



January 1999

Community Reinvestment and Credit Risk: Evidence from an Affordable-Home-Loan Program

Paul S. Calem

Board of Governors of the Federal Reserve System

Susan M. Wachter

University of Pennsylvania, wachter@wharton.upenn.edu

Follow this and additional works at: https://repository.upenn.edu/penniur_papers

Calem, Paul S. and Wachter, Susan M., "Community Reinvestment and Credit Risk: Evidence from an Affordable-Home-Loan Program" (1999). *Penn IUR Publications*. 13.

https://repository.upenn.edu/penniur_papers/13

Copyright The American Real Estate and Urban Economics Association (AREUEA). Reprinted from *Real Estate Economics*, Volume 27, Issue 1, Spring 1999, pages 105-134.

This paper is posted at ScholarlyCommons. https://repository.upenn.edu/penniur_papers/13
For more information, please contact repository@pobox.upenn.edu.

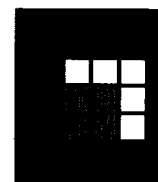
Community Reinvestment and Credit Risk: Evidence from an Affordable-Home-Loan Program

Abstract

This study examines the performance of home purchase loans originated by a major depository institution in Philadelphia under a flexible lending program between 1988 and 1994. We examine long-term delinquency in relation to neighborhood housing market conditions, borrower credit-history scores and other factors. We find that likelihood of delinquency declines with increasing neighborhood housing market activity. Also, likelihood of delinquency is greater for borrowers with low credit-history scores and those with high ratios of housing expense to income, and when the property is unusually expensive for the neighborhood where it is located.

Comments

Copyright The American Real Estate and Urban Economics Association (AREUEA). Reprinted from *Real Estate Economics*, Volume 27, Issue 1, Spring 1999, pages 105-134.



Community Reinvestment and Credit Risk: Evidence from an Affordable-Home- Loan Program

Paul S. Calem* and Susan M. Wachter**

This study examines the performance of home purchase loans originated by a major depository institution in Philadelphia under a flexible lending program between 1988 and 1994. We examine long-term delinquency in relation to neighborhood housing market conditions, borrower credit-history scores and other factors. We find that likelihood of delinquency declines with increasing neighborhood housing market activity. Also, likelihood of delinquency is greater for borrowers with low credit-history scores and those with high ratios of housing expense to income, and when the property is unusually expensive for the neighborhood where it is located.

Recent years have witnessed broad national initiatives and targeted local programs aimed at increasing the supply of mortgage credit to low- and moderate-income households and residents of lower-income neighborhoods, particularly in central cities. Often, these initiatives have been associated with efforts by banks and other depository institutions to comply with community reinvestment regulations.¹ Also, the Federal Housing Enterprises Financial Safety and Soundness Act of 1992 directed the Department of Housing and Urban Development (HUD) to establish annual goals for Fannie Mae and Freddie Mac with respect to the purchase of mortgages extended to low- and moderate-income families, and these institutions subsequently

*Board of Governors of the Federal Reserve System, Washington, DC.

**The Wharton School of the University of Pennsylvania, Philadelphia, PA 19104.

¹ The 1977 Community Reinvestment Act requires depository institutions to help meet the credit needs of their entire community, including low- and moderate-income areas, in a manner consistent with safe and sound banking practices. A recent survey indicates that many bank and thrift institutions have introduced loan programs intended to increase the supply of mortgage credit to low- and moderate-income borrowers. These mortgage products typically provide more flexible terms and underwriting standards, such as flexible debt-to-income requirements or credit history standards. Often, credit counseling and home-buyer education are offered to help people qualify for a mortgage, and loan rejections are typically provided a second review. See Consumer Bankers Association (1995).

initiated special *affordable-home-loan* programs designed to broaden the availability of mortgage credit.

Because these lending initiatives typically incorporate flexible underwriting standards along with enhanced risk-mitigation activities, questions arise regarding their credit-risk implications. In particular, what gradations of credit risk are associated with particular aspects of such programs? In this study, we address this issue with a unique data set that allows us to identify credit risk attributable to specific borrower and neighborhood factors. Our study is the first multivariate analysis of affordable-home-loan performance to assess the relationship between delinquency risk and credit history scores, which is an issue of special importance given the increased use of credit scores in affordable-home-lending contexts.

The study examines the performance of home purchase loans originated by a major depository institution in Philadelphia (henceforth referred to as BANK) under a long-established, portfolio-based, flexible lending program known as the Delaware Valley Mortgage Plan (DVMP).² Using a database of over 2,000 conventional mortgages originated between 1988 and 1994, we conduct a multivariate analysis of factors related to long-term delinquency. Further, we assess relationships between credit risk factors and long-term delinquency by means of simulations based on the multivariate analysis.

Although a large empirical literature examines factors related to mortgage performance, only a few studies specifically consider the performance of conventional mortgages associated with community reinvestment programs.³ There has been little systematic study of the relation between mortgage loan performance and credit scores or similar measures of borrower credit history, due to a lack of data. Available evidence on performance of affordable home loans is from largely proprietary studies conducted by Fannie Mae, Freddie Mac and private mortgage insurance companies.⁴ Reported results from these

² The DVMP program was initiated in 1977 in response to public concerns regarding availability of credit in inner-city Philadelphia neighborhoods. See Calem (1993) for details.

³ See Quercia and Stegman (1992) for a review of the literature on mortgage loan performance. None of the studies cited examine credit scores as predictors of loan performance.

⁴ Also, Mills and Lubuele (1994) present limited evidence based on data obtained from a trade association survey. The sample for their study contained both multi-family and single-family loans, but they had very limited information pertaining to the single-family loans in their sample.

studies concern the relation of a few specific underwriting flexibilities to delinquency risk in nationwide aggregate samples, where the loans are relatively recent in origin.⁵

Our study has several distinguishing features. We focus on one bank's portfolio-based, flexible-lending program, in one city. Hence, difficulties associated with aggregation across metropolitan areas and loan servicing institutions do not arise.⁶ We are able to analyze the relationship between the performance of a portfolio of seasoned and new affordable home loans and (with controls) credit scores. Our analysis yields new evidence on the relation between relaxed underwriting standards and loan delinquency. We also document relationships between housing market variables and loan delinquency that support the view that credit risk is affected by factors potentially related to appraisal risk.

The paper is organized as follows. In the next section, we describe the DVMP program and its greater than proportionate share of loans originated in low- and moderate-income areas of Philadelphia. In the third section, we describe the loan performance data obtained from BANK. The fourth section presents our basic multivariate analysis. In the fifth section, we estimate alternative specifications and present the simulation results. The sixth section concludes.

The DVMP Affordable-Home-Loan Program

BANK belongs to a consortium of depository institutions in Philadelphia that participate in the DVMP. Each loan under the program is originated by a single institution, which typically retains the loan in portfolio. Each bank establishes its own specific underwriting, pricing and servicing policies, but participating institutions agree to abide by the program's broad underwriting guidelines and to submit denied loan applications to a joint review board for second evaluation.⁷ To be eligible to apply for a DVMP loan, a prospective

⁵ Their focus is on using cross-tabulations to show the effects of extending credit to borrowers with "marginal" credit histories, unusually high loan-to-value or payment-to-income ratios, or less than the generally required level of cash reserves. See Avery *et al.* (1996) for a review of these studies.

