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 & 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 the resulting mistakes (Sumit Agarwal et. al. 2010; Brian Bucks and Karen Pence 2008; Annamaria Lusardi 2008; Lusardi and Olivia Mitchell 2008; Lusardi and Peter Tufano 2009; Michelle White 2007, 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,

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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 repairing their credit records, building up savings, and learning about financial products. INHP clients start with a 3-hour class on money management practices. For many clients this class is followed by series of one-on-one meetings with INHP counselors that focus on ways to implement these practices: paying down judgments, developing or repairing a credit history, disputing credit report errors, etc. These meetings occur once a month for up to two years. As a capstone to the program, clients attend an 8-hour class on home buying that deals with the mechanics of the buying process and mortgage choice. Client ability to meet lender underwriting guidelines and qualify for a mortgage serves as the criterion for successful graduation from 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 treatment. 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

As described in the preceding section, INHP focuses on serving low- and moderate-income households that reside 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 sought to bring together local lending institutions, 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 loans are funded.

In a typical case, a prospective client fills out an application either at a counseling center or at one of the frequently held outreach events. At this point, a counselor pulls a credit report and conducts an interview to assess whether a client has sufficient assets for down payment. A certain fraction of applicants are judged to be sufficiently creditworthy at this point and are referred to one of INHP's lending partners. Most, however, are required to enroll in an extensive home ownership counseling program described in the previous section. It should be noted that the majority of applicants referred to outside lenders still end up enrolling in INHP counseling courses. For some, this is a requirement to receive down payment assistance through a City of Indianapolis program. Others respond to the recommendation of INHP staff. 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 loans from an outside lender on the basis of their so-called "hard information" used for underwriting: FICO scores and income level. Yet, they are deemed creditworthy by INHP that has gathered extensive information on such clients 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 both the underwriter and the counselor working with this particular borrower.[2] This dichotomy in funding sources allows us to differentiate between counseled households that qualify on the basis of “hard” and “soft” information, respectively.

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, those that are sold to the GSEs, and loans that banks hold on their balance sheets. In addition to monthly data on loan performance status, LPS contains information on key borrower and loan characteristics at loan origination. This includes the borrower’s FICO credit score,[3] the loan amount and interest rate, whether the loan is a fixed or a variable-rate mortgage, the ratio of the loan amount to the value of the home at origination (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. About 30 percent of these loans (211) were funded internally, while the rest were referred to external lenders partnering with INHP. For the internally funded loans, all information on borrower and loan characteristics and ex post loan performance was available directly from INHP. For loans referred to external lenders, we had to use available data on loan terms at origination to find corresponding loan records in the LPS data. This process identified 266 of 515 lender referred loans, which likely reflects loans originated by lenders that do not use LPS-reporting servicers. Unfortunately, a sizable fraction of identified loans had their

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[2] 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. All INHP-funded loans are 30-year fixed rate mortgages that do not have PMI.

[3] The FICO (Fair Isaac Corporation) score measures a borrower’s creditworthiness prior to taking out the mortgage and ranges between 300 and 850. Typically, a FICO score above 800 is considered very good, while a score below 620 is considered poor.

servicing rights transferred to a non-LPS servicer shortly after origination, which precluded us from tracking their performance. At the end, we have information on 211 internally funded (IN) loans and 148 lender referral (LR) loans.

The rest of LPS loans serve as our source for selecting a control sample. We limit the set of LPS observations to first-lien loans originated in Marion County in 2005-2007. 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 1.

It is apparent that INHP clients have considerably lower FICO scores and household incomes than the rest of the borrowers in the Marion County. Consistent with the INHP mandate, the vast majority of its clients have household incomes less than 80 percent of the median county level, which satisfies CRA lending criteria. INHP clients also purchase less expensive houses and make smaller down payments as evidenced by their higher loan-to-value (LTV) ratios at loan origination. Whereas almost all loans made to INHP clients are in the form of 30-year fixed interest rate contracts, only 81 percent of loans elsewhere in the county fit this description. Yet, the pricing of internally-funded INHP loans appears to reflect the higher risk, lower home equity, and weaker income flows of its clientele. Regardless of year of origination, internally-funded loans carry an interest rate that is about 100 basis points higher than that charged on other fixed rate mortgages in the county. That the lender-referred loans for INHP clients do not have a rate differential is likely due to the high share of such loans financed through the Federal Housing Authority (FHA). The same patterns are also evident in interest rate spreads.

The bottom two rows of the table describe realized 12- and 18-month loan performance for each of the three categories. We define a loan as being in "default" if it is 90 days or more past due, in bankruptcy, in foreclosure or if it has real-estate owned (REO) status in the first 12 (or 18) months since the first mortgage payment date.[4] Over the first 12 months, INHP loans exhibit

[4] 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.

considerably lower unconditional default rates: 3.8 and 4.1 percent as compared to 6.3 percent for non-INHP loans. This is likely 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.[5]

However, as 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 2 summarizes the results of several multivariate analyses. In each formulation, the binary dependent variable takes on a value of 1 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 1, 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 only meaningful for 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

[5] 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.

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 required 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 don't 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 treatment effect while preserving its statistical significance.

The discussion of results in Table 2 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 non-random sample selection is to rely on instrumental variables. In the absence of strong instruments,[6] we turn to an alternative method of accounting for "selection on observables" – propensity-score matching (Paul Rosenbaum and Donald Rubin, 1983) – that is more flexible than the OLS/logit specifications in Table 2. It is likely that borrowers attracted to INHP counseling services are different in terms of some unobservable characteristics or traits. They 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

[6] We considered using borrower's distance and commuting time to the closest counseling center as instruments for selection into treatment. Unfortunately, these proved to be weak instruments that contributed negligibly to explaining program participation in first-stage regressions.

scores are specifically designed to reflect borrower ability and inclination to fulfill loan commitments, which can be broadly synonymous with the traits outlined above.

