of the past 20 years that pre-purchase homeownership counseling can significantly reduce the delinquency rates of borrowers. Our results also demonstrate, however, that not all counseling programs are equally successful. In particular, we find that borrowers receiving individual counseling have the lowest delinquency rates. Classroom and home study also are associated with lower borrower delinquency rates, but telephone counseling is found to have no statistically significant impact.

These empirical results are not unexpected; many in the counseling industry have argued for years that individual and classroom counseling are by far the more effective tools. There is value to validating this claim, however. If nothing else, it confirms the crucial role that counseling can play in expanding affordable homeownership opportunities for America's families.

It also raises implications for whether and how counseling should be provided. Over one-third of the borrowers in Freddie Mac's Affordable Gold program, for example, receive telephone counseling, a delivery mechanism with no demonstrable effectiveness in reducing delinquency rates. That this is the case is not surprising, classroom and individual counseling are much more expensive to provide and in many locations are available only in limited quantity. It does, however, question the necessity of requiring all borrowers in affordable lending programs to receive counseling. A more effective strategy, at least from the point of view of risk mitigation, might be to require counseling only for the highest risk borrowers in affordable lending programs, but to require that it be provided in either an individual, classroom or home study format.

Although we have confidence in our conclusions, our results are not definitive and it is important to close with a few caveats. First, the data used in this study do not come from a true experiment. We attempt to control for differences in the risk characteristics of borrowers, but are unlikely to be entirely successful and omitted variables may bias our results. Borrower assignment/selection, moreover, may account for some of the benefits attributed to homeownership counseling. Our attempt at addressing this endogeneity confirms the effectiveness of classroom counseling, but is unable to do so for either individual or home study counseling.

Second, the data for this study originate between 1993 and 1998. Our conclusions, consequently, pertain only to counseling conducted during that period. The counseling industry recently has undergone significant maturation, however, leading to more consistency in counseling efforts and course content. It is likely that these changes have improved counseling's effectiveness, and therefore our analysis probably underestimates the benefits of current counseling programs.

Third, our data provide no information on post-purchase counseling or course content, so we can say nothing about their risk-mitigating effectiveness. Fourth, and finally, our focus on those who are ever 90 days delinquent ignores any of counseling's possible beneficial impacts on the timing of delinquency or the severity of any ultimately occurring loss.

VII. References

Judge, George G. *et al* (1980), *The Theory and Practice of Econometrics*, New York: John Wiley & Sons, Inc.

Mallach, Allan (2001), "Home Ownership Education and Counseling: Issues in Research and Definition," Federal Reserve Bank of Philadelphia discussion paper.

McCarthy, George and Roberto Quercia (2000), "Bridging the Gap Between Supply and Demand: The Evolution of the Homeownership Education and Counseling Industry," *The Research Institute for Housing America*, Institute Report Number 00-01.

Quercia, Roberto and Susan Wachter (1996), "Homeownership Counseling Performance: How Can It Be Measured?" *Housing Policy Debate*, vol. 7, no. 1.

VIII. Endnotes

IX. Appendix: Details of Borrower Assignment/Selection Analysis

In this section, we briefly describe our borrower assignment/selection analysis. The first step in our analysis is to estimate a four-stage nested logit model in which borrowers are assigned/selected into receiving or not receiving counseling. In the second stage, borrowers receiving counseling are assigned/select either counseling service providers or industry participants. In the third stage, borrowers assigned/selecting counseling service providers are allocated between government agencies and non-profit organizations, and borrowers assigned/selecting industry participants are allocated between lenders and mortgage insurers. In the fourth stage, borrowers are assigned/selected into the four types of counseling (classroom, home study, individual, or "other") available from each counseling provider. Estimation of the model is accomplished separately by stage, starting with the fourth. Appropriate inclusionary terms are incorporated into the estimation of stages three, two and one. Results of the eight separate logit estimations that make up the nested logit model are omitted in an effort to save space and the reader's patience.

Identification of the assignment/selection model is ensured by inclusion of variables not in the delinquency model (seller type, borrower age, borrower gender, loan-to-value ratio, and MSA population) and functional form. There are many unobserved factors, however, that probably are important in explaining counseling assignment/selection (*e.g.*, when, in the process, borrowers apply for/receive counseling and the available supply of counseling providers).

As a result, the nested logit estimation yields an adequately but not especially well-fitting model. This is illustrated in exhibit 6, which shows the mean predicted probabilities of each counseling type/provider combination (converted to percentages) for each subgroup of actual type/provider outcomes. The first row of exhibit 6, for example, shows the predicted probabilities for borrowers actually receiving classroom counseling from lenders.

If the nested logit model is particularly well fitting then the mean predicted probability will be highest for classroom counseling by lenders. This is not the case here, both home study by lenders and telephone counseling by mortgage insurers have higher mean probabilities. This result, however, is not particularly surprising because both home study by lenders and telephone counseling by mortgage insurers occur with high frequently in the data. A less stringent fit criterion is to compare down each column of exhibit 6 rather than across each row. In this instance, the assessment involves comparing across borrower subsets of actual assignment/selection to see if the model assigns the highest mean probability to the type of counseling borrowers actually receive (*i.e.*, are the diagonal elements of the exhibit 6 matrix the largest probability in each column). The nested logit model does far better by this measure; there are only three columns where this criterion is not met: individual counseling by non-profit organizations, and "other" counseling by non-profit organizations and government agencies.

Our next step is to use the predicted probabilities of borrower selection/assignment to estimate the probability of loans becoming 90 days delinquent. The result of this estimation is shown in exhibit 7. The coefficients for the control variables in the borrower selection/assignment model are very similar to those in exhibit 3. The coefficients for counseling type/provider, however, generally are quite a bit larger in absolute value. The standard errors are larger also, and only classroom counseling provided by lenders has a statistically significant effect in this estimation. Finally, as in exhibit 3, most counseling type/provider coefficients are negative, apart from home study counseling provided by government agencies and mortgage insurers and individual counseling provided by government agencies.