⁶ The advantages of disaggregating across metropolitan areas are highlighted by Capozza, Kazarian and Thomson (1997). The effect of servicing policies on measures of loan performance is emphasized by Ambrose and Capone (1998).

⁷ There are three possible outcomes to this second review process: The initial rejection may be confirmed, the institution that originally rejected the loan may reverse its decision or another institution may offer to make the loan.

borrower must meet specified income and house price limits. Generally, DVMP loans are not FHA- or VA-insured.

For several reasons, households may qualify for DVMP loans when they cannot qualify for more traditional loan products. The structural condition of properties located beyond the immediate block are not factored into property appraisals, and allowances are made for the “nontraditional nature of older, inner-city properties.” Certain requirements applied to loans sold to Fannie Mae or Freddie Mac or to FHA-insured loans often have been waived by DVMP lenders. For example, participating institutions have allowed borrowers to pay closing costs with unlimited seller assistance or with funds from undocumented sources (so-called *cash on hand*), whereas the secondary market agencies place restrictions on seller assistance and cash on hand. Also, Fannie Mae and Freddie Mac generally require a loan to be backed by private mortgage insurance unless the borrower provides a down payment of at least 20% of the appraised value of the home. DVMP lenders generally have not required this.⁸

DVMP credit policies, particularly in regard to credit history, employment stability, and sources of income, have tended to be more flexible than those of private mortgage insurers and the secondary market agencies. DVMP credit policies have not been entirely more flexible than those associated with FHA loan products, however. For example, most of BANK’s DVMP loans required a 10% down payment. In contrast, FHA-insured loans usually have loan-to-value ratios of 95% or higher.

DVMP lenders commonly have offered below-market interest rates on DVMP loans. For example, during 1990–1993, BANK usually provided a subsidy of 100 to 125 basis points below the market rate.⁹ Below-market pricing appears to have been motivated by price rivalry among DVMP institutions. FHA and traditional conventional loan products have not been a significant source of price competition for DVMP lenders, because many DVMP borrowers would not qualify for traditional conventional loans and because the price of FHA credit is comparatively high.

⁸ However, some DVMP borrowers do obtain private mortgage insurance, as indicated by our data.

⁹ Not all DVMP borrowers receive subsidies, however. Borrowers who are comparatively well positioned financially are likely to receive the current market rate. Borrowers generally do not receive rebates on points or fees.

Lending Patterns in Philadelphia

Evidently, the DVMP has broadened the availability of mortgage credit in low- and moderate-income areas. Table 1 provides an overview of mortgage lending patterns in Philadelphia for the period 1990–1993, based on data collected by federal regulatory agencies under the Home Mortgage Disclosure Act (HMDA) and on the 1990 U.S. Census of Population and Housing.¹⁰ Column 1 shows the proportion of the city's owner-occupied units in particular Census-tract categories: low- and moderate-income tracts, middle- and upper-income tracts, predominantly minority tracts, non-minority tracts, blighted areas, other economically distressed tracts and non-distressed tracts.¹¹ The last column shows the proportion of all home purchase loans in Philadelphia in each of these tract categories. The three middle columns provide this information for three categories of home purchase loans, respectively: conventional loans originated by DVMP-participating institutions, all other conventional loans, and FHA- or VA-insured loans. As the table clearly indicates, the DVMP has played a major role in financing home purchases in low- and moderate-income areas, minority areas and economically distressed neighborhoods of Philadelphia.¹² For instance, 30% of the loans of DVMP institutions are located in blighted or other economically distressed tracts, compared to only 6% of the conventional loans originated by non-DVMP institutions and only 7% of federally insured loans.¹³

¹⁰ Attention is restricted to loans that financed the purchase of one-to-four family, owner-occupied properties. We focus on the 1990–1993 period because income of the borrower has been reported under HMDA only since 1990. The HMDA data have been edited as described in the appendix to Calem (1996b).

¹¹ Following Calem (1996b), we define a low- or moderate-income tract to be a tract where the median income is less than or equal to 85% of the MSA median income and the median price of a single-family home is no greater than \$82,000. A predominantly minority tract is a tract where the population is at least 75% minority (black, Hispanic or Asian). A blighted tract is one where at least 10% of housing units are vacant and at least 5% are boarded up, or where the vacancy rate is at least 20%. Other economically distressed tracts are those not classified as blighted where the unemployment rate exceeds 15%. Non-residential tracts (those with fewer than 30 owner-occupied units) are excluded, leaving a total of 339 tracts. Of these, about 2 out of 3 are low- or moderate-income; 1 out of 3 are predominantly minority; 1 out of 5 are blighted; and 1 out of 10 are other economically distressed.

¹² BANK's pattern of lending across tract categories is not substantially different from the aggregate DVMP pattern. See Calem (1993, 1996b) for additional discussion of lending patterns in Philadelphia and the greater than proportionate share of loans originated by DVMP institutions in low- and moderate-income areas.

¹³ The citywide market shares are 17.9% for DVMP lenders, 51.6% for conventional non-DVMP and 30.5% for FHA/VA, respectively.

Table 1 ■ Lending patterns in Philadelphia.

Tract Category	Category's Share (%) of Philadelphia Owner-Occupied Units and Its Share of Philadelphia Home Purchase Loans (by Type of Loan)				
	(1) Owner-Occupied Units	(2) DVMP	(3) Non-DVMP Conventional	(4) FHA/VA	(5) All Loan Types
Low- or moderate-income	68.4	86.5	43.3	67.0	58.3
Middle- or upper-income	31.6	13.5	56.7	33.0	41.7
Minority	33.1	32.6	8.7	19.6	16.3
Non-minority	66.9	67.4	91.3	80.4	83.7
Blighted	12.0	11.8	3.6	3.3	5.0
Other distressed	8.7	18.0	2.6	4.0	5.8
Non-distressed	79.3	70.2	93.8	92.7	89.2

The special role of the DVMP also is evident from data on borrower incomes (not shown in the table). The incomes of DVMP borrowers tend to be substantially lower than those of other borrowers in the same neighborhood income category. For instance, within low- and moderate-income areas of Philadelphia, close to half of all loans originated by DVMP institutions during 1990–1993 were to households earning under \$20,000 per year, while only 16% of FHA/VA loans and 14% of the conventional loans of non-DVMP institutions were to borrowers in that income range.

DVMP Loan Performance Data

Analysis of the performance of DVMP loans helps shed light on the credit-risk implications of efforts to broaden access to credit. A variety of measures of loan performance bear on credit risk and related lender costs. In general, performance indicators including delinquency rates, foreclosure rates, losses incurred in the event of foreclosure, and costs related to loss mitigation activities, such as the cost of servicing delinquent loans, are relevant to the overall rate of return to the lender. This paper focuses on only one of these measures: loan delinquency rates. Thus, caution must be exercised in drawing overall conclusions about the costs associated with affordable-home-loan programs like the DVMP.

Table 2 ■ Distribution of DVMP loans by year of origination and term to maturity.

