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Learning to Cope: Voluntary Financial Education and Loan Performance during a Housing Crisis

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As we write this paper at the end of 2009, delinquency and default rates on individual home mortgages have reached unprecedented levels. This wave of defaults reflects a vicious combination of a deep recession, a burst housing bubble, and ill-advised financial choices by home borrowers. These effects are particularly pronounced among the least creditworthy borrowers, many of whom became first-time homeowners in the heady days of the bubble. By one estimate, default rates on loans originated in 2006 by such "subprime" borrowers approached a staggering 36 percent within 18 months of origination, as compared to 7.7 percent for the more traditional, "prime" borrowers (Gene Amromin and Anna Paulson 2009).

This experience prompted calls for increased government intervention in mortgage markets. The ensuing policy discussion has centered on two key (and not mutually exclusive) approaches: (i) tighter oversight of mortgage lenders and products, and (ii) concerted efforts to educate prospective homebuyers to ensure sustainability of their financial commitments. The importance of the latter approach has been buoyed by a growing body of research that showed gross inadequacies in financial literacy and the consequential nature of resulting mistakes (Michelle White 2007; Brian Bucks and Karen Pence 2008; Annamaria Lusardi 2008; Lusardi and Olivia Mitchell 2008; Lusardi and Peter Tufano 2009; Sumit Agarwal et al. 2010, among others).

Whether financial education is an effective means of remedying these shortcomings is, however, subject to some debate (Shawn Cole and Gauri Shastry 2008). Can mortgage defaults, in particular, be prevented by borrower education, credit counseling, and/or disclosure? If so, what features of such programs are most effective? Although empirical evaluation of education programs is notoriously difficult, one of the ways to answer these questions is to amass a battery of results from a number of financial counseling efforts to date that differ along a crucial set of dimensions. This paper contributes to this endeavor.

In earlier work (Agarwal et al. 2009), we evaluated the effectiveness of a *mandatory* counseling program *limited to a review* of approved loan applications of low-FICO score borrowers by certified counselors. This paper deals with a diametrically opposite approach to financial education—a *long-term voluntary* participation program for prospective homebuyers.

The program we study is run by the Indianapolis Neighborhood Housing Partnership, Inc. (INHP). It is designed to assist low- and moderate-income households in their pursuit of sustainable home ownership through improving their credit, savings, and financial literacy. INHP clients start with a three-hour class on money management practices. This class is followed by series of one-on-one meetings with INHP counselors that focus on ways to implement these practices: repairing a credit history, paying down judgments, etc. These meetings occur monthly for up to two years. As a capstone to the program, clients attend an eight-hour class on home buying that deals with mechanics of the process and mortgage choice. Client ability

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to meet lender underwriting guidelines and qualify for a mortgage serves as the criterion for successful graduation.

In our analysis of the program, we find substantially lower ex-post delinquency rates among program graduates, a finding that is robust to an array of controls and several ways of modeling the probability of selection into counseling. We attribute improved performance to the type of mortgage contract extended to the graduates, to the budgeting and credit management skills taught in the program, and to active post-purchase counseling that seeks to cure delinquency at early stages. The effects are strongest among households that appear least creditworthy in terms of their income and FICO scores, but who are granted credit on the basis of non-public (soft) information gathered during the counseling relationship. Finally, the effects of counseling tend to persist over time, suggesting that long-term preparation for homeownership plays an important role in helping households to cope with a number of economic shocks.

I. INHP Counseling Programs

INHP serves low- and moderate-income households in Marion County, Indiana, which incorporates the City of Indianapolis. INHP is a nonprofit organization whose mission is to increase safe, decent, affordable housing opportunities that foster healthy, viable neighborhoods. Since its establishment in 1988, INHP has sought to bring together local lending institutions, state and municipal government, philanthropic organizations, and community development corporations to achieve its goals. The structure of this partnership is reflected in the content of INHP educational programs and in the ways in which loan products are designed and funded.

In a typical case, a counselor pulls a credit report for a prospective client and conducts an interview to evaluate assets. A counselor then discusses the existing barriers to home ownership with the applicant and steps required to overcome them. If the applicant chooses to proceed, he enrolls in an extensive counseling program described in the previous section. Once courses are completed, some graduates are referred to an outside lending partner. However, a sizable fraction of clients are judged unlikely to obtain affordable outside loans on the basis of their so-called "hard information" used in underwriting: FICO scores and income level. Yet, they are deemed creditworthy by INHP, which has gathered extensive information during the lengthy counseling process. These clients' mortgage loans are directly funded by INHP, contingent on approval by an internal loan committee that receives input from counselors working with each particular borrower.[1] This dichotomy in funding sources allows us to differentiate between counseled households that qualify on the basis of "hard" versus "soft" information.