Exhibit 8 provides goodness-of-fit measures for the logit estimation of the borrower selection/assignment model. Despite the high standard errors on the counseling type/provider coefficients, the nested logit model fits roughly as well as the basic model.

The model presented in exhibit 7, however, is not entirely robust to alternative specifications. The far-less-than-perfect fit of the assignment/selection nested logit model provides relatively small variation in the predicted values for many counseling type/provider alternatives, as well as relatively high correlations across predictions of alternative counseling types/providers. As a result, the estimated counseling type/provider coefficients display many symptoms of multicollinearity. We crudely address this problem through a series of auxiliary estimations, each of which reduces the dimensionality of the 1 X column vector.

For example, we estimate separate classroom counseling coefficients for each of the four providers while constraining provider's coefficients to be identical across all other types of counseling (i.e., $\gamma_{ij}^{1} = \gamma_{ik}^{1}\ \forall j,k \in T$ and $\forall i \neq classroom$). This approach yields no significant reduction in log likelihood but does substantially change the point estimates for some coefficients. In particular, we find that the estimated coefficients for classroom counseling are negative and significant for all providers. Because the results of these auxiliary estimations appear more robust, we rely on them and use them to conduct our simulations.

Exhibit 9, the equivalent of exhibit 5, shows the results of simulations designed to estimate the reductions in 90-day delinquency rates provided by each of the counseling types/providers. The overall pattern is not dissimilar to that of the basic model, although the point estimates are far larger in absolute value. From a statistical standpoint, only classroom counseling is found to have a significant impact in reducing 90-day delinquency rates.

[1] The empirical studies that have been conducted are 20 or more years old and generally are viewed as unconvincing. A review and critique of existing statistical studies are provided in Mallach (2001) and Quercia and Wachter (1996).

[2] This section relies heavily on excellent reviews of homeownership counseling programs by Mallach (2001) and McCarthy and Quercia (2000).

[3] Borrower's income generally is restricted to no more than 100 percent of area's median income (120 percent in California, 170 percent in Hawaii, 165 percent in the New York City MSA, and 120 percent in the Boston MSA). Incomes, however, may be higher through specially negotiated Community Development Lending alliances or other specially negotiated programs offered through housing finance agencies, public agencies, and non-profits.

[4] Our investigations reveal that "other" in the administration field consists largely of mortgage insurers. "Other" in the delivery field consists largely of telephone counseling for mortgage insurers, which is a hybrid of classroom and individual counseling for lenders and is unknown for government agencies and non-profit organizations.

[5] Analyses conducted using rates for those who have ever been 60 days delinquent provide qualitative results similar to those presented here.

[6] We use an "emulated" version because some of the variables required by Loan Prospector are unavailable in the Freddie Mac data. The missing variables primarily are limited to borrower reserves and detailed credit variables. The emulated version generally provides a good approximation of the full Loan Prospector model but is unable to fully assess nuances in credit risk.

[7] In addition to the logit estimation, we conduct an equivalent analysis using *ex-post* matched pairs. Each Affordable Gold borrower in our data is matched along observable individual and loan characteristics to a non–Affordable Gold borrower from among Freddie Mac's loan purchasers, few of whom, if any, receive homeownership counseling. The effectiveness of homeownership counseling is then assessed by comparing the mean delinquency rates of Affordable Gold loans (in total, and grouped separately by type of counseling program) to the mean delinquency rates of the loans with which they have been matched. The results of the matched-pair analysis are qualitatively similar to those presented here.

[8] See, for example, Judge (1980, chapter 18.5.1) for a brief discussion of similar procedures.

[9] The estimates of γ^1 resulting from this two-step procedure will be consistent but inefficient, providing a conservative test for our null hypotheses.

[10] The values for the Freddie Mac portfolio are computed for all non–Affordable Gold loans purchased by Freddie Mac that were originated between 1993 and 1998.

[11] Family income in our data is recorded as monthly income. In less than 5 percent of the cases, however, annual rather than monthly income appears to be recorded (*e.g.*, Affordable Gold borrower income as high as 12 times the area median). To address this, we impose an edit screen that borrower income recorded as more than 2.5 times area median is assumed to be annual rather than monthly. This edit has no impact on our logit estimations other than to increase the size and statistical significance of the estimated coefficient on family income.

[12] Using these empirical estimates to repeat the analysis from exhibit 1 suggests that Affordable Gold loans receiving counseling should have $1.5^{43/50} = 1.45$ higher odds of delinquency, implying an average 18 percent reduction in delinquency rates from counseling.

[13] For the Hosmer–Lemeshow goodness-of-fit statistic, the borrowers are grouped into "deciles of risk" by first using the logistic model to calculate each borrower's predicted probability of ever-90-days delinquency and then ranking

borrowers according to this risk probability. The borrowers are then divided into 10 groups, with each group containing approximately 10 percent of the total number of borrowers. Comparing the observed and predicted outcomes for each group then creates a test statistic. A well-fitting model will have a small test statistic (*i.e.*, observed and predicted outcomes will be similar), while a poorly fitting model will have a large test statistic. Simulations have shown that the test statistic is distributed approximately chi-squared with degrees of freedom equal to g-2, where g denotes the number of groups. Our test statistic of 6.51 with eight degrees of freedom yields a p-value of 0.5907. Therefore, we are unable to reject the null hypothesis that the model fits the data.

[14] The K–S statistic is a measure of the difference in the predicted probability cumulative density functions (CDFs) for delinquent and non-delinquent loans. A well fitting model will assign high delinquency probabilities to delinquent loans and low delinquency probabilities to non-delinquent loans, yielding quite distinct CDFs. We strongly reject the hypothesis that the two groups have identical CDFs. In the scoring industry, K–S statistics of 0.30 traditionally are thought to indicate acceptable fit, while values of 0.50 or more indicate an excellently fitting model. The test statistic of 0.46 suggests that our model is reasonably well fitting.