Year of Origination	Number	Percentage
1988	60	2.5
1989	136	5.7
1990	287	12.0
1991	363	15.2
1992	545	22.8
1993	575	24.1
1994	424	17.7
Term to Maturity		
15–25 years	265	11.1
30 years	2,096	87.7
Other	29	1.1
Total	2,390	100.0

Loan delinquency data were drawn from BANK's servicing files as of November 15, 1994. These files contained records on all outstanding loans that had been originated under the DVMP for which first payments were due on or after June 1, 1988. (BANK initiated in-house servicing of its DVMP loan originations as of that date.) We were provided with records on each of the 2,390 outstanding loans that were originated prior to August 1, 1994. All were fixed-rate, conventional loans for the purchase of single-family, owner-occupied properties. The information obtained includes the due date of the first payment, the date of the last payment received by November 15, 1994 and the number of months delinquent (if delinquent) as of November 15, 1994. The records also provide the loan amount, contract interest rate, term to maturity, required monthly payment (principal, interest and escrow amount) and whether the loan was originated with private mortgage insurance. The records also identify whether the loan financed the purchase of a "high-value rehabilitated property."¹⁴

The distribution of the sample by year of origination and term to maturity are shown in Table 2. The distribution of the sample by repayment status is shown in Table 3. Approximately 9% of the loans were delinquent 60 days or more as of November 15, 1994; another 7% were 30–59 days past due.

¹⁴ The mean price for these properties was \$45,768, while the mean for all other properties was \$30,035.

Table 3 ■ Distribution of DVMP loans by repayment status as of November 15, 1994.

Repayment Status	Number	Percentage
Current (not delinquent)	2,012	84.2
30–59 days delinquent	174	7.3
60–89 days delinquent	70	2.9
90–180 days delinquent	64	2.7
> 180 days delinquent	70	2.9

During the period covered by this study, very few loans were foreclosed. Given the relatively small loan amounts, forbearance was viewed as generally less costly than foreclosure. BANK's policy has been to proceed with foreclosure only when it is clear that a borrower has little prospect of resuming payments.¹⁵ Delinquent borrowers are allowed to resume making monthly loan payments and to defer past-due amounts until they become fully capable of making good on the missed payments. Because of these policies, the data include a substantial number of loans that are delinquent six months or more.

Comparison with Performance of FHA Loans

The DVMP program and FHA-insured loans are the primary flexible lending vehicles serving low- and moderate-income borrowers in Philadelphia. Therefore, it is of interest to draw comparisons between these two types of loan products. We have already noted differences in the geographic distributions of DVMP and FHA-insured loans. To provide additional context for our results, we briefly compare the performance of BANK's DVMP loans with that of FHA-insured loans in the Philadelphia metropolitan statistical area (MSA).

From the FHA, we obtained information on the proportion of FHA-insured loans in the Philadelphia MSA that were 90 days or more delinquent (termed

¹⁵ BANK reports that most often, delinquencies were the result of a borrower becoming unemployed or becoming overextended as a result of excessive spending and/or unplanned expenses. In some cases, properties had been rented to tenants, who then fell behind in their rent payments. To further the successful application of its servicing policies, BANK employs collectors who are trained in budget counseling and who are familiar with the local network of non-profit support services for financially stressed households.

the “default rate”) as of year-end 1994, for loans grouped by year of origination. In Pennsylvania, the FHA would generally initiate foreclosure on delinquent loans after 180 days. Therefore, the appropriate comparison is between the FHA default rate and the 90–180-day delinquency rate on BANK’s DVMP loans (calculated after excluding loans more than 180 days delinquent from the sample).¹⁶

To make the FHA and DVMP samples more comparable, we exclude loans originated with a loan-to-value ratio of 80% or less from the DVMP sample. After these exclusions, the 90–180-day delinquency rate for the DVMP sample is 2.8%. After weighting the annual FHA default rates to adjust for differences in the distribution of loans by year of origination between the FHA and DVMP samples, we find that the weighted average FHA default rate for the period 1988–1994 equals 3.1%.

Thus, although DVMP borrowers tend to have much lower-incomes and are purchasing properties in lower-income neighborhoods than borrowers obtaining FHA-insured loans, the overall performance of DVMP loans appears to be very similar to that of FHA-insured loans. In part, this may reflect the fact that the loan-to-value ratios associated with DVMP loans tend to be lower than those associated with FHA-insured loans. This result suggests that overall, the credit risk incurred by DVMP institutions in providing broader access to credit is comparable to that associated with FHA lending. We now turn to a multivariate analysis of factors contributing to delinquency risk on DVMP loans, which may suggest ways that DVMP lenders can mitigate such risk and the associated costs.

Multivariate Analysis of Loan Performance

To analyze the credit-risk implications of efforts to broaden access to mortgage credit, we examine the relationship between long-term delinquency on DVMP loans and neighborhood housing market conditions, borrower

¹⁶ BANK’s forbearance policies give rise to the possibility that some DVMP loans observed to be 90–180 days delinquent in our data may belong to borrowers who had partially caught up after being more than 180 days delinquent earlier on. Thus, this comparison may somewhat overstate the credit risk of DVMP loans relative to that of FHA-insured loans. On the other hand, BANK’s forbearance policies may encourage borrowers to lengthen their delinquency beyond 180 days, which may cause this comparison to understate the relative credit risk of DVMP loans.

credit characteristics and other factors. For this purpose, additional data were obtained and used to estimate multivariate logit equations.¹⁷

Because the Census-tract location of each loan was provided by BANK, we were able to identify neighborhood characteristics from 1990 Census data. The purchase price of the property being financed was determined from data obtained from the Philadelphia Board of Realtors for all but 139 of the 2,390 loans in the sample obtained from BANK. The loan-to-price ratio is used in our analysis as a proxy for the loan-to-value ratio. The ratio of the price to the Census-tract median house value is also used below.

For 1,222 loans in the sample from BANK, we were able to identify the race, income and sex of the borrower and whether a co-borrower was present by merging in HMDA data. Merging in of income data enabled us to calculate the borrower's housing expense-to-income *front-end* ratio. The merging in of HMDA data was accomplished by matching loan amounts and Census-tract locations and requiring that the date of the first payment be close to the origination date recorded in the HMDA data. We were unable to accomplish this in cases where the loans appeared to be missing from the HMDA data and in cases where multiple matches were obtained. Delinquency rates and other characteristics of the subsample with HMDA data are similar to those of the full sample.¹⁸

¹⁷ Proportional-hazard estimation has been employed in recent studies where available data include the repayment history, from the date of origination on, of each mortgage in a loan pool. We cannot adopt this approach, because we only know the payment status of existing loans as of a single date (November 15, 1994). In particular, loans that terminated prior to that date are not in the data set. Specifically, loans that terminated due to foreclosure or because the borrower refinanced are not in the sample. In theory, this could raise sample selection issues. As noted, however, foreclosure was very rare. Refinancing was not available within the DVMP program, and anecdotal information suggests that outside refinancing also was rare. Indeed, the cost advantages of remaining within the program (below-market interest rates, waiving of private mortgage insurance), the proportionately high costs typically associated with refinancing small loan amounts, and borrowers' loss of equity due to declining house values would have discouraged most borrowers from refinancing.

¹⁸ We observe virtually no differences in delinquency rates between the subsample with HMDA data and the original sample after controlling for differing distributions of loans by year of origination (by weighting the annual delinquency rates in the original sample), allaying concerns about selection bias. For instance, 9.2% of the loans in the subsample with HMDA data are delinquent 60 days or more. The corresponding weighted-average delinquency rate for the original sample is 9.4%.