II. Data

We use two main sources of data for our study: loan-level data furnished by LPS Applied Analytics (LPS) and INHP internal tracking data on program participants. LPS aggregates data from loan servicing companies that participate in the HOPE NOW alliance. The most recent LPS data cover about 30 million loans that include prime and subprime mortgages, as well as loans that are privately securitized, sold to the GSEs, or held on bank balance sheets. In addition to monthly data on loan performance status, LPS contains information on key borrower and loan characteristics at origination. This includes the borrower's FICO credit score, the loan amount and interest rate, whether the loan is a fixed or a variable-rate mortgage, the ratio of loan amount to home value (LTV), whether the loan was intended for home purchase or refinancing, etc.

INHP provided data on 726 first-lien mortgage loans originated for program graduates during the calendar years 2005–2007. Of these, we were able to obtain loan performance data on 211 internally funded (IN) loans and 148 lender referral (LR) loans. LPS loans originated in Marion County in 2005–2007 serve as our source for selecting a control sample. Because INHP loans are used for home purchase, we further filter out loans used for refinancing from the LPS dataset. The key characteristics of INHP and LPS (or treated- and non-treated) loans are summarized in Table A of the Appendix posted

[1] Although INHP funds these loans directly, it has a standing loan pool agreement with several lending partners that leverages INHP funds on a 9-to-1 basis. Furthermore, pools of performing INHP-funded loans are periodically sold off, releasing funds for new lending.

on the AER Web site, which also contains other dataset details.

In brief, INHP clients have considerably lower FICO scores and household incomes than the rest of borrowers in Marion County. They purchase less expensive houses and make smaller down payments. Almost all loans made to INHP clients are 30-year fixed-rate contracts, compared to only 81 percent of loans elsewhere in the county. The pricing of internally funded INHP loans appears to reflect higher risk, lower home equity, and weaker income flows of its clientele as they carry an interest rate that is about 100 basis points higher, on average, than that on other fixed rate mortgages in the county. IN loans, however, do not require private mortgage insurance. The same patterns are evident in interest rate spreads.

Table A also describes realized 12- and 18-month loan performance of IN, LR, and non-INHP clients. We define a loan as being in "default" if it is 90 days or more past due, in foreclosure, or if it has real-estate owned (REO) status in the first 12 (or 18) months since the first mortgage payment date.[2] Over the first 12 months, INHP loans exhibit considerably lower unconditional default rates: 3.8 (for IN loans) and 4.1 percent (for LR loans) as compared to 6.3 percent for non-INHP loans. This is due partly to lower incidence of fraud among INHP clients, who are known to counselors for a long period of time. The rapid response to early signs of delinquency by INHP also likely allows more households to cure delinquency and avoid default.[3]

However, as the time horizon lengthens, loan performance deteriorates. By the end of 18 months, both internally-funded INHP loans and non-INHP loans have nearly identical unconditional default rates of 10 percent. This univariate comparison is not very informative, however, as treated and non-treated loan samples differ significantly on most dimensions. To be able to identify the effect of counseling on performance while accounting for multiple differences in observables, we move to multivariate analysis in the next section.

III. Are Counseling Program Graduates Better Able to Sustain Homeownership? Why?

Table 1 summarizes the results of several multivariate analyses. In each formulation, the binary dependent variable takes on a value of one if a loan defaults within a given time window, and is set to 0 otherwise. We attempt to capture the effect of treatment with dummies for IN- and LR-funded loans for INHP clients. The set of covariates encompasses variables summarized in Table A and further includes time dummies. Standard errors are clustered at the zip code level. The sample is limited to first-lien purchase loans that did not get refinanced or transferred within the evaluation window, as default status is meaningful for only such loans.

Columns 1 and 2 show results of estimating OLS regressions for 12- and 18-month defaults, respectively. For each evaluation horizon, INHP clients experience substantially lower default rates. The conditional mean default rates are 8.9 to 10.7 percentage points lower for IN-funded loans and 4.0 to 5.8 percentage points lower for LR-funded loans. These effects are both economically large and statistically significant, even though INHP-treated loans account for less than 3 percent of the sample. That IN-funded loans exhibit a greater (statistically significant) improvement in loan performance may underscore the value of soft information in making credit decisions. Even when counseling does not appear in improved credit scores and soft information is needed for underwriting, it is still associated with substantially lower default rates.