[15] We use likelihood ratio statistics to test our null hypotheses. In this instance, the restricted model has a log-likelihood of –8233.32, while the unrestricted model has a log-likelihood of –8211.84. The likelihood ratio statistic is calculated as twice the difference in these log-likelihoods, giving a value of 42.96 that is distributed chi-squared with 16 degrees of freedom. We therefore are able to reject the null hypothesis with a p-value of 0.0003.

[16] The restricted and unrestricted models have log-likelihoods of –8221.80 and –8211.84, respectively, resulting in a test statistic of 19.92 that is distributed chi-squared with 12 degrees of freedom. We therefore are able to reject the null hypothesis with a p-value of 0.069.

[17] The restricted and unrestricted models have log-likelihoods of –8218.83 and –8211.84, respectively, resulting in a test statistic of 13.98 that is distributed chi-squared with 11 degrees of freedom. This gives us a p-value of 0.23, meaning that we are unable to reject the null hypothesis.

[18] Predictions of the marginal effects are computed with auxiliary estimations that impose the appropriate restrictions on the β^1. For example, to estimate the marginal impact of classroom, we impose the restriction that $\beta^1_{ij} = \beta^1_{ik}$ for $\forall j,k \in T$ and $i = classroom$. Note that this implies an unchanged distribution of providers when computing the marginal effect of counseling type, and an unchanged distribution of counseling type when computing the marginal impacts of providers. We test the null hypotheses that the marginal effects are zero by testing the significance of each "marginal" coefficient in each auxiliary estimation.

[19] "Other" counseling delivered by lenders is primarily a hybrid of classroom and individual counseling, and appears to be as effective as individual counseling alone.

[20] We use log-likelihood ratio test statistics to assess whether differences in the point estimates of the marginal effects are statistically significant. The null hypothesis that individual counseling's effect is the same as that of home study and telephone counseling is rejected with p-values of 0.0212 (test statistic of 5.31 distributed chi-squared with one degree of freedom) and <0.0001 (test statistic of 17.14 distributed chi-squared with one degree of freedom), respectively. The null hypothesis that the effects of classroom and home study counseling are the same as those of telephone counseling is rejected with p-values of .0064 (test statistic of 7.44 distributed chi-squared with one degree of freedom) and 0.0014 (test statistic of 10.14 distributed chi-squared with one degree of freedom), respectively. We cannot reject the null hypothesis that individual and classroom counseling have identical effects, nor can we reject the null hypothesis that classroom and home study counseling have identical effects.

[21] The restricted and unrestricted models have log-likelihoods of –8233.80 and –8213.92, respectively, resulting in a likelihood ratio test statistic of 39.76 that is distributed chi-squared with 16 degrees of freedom. We therefore are able to reject the null hypothesis with a p-value of 0.00084.

[22] The restricted and unrestricted models have log-likelihoods of –8225.42 and –8213.92, respectively, resulting in a likelihood ratio test statistic of 23.00 that is distributed chi-squared with 12 degrees of freedom. We therefore are able to reject the null hypothesis with a p-value of 0.028.

[23] The restricted and unrestricted models have log-likelihoods of –8223.86 and –8213.92, respectively, resulting in a likelihood ratio test statistic of 19.89 that is distributed chi-squared with 11 degrees of freedom. We therefore are able to reject the null hypothesis with a p-value of 0.047.

Exhibit 1
Overview of Affordable Gold (AG) Loan Characteristics and Performance

Type of Counseling	Counseling Provider	Number of Loans	Mean AUS Score	Percent Ever-90-Days Delinquent
Classroom	Government Agency	427	929	7.3%
	Lender	2,317	909	6.1%
	Mortgage Insurer[1]	203	869	6.4%
	Non-profit Organization	609	922	3.9%
Home Study	Government Agency	332	899	4.2%
	Lender	12,148	904	6.7%
	Mortgage Insurer[1]	3,470	885	7.4%
	Non-profit Organization	315	877	4.4%
Individual	Government Agency	98	919	7.1%
	Lender	3,203	908	5.0%
	Mortgage Insurer[1]	304	895	3.0%
	Non-profit Organization	186	867	5.4%
Telephone[2]	Mortgage Insurer[1]	12,901	891	8.3%
Other[3]	Government Agency	51	882	9.8%
	Lender	1,483	941	4.6%
	Non-profit Organization	33	884	9.1%
All AG Loans with Counseling		38,080	900	6.9%
AG Loans without Counseling		1,238	943	5.7%
All AG Loans Used in Analysis		39,318	901	6.9%
Freddie Mac Non-AG Loans[4]		9,246,002	1059	1.8%

[1] Recorded as provided by "other."
[2] Recorded as "other" type of counseling.
[3] Mostly a hybrid of classroom and individual counseling for lenders, and unknown types of counseling for government agencies and non-profit organizations
[4] Non-Affordable Gold Loans purchased by Freddie Mac originated in the same years as the Affordable Gold Loans in our data

Exhibit 2
Summary Statistics of Independent Variables in Logit Estimation

A. Continuous Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
AUS Score	901	104	627	1422
Loan Origination Amount ($100,000)	0.94	0.42	0.07	3.98
Minority Population in Tract (Ratio of Tract Total)	0.20	0.23	0.00	1.00
Family Income (Ratio of Area Median)	0.83	0.33	0.05	2.5
Median Tract Income (Ratio of Area Median)	0.86	0.24	0.00	3.61