Borrower Credit Scores

For 1,157 of the loans in the sample from BANK (including only loans originated subsequent to October 1, 1989), we obtained a score of the borrower's credit history as of the date of loan origination. Specifically, we utilized The Mortgage Score (TMS), a credit score developed by Equifax Mortgage Services.¹⁹ TMS scores represent statistically derived measures of the credit risk associated with a given credit history. This scoring system, which was developed by Equifax on the basis of the credit records of mortgagors and the payment performance on their mortgage accounts, weighs such factors as the number and severity of recorded episodes of delinquency, records of bankruptcy, number of credit lines and age of the oldest credit line. While such credit history information was considered by BANK in evaluating applications for DVMP loans, credit scores were not used.

TMS scores were obtained for 682 of the 1,222 loans for which we were able to merge in HMDA data. For the remaining 540 loans for which HMDA data were available, we imputed a credit history score.²⁰ Using the sample for which both the TMS score and HMDA data were available, we regressed the TMS score on characteristics of the loan and borrower. The model's independent variables included income, race and sex of the borrower, presence of a co-borrower, several race and sex interaction terms, and dummy variables controlling for year of origination and the loan category. The relationship between these variables and the TMS score as represented by the estimated regression equation was used to impute missing scores. The regression equation used to impute scores is described more fully in Appendix A.

The use of imputed data may produce biased estimates if the error term of the regression model used to impute credit scores is correlated with the error term of the statistical model of loan delinquency. Another limitation of the imputation procedure is that the imputed scores are fully determined by the variables included in the imputation equation—there is no random variability. As a result, the use of imputed credit score data may bias statistical tests of the relationship between credit scores and loan

¹⁹ The Mortgage Score and TMS are service marks of Equifax Mortgage Services.

²⁰ Scores were more frequently missing for loans originated in earlier years, due to difficulties associated with retrieving archived credit records. In addition, scores were missing for male borrowers more frequently than for female borrowers. Once these factors are controlled for, delinquency rates do not differ between borrowers with and without scores.

performance. These issues are addressed in the section on “Additional Tests” below.

Model Specification

BANK’s servicing data, together with TMS scores (known or imputed), borrower characteristics from HMDA, purchase prices, and tract-level Census data, form the database for our multivariate logit analysis of loan performance. Alternative measures of loan performance are employed as the dependent variable: *DELINQ60*, which identifies whether a loan is 60 days or more delinquent (*DELINQ60* = 1) or not (*DELINQ60* = 0), and *DELINQ90*, which identifies whether a loan is 90 days or more delinquent.

Most models of mortgage loan performance emphasize the role of homeowner equity in the decision to default. So long as the market value of the home (after allowing for sales expenses and related costs) exceeds the market value of the mortgage, the borrower has a financial incentive to sell the property to extract the equity rather than default or remain delinquent. If property values have declined, it may be difficult for a borrower to sell a property at a price sufficient to enable repayment of the mortgage. Hence, changes in property values are a major factor affecting mortgage loan delinquency rates (Quercia and Stegman 1992).

Property values in Philadelphia, as reflected in the median sale price, declined during 1990 and 1991, due to a slackening of demand, after increasing steadily through most of the 1980s. While the median sale price rose some after 1992, anecdotal evidence suggests that market values continued to decline well into 1993. We control for the potential effects these movements in property values may have had on likelihood of delinquency, as well as any potential effects of loan seasoning, by including dummy variables for year of origination (*YEAR94*, *YEAR93*, *YEAR92*, etc.) in each of our estimated equations. Since the sample contains observations from only part of 1988 and 1994, we combined 1988 with 1989 and appended the fourth quarter of 1993 to 1994 in controlling for year of origination. All equations are estimated with *YEAR92* as the omitted year dummy variable.

We employ dummy variables (*LTVLE80* and *LTVGT90*) to control for the relationship between loan performance and the loan-to-value ratio at time of origination. Respectively, *LTVLE80* and *LTVGT90* identify loans originated with a loan-to-value ratio of 80% or less and those originated with loan-to-value ratios of 91%–95% at the time of origination. Dummy variables are

used for this purpose because a comparatively small number of loans were originated with loan-to-value ratios other than 90%.

We are particularly interested in the extent to which DVMP lenders face increased delinquency risk as a consequence of extending credit to borrowers with weaker credit histories. The TMS score (known or imputed) is included to capture this relationship.

We also are interested in the credit risk implications of the DVMP's emphasis on lending in economically disadvantaged neighborhoods. Theory suggests that higher levels of capital consumption and consequent value declines may occur in lower income neighborhoods, neighborhoods experiencing population declines, or areas with high or increasing rates of unemployment.²¹ Theory also suggests that neighborhood housing market activity may affect credit risk. One view is that the accuracy of property appraisals increases with neighborhood housing market activity (Lang and Nakamura 1993). An alternative model rests on neighborhood effects whereby improvements in one property can increase the value of other properties in the vicinity (Guttentag and Wachter 1980). We test relationships between neighborhood factors and credit risk using tract-level economic and demographic variables, as discussed below.²²

It may be difficult to accurately appraise the value of properties that are unusually expensive for the neighborhood where they are located—for example, rehabilitated properties in blighted neighborhoods. Thus, such properties may be associated with increased lending risk. In addition, such properties may be overvalued relative to the market. Hence, we include a dummy variable (*RELPRICE*) indicating whether the purchase price of the property exceeded the 1990 tract median value by 33% or more (*RELPRICE* = 1), which we expect to be positively related to likelihood of delinquency.²³

We also include a dummy variable identifying the small subsample of loans backed by private mortgage insurance (*INSURED*). These loans had to

²¹ Previous studies have found that foreclosure rates tend to be higher in neighborhoods with higher rates of unemployment and in blighted neighborhoods. See Barth, Cordes and Yezer (1979), Berkovec *et al.* (1994, 1996, 1998), or the references in Quercia and Stegman (1992).

²² Empirical evidence based on mortgage application denial rates also is consistent with these arguments (Calem 1996a; Avery, Beeson and Sniderman 1998; Ling and Wachter 1999.) To our knowledge, ours is the first loan performance study to directly evaluate the effect of neighborhood housing market activity.

²³ For loans originated prior to 1990, when values were appreciating, we set *RELPRICE* = 0.

satisfy the insurer's credit standards, which may have helped mitigate credit risk.²⁴

A borrower's front-end ratio may measure a borrower's ability to repay a mortgage. To test this relationship, we employ a dummy variable (*FRONTEND*) identifying households with a front-end ratio exceeding 28%. To control for race and sex of the borrower and presence of a co-borrower, we employ dummy variables identifying female borrowers (*FEMALE*), African-American borrowers (*BLACK*) and individual (as opposed to joint) borrowers (*SINGLE*).

Empirical Results

The results discussed in this section pertain to model specifications that include each of the variables defined above, plus neighborhood variables. (Results from estimating alternative models are discussed in the section on "Additional Tests" below.) As noted, for a number of observations we were unable to merge in HMDA data. Exclusion of these observations (and a few observations with other missing data) left a sample of 1,172 observations for these estimations. Sample means are shown in Table 4.²⁵ The logit estimation results are presented in Table 5.