Coefficient estimates on covariates do not contain any surprises: loan defaults are less common among borrowers with higher FICO scores and income, and with lower LTV and loan spreads. Defaults are also less common among FHA-insured loans, and fixed-rate loans that do not allow either interest rate fluctuations or negative amortization. This latter set of results highlights the beneficial effect of INHP clients' receiving fixed rate loans.

Columns 3 and 4 repeat this exercise in a logit framework. The reported marginal effects are estimated at the mean, with interactions among variables reducing the estimated magnitude of

[2] We do not consider horizons longer than 18 months, so that loans made in 2007 can be analyzed the same way as earlier loans, as our data are complete through the end of 2008.

[3] As soon as payment on an IN-funded loan is more than 15 days late, INHP contacts the borrower. If a loan becomes non-performing, clients are asked to attend counseling sessions that focus on curing delinquencies. LR loans do not get such proactive post-purchase treatment.

Table 1—Regression Analysis of Loan Performance

	OLS		Logit (marginal effects)	
	12-mo. default (1)	18-mo. default (2)	12-mo. default (3)	18-mo. default (4)
INHP clients—IN	−0.089***	−0.107***	−0.022***	−0.034***
	[0.016]	[0.021]	[0.005]	[0.006]
INHP clients—LR	−0.040**	−0.058***	−0.015*	−0.025***
	[0.016]	[0.019]	[0.008]	[0.01]
FICO score (in 100s)	−0.059***	−0.092***	−0.037***	−0.066***
	[0.006]	[0.008]	[0.003]	[0.005]
log(Income)	−0.020***	−0.026***	−0.010***	−0.015***
	[0.003]	[0.004]	[0.003]	[0.003]
LTV (ppt)	0.001***	0.002***	0.000***	0.001***
	[0.000]	[0.000]	[0.000]	[0.000]
Loan spread (ppt)	0.008***	0.014***	0.002***	0.004***
	[0.002]	[0.003]	[0.001]	[0.001]
ARM loan flag	0.048***	0.058***	0.024***	0.039***
	[0.012]	[0.014]	[0.007]	[0.011]
optionARM loan flag	0.098***	0.182***	0.034***	0.091***
	[0.019]	[0.023]	[0.01]	[0.019]
FHA/VA loan flag	−0.059***	−0.078***	−0.020***	−0.032***
	[0.006]	[0.008]	[0.003]	[0.005]
Observations	12,919	12,300	12,919	12,300
Adjusted/pseudo R^2	0.159	0.226	0.250	0.291

Notes: Regressions also include a set of time dummies. Standard errors are clustered at zip code level. Specifications with a full set of zip code fixed effects are qualitatively similar and are available on request. INHP–IN dummy refers to loans to INHP clients funded directly by INHP. INHP–LR identifies lender-referred loans to INHP clients. Variable and sample definitions are the same as in Appendix Table A.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

treatment effect while preserving its statistical significance.

The discussion of results in Table 1 makes an implicit assumption that INHP clients are chosen at random from the set of Marion County borrowers. However, the voluntary nature of INHP counseling suggests that INHP clients are systematically different from other borrowers. The usual approach to nonrandom sample selection is to rely on instrumental variables. In the absence of strong instruments,[4] we turn to an alternative method of accounting for "selection on observables"—propensity-score matching (Paul Rosenbaum and Donald Rubin 1983). Borrowers attracted to INHP counseling may well be more disciplined, conscientious, thrifty, etc. After all, successful graduation from INHP programs requires a considerable commitment of time and often entails budget austerity measures. However, one could argue that such differences are spanned by observable borrower and loan characteristics, such as credit scores and loan spreads. In particular, FICO scores are specifically designed to reflect borrower ability and inclination to fulfill loan commitments, which can be broadly synonymous with traits outlined above.

To use notation common in program evaluation literature, we define Y_1 as loan performance

[4] We considered using borrower's distance and commuting time to the closest counseling center as instruments for selection into treatment. These proved to be weak predictors of program participation in first-stage regressions.

of INHP counseled borrowers and Y_0 as that of non-INHP clients. Let $D = 1$ denote the choice to enroll in the INHP program. We measure the average effect of counseling treatment on the treated, defined formally as: $ATT = E[Y_1 | D = 1] - E[Y_0 | D = 1]$. The first term of this expression is observed loan performance of INHP clients. The second term is the unobserved counterfactual—expected performance of borrowers who chose to enroll in the INHP programs but did not receive counseling.