B. Categorical Variables

Variable		Number of Loans	% of Data
Number of Units	One	36,903	94.3%
	Two or more	2,235	5.7%
Property Type	Condominium	3,586	9.2%
	Other	3,365	8.6%
	Single Family	32,190	82.2%
Loan Purpose	Purchase	38,192	97.6%
	Refi/2nd home	949	2.4%
First Time Home Buyer	No	16,763	42.8%
	Unknown	323	0.8%
	Yes	22,055	56.4%
Borrower Race/Ethnicity	Black	3,595	9.2%
	Hispanic	4,161	10.6%
	Other minority	2,569	6.6%
	Unknown	1,257	3.2%
	White	27,559	70.4%
MSA	Metro	36,300	92.7%
	Non-metro	2,841	7.3%

Exhibit 3
Logit Estimation of Loans Ever Becoming 90 Days Delinquent

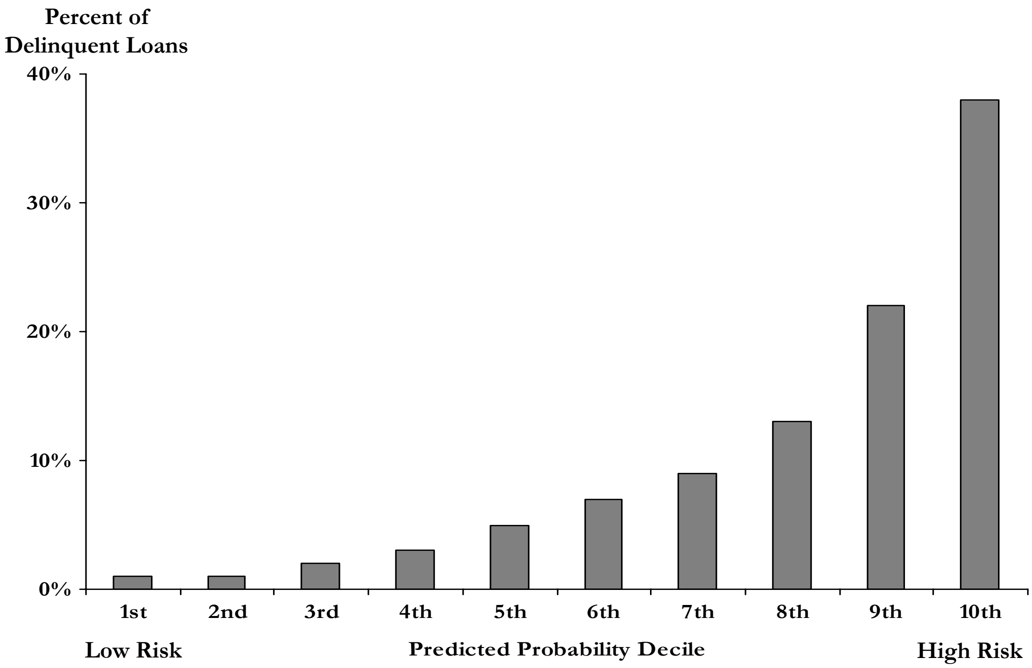
Variable		Coefficient Estimate	Standard Error	P-value
Intercept		-5.639	1.109	0.0001
Classroom Counseling	Government	0.032	0.239	0.8941
	Lender	-0.318	0.162	0.0495
	Mortgage Insurer	-0.498	0.327	0.1271
	Non-profit	-0.592	0.261	0.0231
Home Study Counseling	Government	-0.531	0.318	0.095
	Lender	-0.279	0.139	0.045
	Mortgage Insurer	-0.129	0.151	0.3925
	Non-profit	-0.475	0.316	0.1326
Individual Counseling	Government	0.147	0.434	0.7345
	Lender	-0.446	0.158	0.0046
	Mortgage Insurer	-0.843	0.372	0.0236
	Non-profit	-0.470	0.370	0.2031
Telephone Counseling	Mortgage Insurer	-0.086	0.138	0.5343
Other Counseling	Government	-0.129	0.513	0.8009
	Lender	-0.475	0.189	0.0118
	Non-profit	-0.095	0.657	0.8846
No Counseling		0.000	0.000	.
AUS Score	Unknown	2.975	0.297	0.0001
	700 or less	4.642	0.351	0.0001
	701 to 750	3.985	0.304	0.0001
	750 to 800	3.468	0.297	0.0001
	801 to 850	2.833	0.296	0.0001
	850 to 900	2.212	0.297	0.0001
	901 to 950	1.762	0.301	0.0001
	950 to 1000	1.111	0.311	0.0004
	1000 to 1050	0.705	0.334	0.0349
	1050 to 1100	0.491	0.385	0.2022
	1101 and up	0.000	0.000	.
Loan Origination Amount ($100,000)		-0.247	0.084	0.0031
Number of Units	One	0.574	0.117	0.0001
	Two or more	0.000	0.000	.
Property Type	Condominium	-0.639	0.087	0.0001
	Other	-0.041	0.087	0.6415
	Single Family	0.000	0.000	.
Loan Purpose	Purchase	-0.720	0.163	0.0001
	Refi/2nd home	0.000	0.000	.

Exhibit 3 (continued)
Logit Estimation of Loans Ever Becoming 90 Days Delinquent

Variable		Coefficien t Estimate	Standard Error	P-value
First Time Home Buyer	No	0.039	0.046	0.4051
	Unknown	-0.522	0.330	0.1137
	Yes	0.000	0.000	.
Borrower Race/Ethnicity	Black	0.503	0.068	0.0001
	Hispanic	-0.071	0.073	0.3314
	Other minority	-0.083	0.094	0.3780
	Unknown	0.198	0.117	0.0908
	White	0.000	0.000	.
Minority Population in Tract (Ratio of Tract Total)		0.460	0.109	0.0001
Family Income (Ratio of Area Median)		-0.157	0.087	0.0726
Median Tract Income (Ratio of Area Median)		-0.155	0.110	0.1589
MSA	Metro	-0.289	0.085	0.0007
	Non-metro	0.000	0.000	.
Loan Origination Date[1]		…..	…..	…..
State[2]		…..	…..	…..
Number of Observations	39,141			

[1] Fixed effects for the year and quarter when the loan was originated.
[2] Fixed effects for the state in which the property is located.