Three neighborhood factors—Census-tract housing market activity (*ACTIVITY*), squared activity (*ACTVTYSQ*) and the proportion of residents age 55 or older (*AGE55*)—are included in the estimated equations shown in Table 5. Housing market activity is measured as the number of HMDA-reported home purchase loans in a Census tract during 1990–1993, per 10 owner-occupied units in the tract, and is included in the model for the reasons noted. *AGE55* is included because previous research suggests that in recent years, Philadelphia neighborhoods with larger proportions of older residents have had more stable populations (compared to the city as a whole, which has been losing residents), contributing to overall neighborhood stability (Calem 1996b). Substitution of other tract variables for these three, or inclusion of additional tract variables, does not appear to substantially improve model performance (details are provided below in this section and

²⁴ For most loans, the loan-to-value category was indicated in BANK's servicing records. Otherwise, we used the loan-to-price ratio as a proxy for the loan-to-value ratio. Most loans in the sample (about 3 out of 4) were originated with a loan-to-value ratio between 81% and 90%. Relatively few loans (about 5% of the sample) were backed by private mortgage insurance. (Why these loans were originated within the program is not clear.)

²⁵ Mean values are very similar for the full sample.

Table 4 ■ Means of variables.

Variable	Mean Value	Variable	Mean Value
<i>ACTIVITY</i> ^a	0.85	<i>FRONTEND</i> ^c	0.08
Loan amount	\$27,486	Borrower income	\$20,496
TMS credit score	658	<i>FEMALE</i>	0.39
Purchase price	\$30,806	<i>BLACK</i>	0.30
<i>RELPRICE</i> ^b	0.24	<i>SINGLE</i>	0.78
<i>INSURED</i>	0.05	<i>DELINQ60</i>	0.10
<i>LTVGT90</i>	0.11	<i>DELINQ90</i>	0.06
<i>LTVLE80</i>	0.06	<i>AGE55</i> ^d	0.39

^a Number of mortgages originated during 1990–1993 per 10 owner-occupied units in the Census tract where the property is located.

^b Dummy variable that equals 1 if the purchase price of the property exceeds the Census-tract median house value by 33% or more, and equals 0 otherwise.

^c Dummy variable that equals 1 if the borrower's ratio of housing expense to income exceeds 28%, and equals 0 otherwise.

^d Fraction of the population age 55 or older in the Census tract where the property is located.

in the one on “Additional Tests”). In particular, these three variables consistently yielded a better fit to the data (a larger model chi-square statistic) than any other trio of neighborhood factors.

Results obtained with *DELINQ60* as the dependent variable are shown in panel 1. A borrower's credit score (TMS) appears to be a strong predictor of performance. Borrowers with higher scores at the time of loan origination are less likely to become delinquent. In addition, female borrowers are less likely to become delinquent.²⁶

The results indicate that likelihood of delinquency declines with housing market activity once the level of activity becomes sufficiently high. Specifically, the partial derivative with respect to activity is positive and

²⁶ Although the coefficient on *BLACK* indicates that black borrowers are more likely to become delinquent, this relationship is not statistically significant. Dropping the TMS score from our estimated equation does not result in *BLACK* becoming statistically significant at even the 10% level, although its chi-square value does increase some. Previous studies, without controlling for borrower credit history, found that race bears a statistically significant relation to cumulative default rates on FHA loans (e.g., Van Order, Westin and Zorn 1993; Berkovec *et al.* 1994, 1996, 1998). However, these studies are not directly comparable to our study, because they employ different measures of loan performance and are based on much larger and more heterogeneous samples.

Table 5 ■ Logit estimation of loan performance equations.

Variable	Panel 1: 60+ Delinquency Equation		Panel 2: 90+ Delinquency Equation	
	Coefficient Estimate	Chi-Square	Coefficient Estimate	Chi-Square
Intercept	-2.19	2.2	1.47	0.7
<i>ACTIVITY</i> ^a	2.68	4.3**	1.99	1.8
<i>ACTVTYSQ</i>	-1.72	6.2**	-1.51	3.4*
<i>AGE55</i> ^b	-2.24	3.5*	3.11	4.9**
<i>YEAR94</i>	-2.24	4.4**	-1.49	1.1
<i>YEAR93</i>	-1.28	12.8**	-1.19	6.9**
<i>YEAR91</i>	0.44	2.8*	0.66	4.4**
<i>YEAR90</i>	0.73	5.9**	1.02	8.6**
<i>RELPRICE</i> ^c	0.56	6.2**	0.74	7.8**
(TMS score)/100	-0.71	13.6**	-0.64	8.1**
<i>FRONTEND</i> ^d	0.86	7.2**	0.56	1.9
<i>FEMALE</i>	-0.92	14.0**	-0.87	9.0**
<i>BLACK</i>	0.29	1.2	0.39	1.6
<i>SINGLE</i>	0.39	2.1	0.74	4.3**
<i>INSURED</i>	-2.13	3.4*	-0.74	0.2
<i>LTVGT90</i>	1.03	1.3	0.02	0.0
<i>LTVLE80</i>	-0.71	1.7	-0.56	0.8
No. of observations	1,172		1,172	
Model chi-square	97.8		80.2	

^a Number of mortgages originated during 1990–1993 per 10 owner-occupied units in the Census tract where the property is located.

^b Fraction of the population age 55 or older in the Census tract where the property is located.

^c Dummy variable that equals 1 if the purchase price of the property exceeds the Census-tract median house value by 33% or more, and equals 0 otherwise.

^d Dummy variable that equals 1 if the borrower's ratio of housing expense to income exceeds 28% and equals 0 otherwise.

**Statistically significant at the 5% level or better.

*Statistically significant at the 10% level.

statistically significant (at the 5% level or stronger) at levels of activity above 0.92 (corresponding to 40% of the sample). This finding is consistent with the view that neighborhood housing market activity affects credit risk, perhaps by influencing the accuracy of property appraisals.

AGE55 is statistically significant at the 10% level and inversely related to likelihood of delinquency, consistent with the view that neighborhoods with a large proportion of older residents were less likely to lose population and experience abandonment or blight during the period covered by this study.²⁷ In part, this result may also reflect the fact that age of the residents is negatively correlated with the neighborhood unemployment rate.²⁸

RELPRICE is positively related to likelihood of delinquency and is statistically significant. This is consistent with the view that a high relative purchase price is associated with increased delinquency risk. Also as expected, the likelihood of long-term delinquency decreases the more recent the date of origination, consistent with the expected effects of loan seasoning and declining house values.

The dummy variable *FRONTEND*, which identifies loans with a housing-expense-to-income ratio greater than or equal to 28%, exhibits the expected positive sign and is statistically significant at the 1% level. This is consistent with previous studies (*e.g.*, Berkovec *et al.* 1998), where payment-to-income ratios typically have been found to be predictive of delinquency or default.

Estimation with *DELINQ90* as the dependent variable yields the results shown in panel 2 of Table 5. These differ in just a few ways from those shown in panel 1. *AGE55* is now statistically significant at the 5% level. *SINGLE* is now statistically significant, while *FRONTEND* exhibits a weaker relationship to the dependent variable.

Robustness Checks

Similar results are obtained when the level of housing market activity is represented by dummy variables in place of *ACTIVITY* and *ACTVTYSQ*. Again, a high level of housing market activity is associated with lower likelihood of delinquency, and this relationship is statistically significant.

²⁷ This result should not be interpreted as predictive of future relationships between the age profile of neighborhood residents and credit risk. Indeed, aging populations in many sections of Philadelphia may ultimately have destabilizing effects.

²⁸ The correlation coefficient between *AGE55* and the Census-tract unemployment rate (*UNEMP*) is -0.40 . *UNEMP* is statistically significant in some specifications when included in place of *AGE55*. However, *AGE55* generally exhibits a stronger relation to likelihood of delinquency, perhaps because it captures the effect of lower unemployment rates along with other factors contributing to stability. Other estimation results are not affected in any important way if *UNEMP* is used in place of *AGE55*.