The identifying assumption of propensity-score matching is that conditioning on the probability of becoming an INHP client removes the confounding effects of selection. We first estimate this probability, $\Pr(\mathbf{Z})$, on the entire data sample, where $\mathbf{Z}$ includes credit and location information. Then for each INHP loan we identify a non-INHP loan with the closest $\Pr(\mathbf{Z})$ value. We compute the *ATT* from comparison of mean default rates of INHP loans and their matched counterparts.[5]

Estimates of the *ATT* effect obtained in this fashion are reported in Table 2. The average default rates of the treated and the matched control groups are substantially different. When the propensity model is estimated only on observable borrower characteristics, location and time (the "Borrower" model), the *ATT* exceeds ten percentage points for the 12-month default rate and 14 percentage points for the 18-month rate. Both *ATT* estimates are strongly statistically significant.

The Borrower model effectively allows the matched group to differ in terms of loan contract type and terms. Indeed, the matched group has a much higher share of adjustable-rate and option ARM loans (23 and 5 percent versus none in the treated group), underscoring the contribution of contract choice to default. To remove this degree of freedom from the matching exercise, we add loan terms and type to the vector of propensity score covariates. The results in the bottom half of Table 2 (the "Borrower + Loan" model) show sizable and significant *ATT* estimates. Not surprisingly, these estimates are smaller in magnitude than those from the Borrower model.

In both models, the magnitude of the *ATT* effect does not attenuate as the evaluation horizon gets longer, suggesting a persistent effect of counseling treatment. There is little reason to believe that INHP clients, on average, experienced a different set of external economic shocks than similar nontreated households. Thus, counseled borrowers appear to have developed a sustained ability to maintain superior loan performance.

IV. Policy Discussion and Conclusion

We find substantially lower default rates among graduates of a long-term voluntary counseling program targeting low- to moderate-income households. The program requirements for successful graduation compel prospective borrowers to acquire budgeting and credit-management skills. During this multi-month process counselors also pick up valuable soft information on client creditworthiness. This information is critical for extending credit to graduates whose new skills have not yet been reflected in credit scores. Such graduates also benefit from an aggressive post-purchase counseling program targeting early delinquency.

These features stand in stark contrast with an approach evaluated in Agarwal et al. (2009). In that instance, a mandatory counselor review of approved loan applications created severe market disruptions. Although ex post performance of counseled borrowers improved, it can be better explained by tighter screening actions of lenders subject to regulation than by counseling per se.

These two case studies highlight some of the policy tradeoffs in counseling of prospective homeowners. Both programs restricted credit for low- and moderate-income borrowers. In case of mandatory counseling, credit was limited primarily by exit of lenders unwilling to operate under counselor oversight. In the case of INHP, credit is limited to borrowers with proven ability to carry a mortgage. Only in the latter case did the counseled borrowers acquire lasting skills.

The program studied here contains many elements that appear to be necessary for a broad-scale successful counseling initiative. It attracts private capital from lenders seeking to satisfy their Community Reinvestment Act

[5] As pointed out by James Heckman and Salvador Navarro-Lozano (2004), the use of *ATT* has an attractive quality of weakening strong economic restrictions implicit in matching applications. In particular, it does not require an assumption of no effect of selection into treatment on the outcome of the *treated* agents. This allows the estimated treatment effect on the average person to be different from that on the marginal person.

Table 2—Differences in Loan Performance in Propensity-Matched Samples

Matching model		Borrower group: INHP	Borrower group: Non-INHP	*ATT*	SE	*t*-stat
Borrower	Avg. 12-month default rate	0.032	0.138	−0.106	0.024	4.52
	Avg. 18-month default rate	0.084	0.226	−0.141	0.030	4.75
Borrower + Loan	Avg. 12-month default rate	0.031	0.111	−0.080	0.021	3.78
	Avg. 18-month default rate	0.080	0.170	−0.090	0.027	3.30

Notes: In the Borrower matching model, a propensity score is constructed on the basis of a borrower's FICO score, income, zip code and month of loan origination. In the Borrower + Loan model, loan spread, LTV ratio, and loan type dummies are added to the set of covariates. *ATT* refers to the average treatment effect on the treated. The table reports analytical standard errors. Bootstrapped errors are of similar magnitude and are available on request.

requirements. It offers training and thorough underwriting to screen households on their ability and willingness to sustain a long-term financial obligation, which allows for better deployment of this capital. Its incentives are well-aligned since INHP retains an equity stake in every mortgage it funds and is only able to sell performing loans. Finally, it imparts financial management skills that potentially go well beyond a single, albeit very important, transaction.

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