Exhibit 4
Goodness-of-Fit Measures for Logit Estimation



Hosmer–Lemeshow Test

Statistic: 6.51

P-value: 0.5907

Mean Prediction of Ever 90 Days Delinquent

Delinquent Loans: 17.7%,

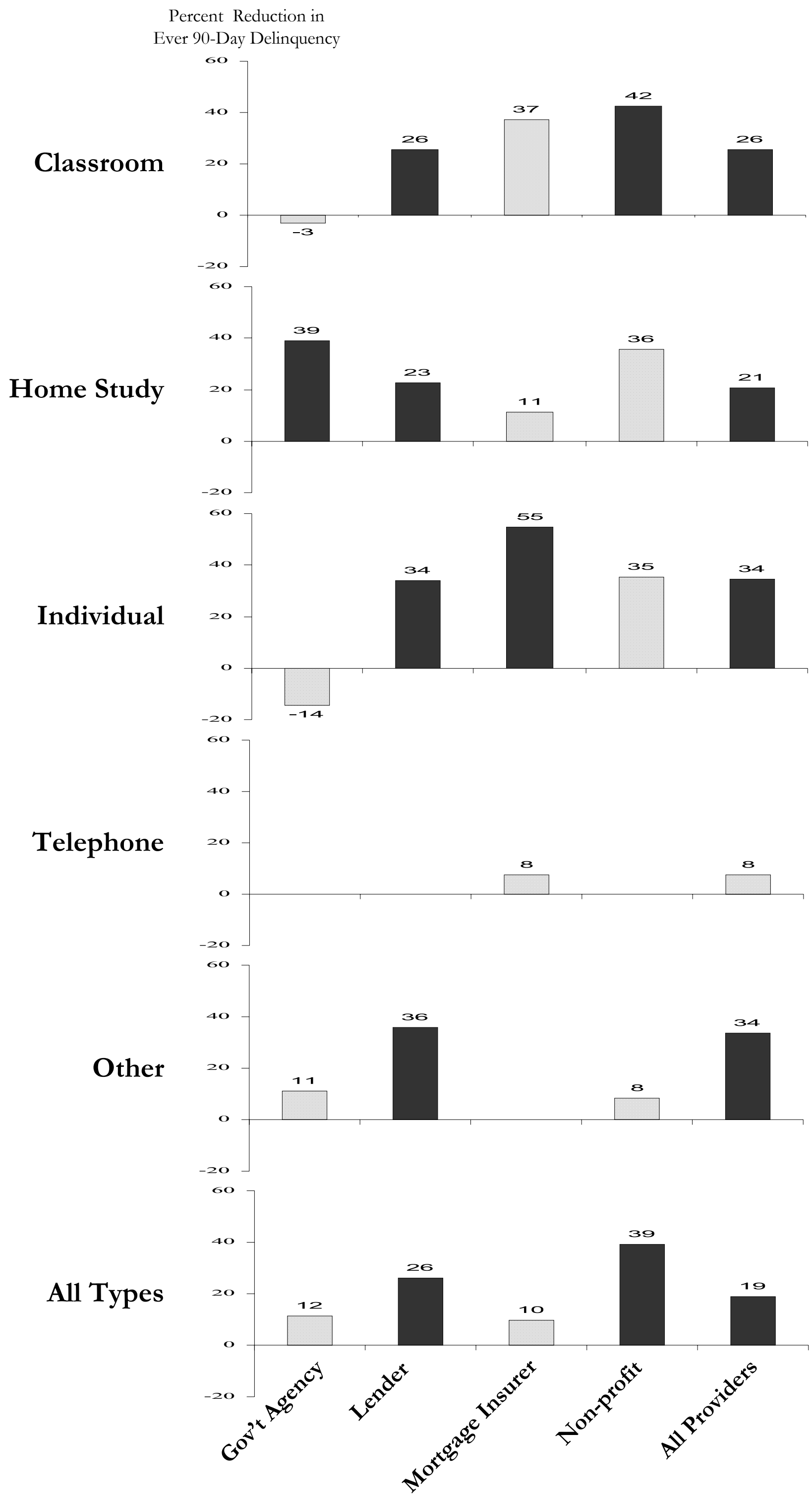
Non-Delinquent Loans: 6.2%

Kolmogrorov–Smirov Test

Statistic: 0.46

P-value: < 0.0001

Exhibit 5
Estimated Reduction in 90-Day Delinquency Rates from Counseling



Note: Dark-shaded bars indicate reductions in 90-day delinquency rates that are statistically significant at the 10 percent level