The results in Table 5 also are robust to adding any of the following variables to the estimated equation: borrower income, a dummy variable identifying Hispanic borrowers, a dummy variable identifying loans with an original term to maturity shorter than 30 years, a dummy variable identifying “high-value rehabilitated properties,” a dummy variable identifying observations with imputed credit scores, and various Census-tract characteristics (unemployment rate, median income, median house value, proportion of residents of age 45 to 54, proportion of housing units that are rental properties, percentage of households earning under \$15,000 per year, and dummy variables identifying predominantly minority areas and blighted areas). None of these variables are statistically significant when added to the empirical model.²⁹ Further, the results are robust to excluding variables that are not statistically significant and to varying the criteria defining *RELPRICE* = 1 and *FRONTEND* = 1.

Several borrower characteristics that prior studies have found to be related to loan performance were omitted from our estimated equations due to lack of data. These include non-mortgage debt payments as a proportion of income, cash reserves, and measures of income stability such as employment tenure. These omitted factors may be correlated with the borrower’s credit score or sex, in which case our results would need to be reinterpreted.³⁰ For instance, it is possible that female borrowers and those with higher TMS scores have a lower likelihood of delinquency in part because they have more stable income. The possibility that estimated relationships between credit score or sex and likelihood of delinquency may in part reflect omitted variables should be borne in mind.

Discussion

The estimation results indicate that the TMS score and neighborhood and property factors are strongly related to likelihood of delinquency. Thus, the results suggest that there are substantial gradations of credit risk among DVMP borrowers, who represent a diversity of TMS scores, properties and neighborhoods. In the next section, we attempt to quantify these gradations of credit risk by means of a simulation analysis.

²⁹ Also, none of these variables are statistically significant when included in place of *AGE55* (with the exception of *UNEMP* in the equation with *DELINQ90* as the dependent variable).

³⁰ It seems doubtful, however, that *ACTIVITY* or *RELPRICE* would be correlated with these omitted borrower characteristics, since there is no correlation between these tract variables and included borrower characteristics such as the TMS score and sex.

Table 6 ■ Borrower characteristics by credit-score range.

Variable	Value	
	Borrowers with Scores Below Median	Borrowers with Scores Above Median
Mean income	20,530	22,624
Percentage black	35.4	31.3
Percentage Hispanic	19.3	16.3
Percentage female	42.1	45.7
Mean of tract median income	24,055	25,395
Mean of tract median value	30,123	32,915
Percentage in predominantly minority tracts	29.5	27.3
Percentage in blighted or distressed tracts	25.0	18.4

Further, the results suggest that the risks associated with DVMP lending could potentially be reduced by applying more conservative lending standards with respect to borrower credit history, or by developing improved methods of screening borrowers with weaknesses in their credit records. One possible enhancement would be the application of credit history scoring, which has not, in the past, been used to screen DVMP applicants. Credit scoring provides an objective assessment of the relative credit risk posed by a prospective borrower. Those with low scores may be further screened through careful identification of compensating factors (such as legitimate explanations of past credit problems.)

Moreover, our data suggest that more conservative screening of borrowers with weak credit histories would not significantly affect the program's ability to serve a broad cross section of the community. Table 6 compares characteristics of borrowers having scores above the median with those having scores below the median. Although differences are observed, they are not considerable. For instance, the mean income of borrowers with scores above the median is \$22,624, which is not much larger than \$20,530 for borrowers with lower scores.³¹

³¹ The median TMS score of borrowers for whom scores were obtained is 650, a score which ordinarily would be viewed as indicative of moderate credit risk (see Avery *et al.* 1996).

Finally, the results suggest that the risks associated with DVMP lending could potentially be reduced by placing increased emphasis on evaluations of appraisal risk or by developing improved property valuation methods. For instance, compensating factors could be required in the case of properties that are unusually expensive for the tract where they are located, such as rehabilitated properties located in blighted neighborhoods. Also, collaborative community reinvestment efforts together with public sector support focused on targeted neighborhoods may help create more active housing markets in those neighborhoods, thereby mitigating credit risk.

Additional Tests

As noted, the use of imputed data can yield biased estimates if the error term of the imputation regression equation is correlated with the error term of the loan performance equation. Moreover, there is no random variability in the imputed credit history scores. Consequently, the estimation results reported above—particularly those pertaining to statistical significance of the TMS score—may be biased. We checked the robustness of the estimated relationships in several ways.

To add variability to the imputed scores, we employed a randomized imputation procedure. To the imputed scores, we added simulated noise generated from a normal distribution with mean zero and variance equal to the mean squared error of the imputation regression equation. The significance tests were found to be robust. For instance, 100 iterative estimations of the loan performance model of panel 1 of Table 5 with randomized imputation yielded a mean chi-square value of 6.8 for the coefficient of TMS, corresponding to a 1% significance level.

As an additional test of the relationship between credit scores and likelihood of delinquency, we dropped observations with imputed scores. At the same time, we excluded variables requiring merged-in HMDA data (*FRONTEND*, *FEMALE*, *BLACK* and *SINGLE*) from the estimated equation, enabling us to include observations for which TMS scores were obtained but HMDA data were missing. The results obtained with *DELINQ60* as the dependent variable are presented in Table 7, panel 1; similar results were obtained with *DELINQ90* as the dependent variable. These results correspond closely to those reported in Table 5 for TMS as well as for the tract variables and *RELPRICE*.

Finally, we re-estimated the loan performance models using the two-stage (bivariate) probit procedure described in Greene (1993) and further developed in Hardin (1996). This involves joint estimation of a loan

Table 7 ■ Estimation of 60+ delinquency equation excluding observations with imputed credit scores.

Variable	Panel 1: Logit Estimation		Panel 2: Two-Stage Probit Estimation	
	Estimated Coefficient	Chi-Square	Estimated Coefficient	Chi-Square
Intercept	1.78	2.0	0.93	2.1
<i>ACTIVITY</i> ^a	2.17	2.6	1.19	3.2*
<i>ACTVTYSQ</i>	-1.29	3.1*	-0.68	3.7*
<i>AGE55</i> ^b	-2.98	4.6**	-1.54	4.7**
<i>YEAR94</i>	-1.70	5.8**	-0.87	7.0**
<i>YEAR93</i>	-0.86	5.9**	-0.40	4.8**
<i>YEAR91</i>	-0.23	0.4	-0.00	0.0
<i>YEAR90</i>	0.41	1.4	0.30	1.9
<i>RELPRICE</i> ^c	0.64	6.3**	0.33	6.5**
<i>INSURED</i>	-1.25	1.4	-0.66	1.8
<i>LTVGT90</i>	0.45	0.4	0.20	0.3
<i>LTVLE80</i>	-0.63	0.7	-0.28	0.7
(TMS score)/100	-0.57	12.9**	-0.31	14.0**
No. of observations	1,082		1,614	
Model chi-square	54.0		1,124.3	

^a Number of mortgages originated during 1990–1993 per 10 owner-occupied units in the Census tract where the property is located.

^b Fraction of the population age 55 or older in the Census tract where the property is located.

^c Dummy variable that equals 1 if the purchase price of the property exceeds the Census-tract median house value by 33% or more, and equals 0 otherwise.