To use the notation common in the program evaluation literature, we define Y_1 as loan performance of INHP counseled borrowers and Y_0 as that of non-INHP clients. Further, let D=1 denote the choice to enroll in the INHP program, and D=0 be the choice to obtain a mortgage without INHP help. We are looking to measure the average effect of the counseling treatment on the treated, which is formally defined as: ATT = $E[Y_1|D=1] - E[Y_0|D=1]$. The first term of this expression is simply the observed loan performance of INHP clients. The second term is the unobserved counterfactual – expected loan performance of borrowers who chose to enroll in INHP programs but did not receive counseling.

The identifying assumption of propensity-score matching here is that conditioning on the probability of becoming an INHP client removes the confounding effects of selection on the average estimate of the effect of treatment itself. Formally, we are assuming that $E[Y_0|Pr(\mathbf{Z}), D=0] = E[Y_0|Pr(\mathbf{Z}), D=1]$. At the outset, we model probability of selection as a function of **Z** that includes borrower observable credit information and location.

Mechanically, we first estimate Pr(**Z**) using a logit model on the entire data sample. Then for each INHP loan we identify a non-INHP loan with the closest value of Pr(**Z**). We compute the ATT from comparison of mean default rates of INHP loans and their matched counterparts.[7]

The estimates of the ATT effect obtained in this fashion are reported in Table 3. The average default rates of the treated and the matched control groups are substantially different. When the propensity model is estimated only on borrower characteristics, location and time (the "Borrower" model), the estimated ATT exceeds 10 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 control group to also differ in

[7] 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.

terms of loan contract choices and terms. Indeed, the matched group ends up having a much higher share of adjustable-rate and option ARM loans (23 and 5 percent versus none in the treated group). This again underscores the contribution of the 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 3 (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. This suggests that the effect of counseling treatment is persistent, although one would like to be able to track counseled loans over longer time periods to confirm this. There is little reason to believe that INHP clients, on average, experienced a different set of external economic shocks than similar non-treated 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 another approach evaluated in Agarwal et. al. (2009). In that instance, a mandatory review of approved loan applications and perceived regulatory oversight resulted in severe market disruptions. Although observed ex post performance of counseled borrowers improved, the change can be better explained by tighter screening actions of lenders subject to regulation than counseling per se.

These two case studies highlight some of the policy tradeoffs in counseling of prospective homeowners. Both of these programs restricted credit for low- and moderate income borrowers. In case of mandatory counseling, credit was limited primarily through a reduction in the number of lenders willing to operate under the legislative mandate. In the case of INHP, credit is limited to borrowers with demonstrated ability to carry a mortgage. Only in the latter case did the counseled borrowers acquire lasting skills.

The program studied here contains many of the elements that appear to be necessary ingredients for any broad-scale successful counseling initiative. It attracts private capital from lending partners seeking to satisfy their CRA requirements. It offers financial training and thorough internal 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 underwriting 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, financial transaction.

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TABLE 1 – SUMMARY STATISTICS OF MORTGAGE LOANS AND BORROWERS (2005-2007)

Variable	INHP clients: Internal loans	INHP clients: External loans	Rest of Marion Co.
Number of first-lien mortgage loans	211	148	16,677
FICO score at origination (mean)	614	638	691
[interquartile range]	[569 - 646]	[594 - 676]	[637 - 752]
Income (median)	27,600	35,000	54,000
[interquartile range]	[22,800 - 35,047]	[26,000 - 44,700]	[37,000 - 82,000]
Loan amount (median)	69,900	93,344	108,000
LTV at origination (mean)	93%	93%	90%
Share of fixed-rate mortgages (FRM)	100%	99%	81%
Interest rates on FRM (mean)			
loans originated in 2005	7.2%	5.7%	6.1%
loans originated in 2006	7.7%	6.5%	6.8%
loans originated in 2007	7.8%	6.7%	6.7%
Loan spread (mean)	2.7%	1.5%	2.3%
Share of FHA-insured loans	0%	47%	22%
12-month default rate	3.8%	4.1%	6.3%
18-month default rate	10.0%	6.3%	10.1%

Notes: Unless otherwise noted all statistics are computed for first-lien home purchase mortgage loans that did not get refinanced or transferred within 12 months of origination. Directly-financed loans are funded and underwritten by INHP and are typically sold off in pools after seasoning. Lender-referred (LR) loans are funded and underwritten by INHP lending partners. Loan spread for fixed-rate mortgages is defined as a difference between the contract rate and the contemporaneous rate on Treasury bonds of same maturity. For adjustable-rate mortgages, loan spread is set equal to the loan margin applied at first interest rate reset. A loan is considered in "default" if it is 90 days or more past dure, in foreclosure, or real-estate owned. The 18-month default rate is computed for loans that did not get refinanced or transferred within 18 months of origination.

TABLE 2 – REGRESSION ANALYSIS OF LOAN PERFORMANCE

	OLS		logit (marginal effects)	
	12-mo default	18-mo default	12-mo default	18-mo default
	(1)	(2)	(3)	(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-squared	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 reported in the Web appendix. 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 Table 1. ***, **, * indicate statistical significance at the 1, 5, and 10 percent level.

TABLE 3 – DIFFERENCES IN LOAN PERFORMANCE IN PROPENSITY-MATCHED SAMPLES

		borrower group				
Maching model		INHP	Non-INHP	ATT	Std. error	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 orignation. 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 reported in the Web appendix.