Exhibit 6
Goodness-of Fit for Nested Logit Selection/Assignment Estimation

Actual Selection/Assignment		**Mean Predicted Probabilities of Selection/Assignment**																
		Classroom				**Home Study**				**Individual**				**Phone**	**Other**			**None**
Type of Counseling	**Counseling Provider**	Lender	Non-profit	Government	Mortgage Insurer	Lender	Non-profit	Government	Mortgage Insurer	Lender	Non-profit	Government	Mortgage Insurer	Mortgage Insurer	Lender	Non-profit	Government	None
Classroom	Lender	10.4	1.4	1.5	0.5	31.6	0.8	0.7	9.2	8.7	0.4	0.3	0.9	24.3	5.2	0.1	0.1	3.9
	Non-profit	7.3	31.8	2.4	0.3	24.4	2.6	1.5	5.5	5.3	1.8	0.2	0.4	12.3	1.8	0.4	0.2	1.9
	Government	6.8	2.7	3.2	0.7	34.0	0.8	1.5	8.2	8.5	0.5	0.4	0.9	25.9	2.4	0.1	0.3	3.1
	Mortgage Insurer	6.2	1.4	1.4	1.6	33.4	2.8	1.0	7.7	6.1	1.2	0.4	0.8	29.9	3.3	0.2	0.2	2.1
Home Study	Lender	6.1	1.0	1.3	0.5	43.3	0.6	0.8	7.7	8.5	0.4	0.2	0.7	23.4	2.7	0.1	0.1	2.6
	Non-profit	4.7	2.5	1.6	1.6	22.2	4.9	2.0	9.2	8.4	2.5	0.4	1.2	32.0	3.2	0.3	0.2	3.2
	Government	5.3	2.1	3.1	0.8	28.8	2.0	6.7	7.3	8.3	1.7	0.8	0.7	26.5	1.8	0.2	0.5	3.3
	Mortgage Insurer	6.3	1.4	1.4	0.5	27.4	1.0	1.0	14.9	9.1	0.6	0.3	1.0	27.5	4.4	0.1	0.2	3.1
Individual	Lender	6.4	1.3	1.2	0.4	32.3	1.0	0.8	8.1	12.8	0.5	0.3	0.8	26.8	3.4	0.1	0.1	3.6
	Non-profit	4.6	1.5	1.1	1.4	34.6	2.2	1.1	10.8	6.1	2.1	0.3	1.6	24.0	4.9	0.1	0.1	3.4
	Government	6.8	1.3	2.0	0.8	28.4	1.4	1.6	7.5	10.2	1.2	1.4	1.0	31.8	2.1	0.2	0.3	2.1
	Mortgage Insurer	6.3	1.5	1.6	0.6	30.6	1.3	1.1	10.7	9.9	0.7	0.3	2.2	26.4	3.0	0.1	0.1	3.4
Phone	Mortgage Insurer	4.4	0.7	0.7	0.6	21.3	0.8	0.5	8.4	6.4	0.3	0.2	0.7	49.1	2.9	0.1	0.1	2.8
Other	Lender	7.9	0.7	0.7	0.4	22.9	0.7	0.4	11.2	7.3	0.4	0.1	0.7	23.3	18.1	0.1	0.1	5.0
	Non-profit	6.1	1.6	0.7	0.7	20.2	1.7	1.0	8.9	6.0	0.9	0.3	1.1	42.1	4.9	0.2	0.1	3.6
	Government	4.5	0.8	1.7	0.7	28.5	0.8	1.2	9.3	7.3	0.6	0.3	1.0	36.2	3.7	0.1	0.3	3.0
None	None	6.6	1.0	1.2	0.4	26.6	0.7	0.8	9.9	9.1	0.4	0.2	1.2	28.6	4.6	0.1	0.1	8.5

Exhibit 7
Logit Estimation of Loans Ever Becoming 90 Days Delinquent of Borrower Selection/Assignment

Variable		Coefficien t Estimate	Standard Error	P-value
Intercept		-5.123	1.666	0.0021
Classroom Counseling[1]	Government	-4.157	2.921	0.1548
	Lender	-3.587	1.662	0.0310
	Mortgage Insurer	-5.443	3.512	0.1212
	Non-profit	-1.088	1.413	0.4411
Home Study Counseling	Government	1.849	3.606	0.6082
	Lender	-0.924	1.287	0.4726
	Mortgage Insurer	1.045	1.497	0.4852
	Non-profit	-0.365	2.338	0.8760
Individual Counseling	Government	0.799	6.012	0.8943
	Lender	-1.306	1.655	0.4299
	Mortgage Insurer	-1.711	3.086	0.5794
	Non-profit	-1.555	3.574	0.6634
Telephone Counseling	Mortgage Insurer	-0.635	1.281	0.6199
Other Counseling	Government	-2.032	14.739	0.8903
	Lender	-0.796	1.515	0.5996
	Non-profit	-6.650	16.577	0.6883
No Counseling		0.000	0.000	.
AUS Score	Unknown	2.929	0.309	0.0001
	700 or less	4.559	0.364	0.0001
	701 to 750	3.873	0.319	0.0001
	750 to 800	3.361	0.312	0.0001
	801 to 850	2.772	0.311	0.0001
	850 to 900	2.153	0.312	0.0001
	901 to 950	1.712	0.311	0.0001
	950 to 1000	1.047	0.321	0.0011
	1000 to 1050	0.678	0.339	0.0453
	1050 to 1100	0.473	0.389	0.2234
	1101 and up	0.000	0.000	.
Loan Origination Amount ($100,000)		-0.330	0.099	0.0009
Number of Units	One	0.793	0.143	0.0001
	Two or more	0.000	0.000	.
Property Type	Condominium	-0.630	0.092	0.0001
	Other	0.046	0.093	0.6195
	Single Family	0.000	0.000	.
Loan Purpose	Purchase	-0.594	0.168	0.0004
	Refi/2nd home	0.000	0.000	.