**Statistically significant at the 5% level or better.

*Statistically significant at the 10% level.

performance equation (the *second-stage* equation) and a sample selection equation (the *first-stage* equation), where the dependent variable for the latter is a dummy variable indicating whether an observation is missing from the sample for the second stage. We classified an observation as missing from the sample for the loan performance equation if it was missing a TMS score. The procedure incorporates a correction for potential sample selection bias; that is, it allows for correlation between the error terms of the two equations.³²

³² The procedure was implemented using the statistical package Stata.

When the loan performance equation of Table 7, panel 1 was re-estimated using the bivariate probit procedure, we obtained the results shown in panel 2. These do not differ in any important way from those in panel 1; in particular, the TMS score remains strongly predictive of loan performance. Details pertaining to the first-stage equation are provided in Appendix B. Similar results were obtained using the bivariate probit procedure with *DELINQ90* as the dependent variable for the loan performance equation. We also re-estimated the model specification of Table 5, panel 1, applying the two-stage method, and again found the results to be robust.

Tests of Tract Relationships Using a Larger Sample

Because model specifications that omit TMS scores and variables derived from merged-in HMDA data can be estimated over a larger sample, we also estimated equations with TMS score, *FRONTEND*, *FEMALE*, *SINGLE* and *BLACK* excluded, to verify the robustness of the estimated relationships between tract variables and likelihood of delinquency. With these variables excluded, the sample size increases to 2,248. The results obtained with *DELINQ60* as the dependent variable are shown in Table 8, panel 1; similar results were obtained with *DELINQ90*. The estimated relationships are similar to those shown in Table 5. For instance, the partial derivative with respect to activity is positive and statistically significant (at the 5% level or better) at levels of activity above 0.88.

Substitution of Other Tract Variables for Activity

We also experimented with model specifications where we replaced *ACTIVITY* and *ACTVTYSQ* with other neighborhood variables. In most cases, the substituted variables did not exhibit a statistically significant relation to likelihood of delinquency. In cases where we did observe statistical significance, the results were not robust and the models did not fit the data as well as the original specification with activity variables. These results suggest that housing market activity is directly related to likelihood of delinquency and is not simply proxying for other neighborhood factors.

For illustrative purposes, we present the results from one such alternative specification in Table 8, panel 2. It is identical to the specification in panel 1, except that *ACTIVITY* and *ACTVTYSQ* are replaced by the Census-tract unemployment rate (*UNEMP*) and the proportion of households earning less than \$15,000 (*PCTPOOR*). The model with these substitutions does not fit

Table 8 ■ Logit estimation of tract relationships using the larger sample.

Variable	Panel 1: 60+ Delinquency Equation with Housing Market Activity Variables		Panel 2: 60+ Delinquency Equation with Substitute Census-Tract Variables	
	Estimated Coefficient	Chi-Square	Estimated Coefficient	Chi-Square
Intercept	1.52	10.1**	-1.19	5.1**
<i>ACTIVITY</i> ^a	1.46	3.2*		
<i>ACTVTYSQ</i>	-1.02	5.2**		
<i>UNEMP</i> ^b			6.02	5.0 **
<i>PCTPOOR</i> ^c			-2.51	4.2**
<i>AGE55</i> ^d	-2.53	9.0**	-2.03	4.8**
<i>YEAR94</i>	-1.00	7.0**	-0.99	6.8**
<i>YEAR93</i>	-0.74	7.8**	-0.69	6.9**
<i>YEAR91</i>	0.09	0.2	0.09	0.2
<i>YEAR90</i>	0.47	4.3**	0.46	4.1**
<i>YEAR89</i>	0.35	1.5	0.36	1.6
<i>RELPRICE</i> ^e	0.35	4.3**	0.35	3.7*
<i>INSURED</i>	-0.75	1.4	-0.77	1.5
<i>LTVGT90</i>	0.43	0.9	0.41	0.8
<i>LTVLE80</i>	-0.81	3.5*	-0.84	3.8*
No. of observations	2,248		2,248	
Model chi-square	88.4		83.9	

^a Number of mortgages originated during 1990–1993 per 10 owner-occupied units in the Census tract where the property is located.

^b Unemployment rate in the Census tract where the property is located.

^c Fraction of households earning less than \$15,000 per year in the Census tract where the property is located.

^d Fraction of the population age 55 or older in the Census tract where the property is located.

^e Dummy variable that equals 1 if the purchase price of the property exceeds the Census-tract median house value by 33% or more, and equals 0 otherwise.

**Statistically significant at the 5% level or better.

*Statistically significant at the 10% level.

Table 9 ■ Predicted probabilities of serious delinquency: probability of becoming delinquent 60 days or more, by TMS score and Census-tract mortgage lending activity.^a

	TMS = 550	TMS = 625	TMS = 700	TMS = 775
<i>ACTIVITY</i> = 0.09	0.237	0.155	0.097	0.060
<i>ACTIVITY</i> = 0.12	0.191	0.122	0.075	0.046
<i>ACTIVITY</i> = 0.15	0.116	0.072	0.043	0.026
<i>ACTIVITY</i> = 0.18	0.051	0.031	0.018	0.011

^a Assumptions: Borrower is male, non-black and single; year of origination is 1992; purchase price of the property is less than 1.33 times the Census-tract median house value; borrower's housing-expense-to-income ratio is under 28%; loan-to-value ratio is greater than 80% and does not exceed 90%; loan is not guaranteed by private mortgage and insurance; and percentage of the Census population age 55 or older equals the sample mean (39%).

the data as well as with *ACTIVITY* and *ACTVTYSQ*, as indicated by the model chi-square statistics.³³

Simulation Results

The estimation results suggest that there are substantial gradations of credit risk among DVMP borrowers, who represent a diversity of TMS scores, properties and neighborhoods. We now use the estimation results from Table 5, panel 1, to calculate likelihoods of 60-day or longer delinquency for borrowers with differing credit scores and property locations, thus obtaining a quantitative assessment of the gradations of credit risk associated with the DVMP program.

Specifically, we explore the effects on likelihood of 60-day or longer delinquency of varying TMS score and *ACTIVITY*. A borrower is assumed to be male, non-black and single (since these are majority categories). The year of origination is assumed to be 1992, and the original loan-to-value ratio is assumed to be in the 81%–90% range. We set *INSURED* = 0, *RELPRICE* = 0 and *FRONTEND* = 0 and set *AGE55* equal to its sample mean value. The results from this simulation analysis are presented in Table 9.

³³ Moreover, *UNEMP* and *PCTPOOR* lose their statistical significance when the TMS score is added to the model. There is significant correlation between *UNEMP* and *ACTIVITY* (0.24), between *UNEMP* and *PCTPOOR* (0.84) and between *UNEMP* and *TMS* (0.09). Thus, the results shown in panel 2 of Table 8 may reflect these correlations among included and omitted variables.

The quantitative effect of the two variables on loan performance is quite substantial. For instance, the probability of being long-term delinquent is about five times as large in tracts with mortgage activity of 0.90 (about average for our sample) as in tracts with activity level 1.80. It is about four times as large for borrowers with credit scores of 550 (the 10th percentile) as for borrowers with scores of 775 (the 90th percentile.) A borrower with a TMS score of 550 whose property is located in a tract with activity level 0.90 is 22 times more likely to become 60 days or more delinquent than a borrower with TMS score 775 and *ACTIVITY* = 1.80.