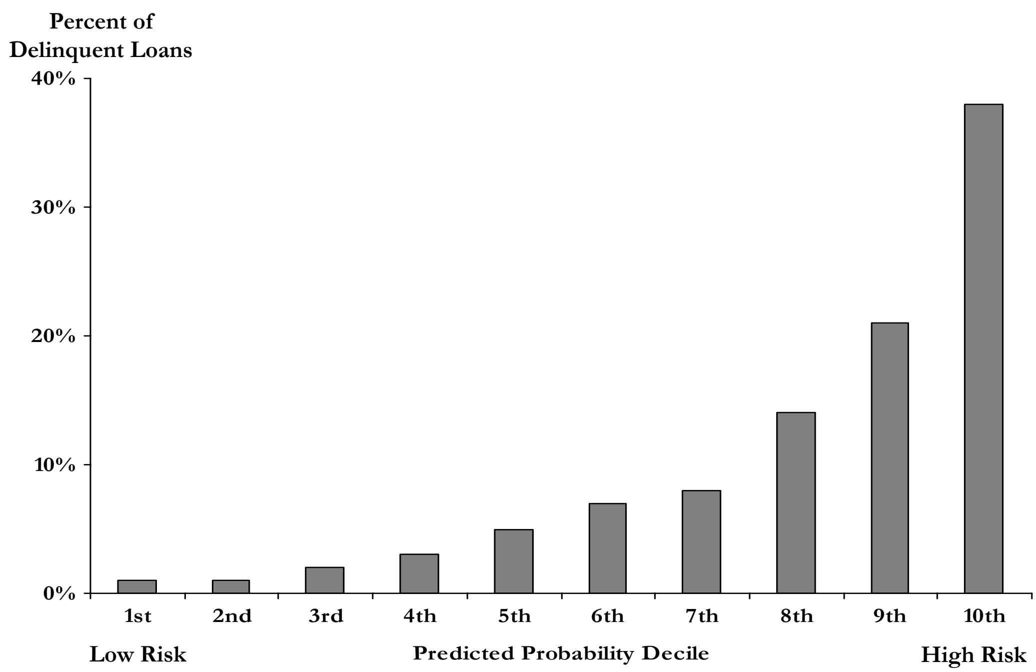
Exhibit 7 (continued)

[1] Predicted probability of borrower selection/assignment

Logit Estimation of Loans Ever Becoming 90 Days Delinquent of Borrower Selection/Assignment

Variable		Coefficient Estimate	Standard Error	P-value
First Time Home Buyer	No	-0.096	0.062	0.1232
	Unknown	-0.498	0.334	0.1359
	Yes	0.000	0.000	.
Borrower Race/Ethnicity	Black	0.513	0.071	0.0001
	Hispanic	-0.076	0.074	0.3037
	Other minority	-0.042	0.097	0.6635
	Unknown	0.192	0.122	0.1154
	White	0.000	0.000	.
Minority Population in Tract (Ratio of Tract Total)		0.378	0.117	0.0012
Family Income (Ratio of Area Median)		-0.118	0.092	0.1984
Median Tract Income (Ratio of Area Median)		-0.205	0.116	0.0766
MSA	Metro	-0.198	0.091	0.0297
	Non-metro	0.000	0.000	.
Loan Origination Date		…..	…..	…..
State		…..	…..	…..
Number of Observations	39,141			

Exhibit 8
Goodness-of-Fit Measures for Selection/Assignment Logit Estimation



Hosmer & Lemeshow Test

Statistic: 8.42

P-value: 0.3940

Mean Prediction of Ever 90-Day Delinquent

Delinquent Loans: 16.7%,

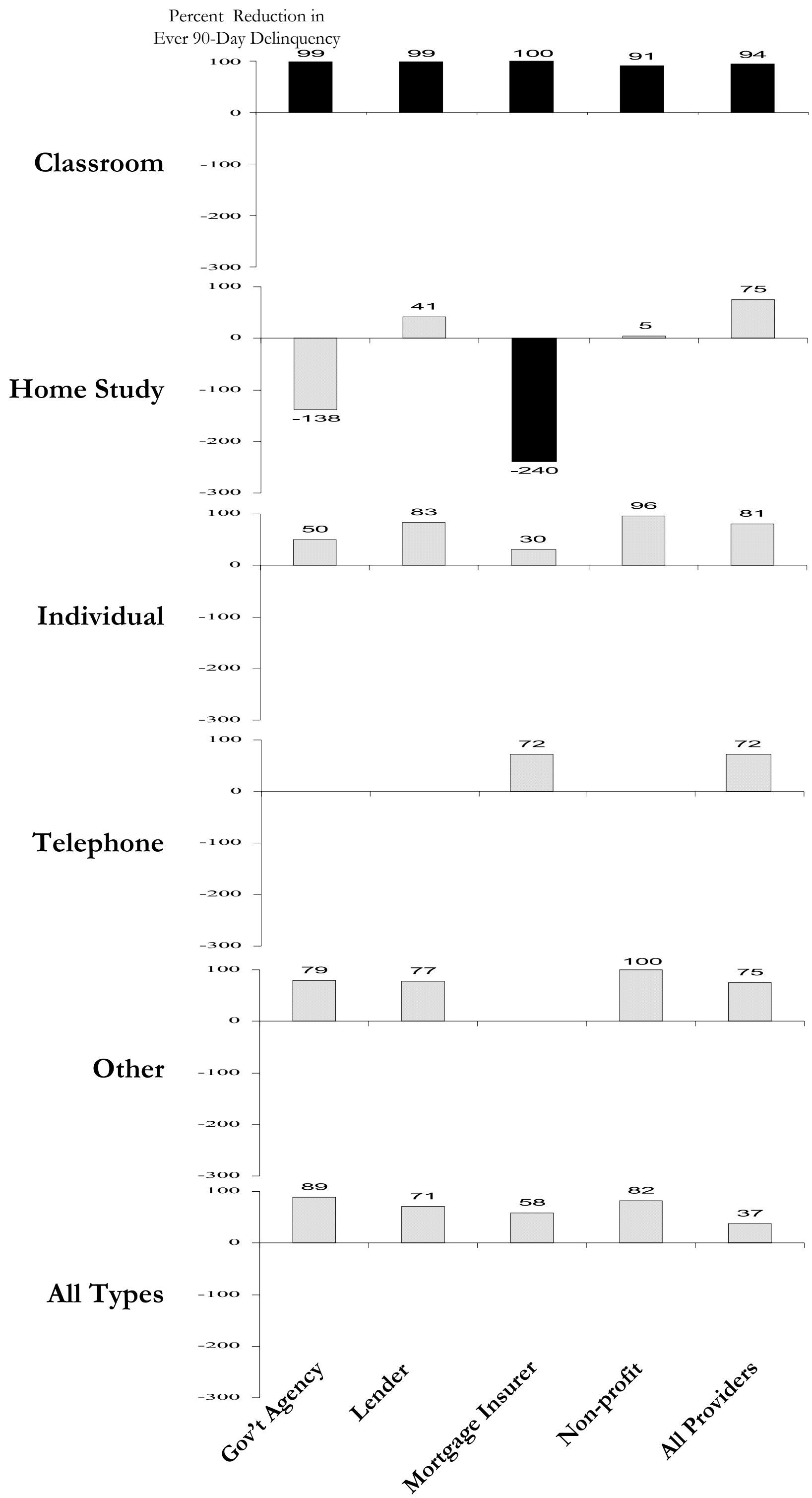
Non-Delinquent Loans: 6.2%

Kolmogrorov-Smirov Test

Statistic: 0.46

P-value: < 0.0001

Exhibit 9
Estimated Reduction in 90-Day Delinquency Rates from Counseling for Selection/Assignment Logit Estimation



Note: Dark-shaded bars indicate reductions in 90-day delinquency rates that are statistically significant at the 10 percent level

IX. Appendix: Details of Borrower Assignment/Selection Analysis

In this section we briefly describe our borrower assignment/selection analysis. The first step in our analysis is to estimate a four-stage nested logit model. In the first stage borrowers are assigned/selected into receiving or not receiving counseling. In the second stage borrowers receiving counseling are assigned/select either counseling service providers or industry participants. In the third stage borrowers assigned/selecting counseling service providers are allocated between government agencies and non-profit organizations, and borrowers assigned/selecting industry participants are allocated between lenders and mortgage insurers. In the fourth stage borrowers are assigned/selected into the four types of counseling (classroom, home study, individual, or "other") available from each counseling provider. Estimation of the model is accomplished separately by stage, starting with the fourth. Appropriate inclusionary terms are incorporated into the estimation of stages three, two and one. Results of the eight separate logit estimations that make up the nested logit model are not presented in an effort to save space and the reader's patience.

Identification of the assignment/selection model is ensured by inclusion of variables not in the delinquency model (seller type, borrower age, borrower gender, loan-to-value ratio and MSA population) and functional form. There are many unobserved factors, however, that likely are important in explaining counseling assignment/selection (e.g., when in the process borrowers apply for/receive counseling and the available supply of counseling providers). As a result, the nested logit estimation yields an adequately- but not especially well-fitting model. This is illustrated in Exhibit 6, which shows the mean predicted probabilities of each counseling type/provider combination (converted to percentages) for each subgroup of actual type/provider outcomes. The first row of Exhibit 6, for example, shows the predicted probabilities for borrowers actually receiving classroom counseling from lenders. If the nested logit model is particularly well fitting then the mean predicted probability will be highest for classroom counseling by lenders. This is not the case here, both home study by lenders and telephone counseling by mortgage insurers have higher mean probabilities. This result, however, is not particularly surprising because both home study by lenders and telephone counseling by mortgage insurers occur with high frequently in the data. A less stringent fit criterion is to compare down each column of Exhibit 6 rather than across each row. In this instance the assessment involves comparing across borrower subsets of actual assignment/selection to see if the model assigns the highest mean probability to the type of counseling borrowers actually receive (i.e., are the diagonal elements of the Exhibit 6 matrix the largest probability in each column). The nested logit model does far better by this measure; there are only three columns where this criterion is not met, individual counseling by non-profit organizations, and "other" counseling by non-profit organizations and government agencies.

Our next step is to use the predicted probabilities of borrower selection/assignment to estimate the probability of loans becoming 90-day delinquent. The result of this estimation is shown in Exhibit 7. The coefficients for the control variables in the borrower selection/assignment model are very similar to those in Exhibit 3. The coefficients for counseling type/provider, however, generally are quite a bit larger in absolute value. The standard errors are larger also, and only classroom counseling provided by lenders has a statistically significant effect in this estimation. Finally, as in Exhibit 3, most counseling type/provider coefficients are negative, other than home study counseling provided by government agencies and mortgage insurers and individual counseling provided by government agencies.

Exhibit 8 provides goodness-of-fit measures for the logit estimation of the borrower selection/assignment model. Despite the high standard errors on the counseling type/provider coefficients, the nested logit model fits roughly as well as the basic model.

The model presented in Exhibit 7, however, is not entirely robust to alternative specifications. The far less than perfect fit of the assignment/selection nested logit model provides relatively small variation in the predicted values for many counseling type/provider alternatives, as well as relatively high correlations across predictions of alternative counseling types/providers. As a result the estimated counseling type/provider coefficients display many symptoms of multicollinearity. We crudely address this problem through a series of auxiliary estimations that each reduces the dimensionality of the 1 X column vector. For example, we estimate separate classroom counseling coefficients for each of the four providers while constraining provider's coefficients to be identical across all other types of counseling (i.e., $\gamma_{ij}^{1} = \gamma_{ik}^{1}\ \forall j,k \in T$ and $\forall i \neq classroom$). This approach yields no significant reduction in log likelihood but does substantially change the point estimates for some coefficients. In particular we find that the estimated coefficients for classroom counseling are negative and significant for all providers. Because the results of these auxiliary estimations appear more robust, we rely on them and use them to conduct our simulations. Exhibit 9 is the equivalent of Exhibit 5, and shows the results of simulations designed to estimate the reductions in 90-day delinquency rates provided by each of the counseling types/providers. The overall pattern is not dissimilar to that of the basic model, although the point estimates are far larger in absolute value. From a statistical standpoint, only classroom counseling is found to have a significant impact in reducing 90-day delinquency rates.