Conclusion

In recent years, Fannie Mae, Freddie Mac, private mortgage insurers and many depository institutions have developed affordable-home-loan programs, relying on non-traditional underwriting standards to increase the supply of credit to targeted neighborhoods and households. To date, limited information has been available regarding the credit risk trade-offs associated with such efforts to make mortgage credit more broadly accessible.

This study examines this issue in a particular context: a long-established affordable-home-loan program in Philadelphia known as the Delaware Valley Mortgage Plan (DVMP). Using a database of over 2,000 DVMP loans originated between 1988 and 1994, we examine the relationship of neighborhood housing market conditions, borrower credit characteristics and other factors to long-term delinquency on DVMP loans.

Consistent with the view that the accuracy of property appraisals increases with neighborhood housing market activity (Lang and Nakamura 1993), we find that likelihood of delinquency declines with increasing tract housing market activity once the level of activity becomes sufficiently high. Further, we find that properties that are unusually expensive for the tract where they are located are associated with increased delinquency risk.

Credit history scores are found to be strongly predictive of delinquency: borrowers with low credit scores at the time of loan origination are much more likely to become delinquent. In addition, the likelihood of delinquency is greater for borrowers with high ratios of housing expense to income.

To assess quantitatively the effect of borrower credit and market conditions, simulations were performed. The probability of being 60 days or more delinquent is five times as large in tracts with mortgage activity near the sample mean as in those tracts with activity levels about twice the mean. We also find that the probability of being 60 days or more delinquent is four

times as large for borrowers with credit scores near the low end of the score range as for borrowers with scores near the high end.

These empirical results indicate that there are substantial gradations of credit risk among DVMP borrowers, particularly because DVMP borrowers represent a diversity of credit scores, properties and neighborhoods. This suggests that some reduction in credit risk might be achievable from some tightening of lending standards with respect to borrower credit history or by developing improved methods of screening borrowers with weaknesses in their credit records.

One possible enhancement would be the use of credit history scores, which have not, in the past, been used to screen DVMP applicants. Our data suggest that more conservative screening of borrowers with weak credit histories would not significantly affect the program's ability to serve a broad cross section of the community. The results also suggest that the risk associated with DVMP lending could be reduced by placing increased emphasis on evaluations of appraisal risk or by developing improved property valuation methods. Collaborative community reinvestment efforts focused on targeted neighborhoods, which may help create active housing markets in those neighborhoods, might also mitigate credit risk.

The views expressed in this paper are those of the authors and do not necessarily represent the views of the Board of Governors or its staff. We thank Robert Avery, Jim Berkovec, Glenn Canner, Joe Gyourko, Patrick Lampani, Peter Linneman, Loretta Mester, Leonard Nakamura, John Rizzo, Robert Van Order, Richard Voith and two anonymous referees for helpful comments. We also thank Michael Howell and Kevin Gillen for excellent research assistance. Special thanks are due to bank personnel who provided assistance and comments, especially Mark Green. The authors thank the Zell/Lurie Real Estate Center at Wharton for financial support.

References

- Ambrose, B.W. and C.A. Capone. 1998. Modelling the Conditional Probability of Foreclosure in the Context of Single-Family Mortgage Default Resolutions. *Real Estate Economics*. 26 (Fall): pp. 391–430.
- Avery, R.B., P.E. Beeson and M.S. Sniderman. 1999. Neighborhood Lending and the Community Reinvestment Act: Should Lenders Be Allowed to Specialize? *Journal of Urban Economics*. (forthcoming 1999).
- Avery, R.B., R.W. Bostic, P.S. Calem and G.B. Canner. 1996. Credit Risk, Credit Scoring, and the Performance of Home Mortgages. *Federal Reserve Bulletin* 82 (July): 621–648.
- Barth, J.R., J.J. Cordes and A.M.J. Yezer. 1979. Financial Institution Regulations, Redlining, and Mortgage Markets. *The Regulation of Financial Institutions*, Conference Series 21. Federal Reserve Bank of Boston, 144–195.

- Berkovec, J.A., G.B. Canner, S.A. Gabriel and T.H. Hannan. 1994. Race, Redlining, and Residential Mortgage Loan Performance. *Journal of Real Estate Finance and Economics* 9: 263–294.
- . 1996. Mortgage Discrimination and FHA Loan Performance. *Cityscape* 2: 9–23.
- . 1998. Discrimination, Competition, and Loan Performance in FHA Mortgage Lending. *Review of Economics and Statistics*, 80: 241–250.
- Calem, P.S. 1993. The Delaware Valley Mortgage Plan: Extending the Reach of Mortgage Lenders. *Journal of Housing Research* 4: 337–358.
- . 1996a. Mortgage Credit Availability in Low- and Moderate-Income Minority Neighborhoods: Are Information Externalities Critical? *Journal of Real Estate Finance and Economics* 13: 71–89.
- . 1996b. Patterns of Residential Mortgage Activity in Philadelphia's Low- and Moderate-Income Neighborhoods: 1990–1991. *Home Mortgage Lending and Discrimination: Research and Enforcement*. U.S. Department of Housing and Urban Development.
- Capozza, D.R., D. Kazarian and T.A. Thomson. 1997. Mortgage Default in Local Markets. *Real Estate Economics*, 25: 631–655.
- Consumer Bankers Association. 1995. *Affordable Mortgage Program Survey*.
- Greene, W.H. 1993. *Econometric Analysis*. Macmillan: New York.
- Guttentag, J.M. and S.L. Wachter. 1980. Redlining and Public Policy. Monograph Series on Finance and Economics, No. 1. Solomon Brothers Center for the Study of Financial Institutions: New York.
- Hardin, J.W. 1996. Bivariate Probit Models. *Stata Technical Bulletin* 33(September): 152–158.
- Lang, W.W. and L.I. Nakamura. 1993. A Model of Redlining. *Journal of Urban Economics* 33: 223–234.
- Ling, D.C. and S.M. Wachter. Information Externalities and Home Mortgage Underwriting. *Journal of Urban Economics*. (forthcoming 1999).
- Mills, E.S. and L.S. Lubuele. 1994. Performance of Residential Mortgage Loans in Low and Moderate Income Neighborhoods. *Journal of Real Estate Finance and Economics* 9: 245–262.
- Quercia, R.G. and M.A. Stegman. 1992. Residential Mortgage Default: A Review of the Literature. *Journal of Housing Research* 3: 341–379.
- Van Order, R., A.-M. Westin and P. Zorn. 1993. Effects of the Racial Composition of Neighborhoods on Default, and Implications for Racial Discrimination in Mortgage Markets. Draft. Freddie Mac: McLean, VA.

Appendix A

Imputation Regression Model

Imputation of credit scores was based on an ordinary least-squares regression of TMS on borrower and loan characteristics. The following borrower and loan characteristics were employed as independent variables: year-of-origination dummy variables (*YEAR94*, *YEAR93*, etc.), *INSURED*, *SINGLE*, the borrower's income (*INCOME*), a dummy variable identifying loans associated with "high-value rehabilitated properties" (*SPECIAL*), a dummy

variable identifying “white” (*i.e.*, non-black, non-Hispanic) female borrowers (*FEMALE_W*), a dummy variable identifying black female borrowers (*FEMALE_B*), a dummy variable identifying Hispanic female borrowers (*FEMALE_H*), a dummy variable identifying black male borrowers (*MALE_B*) and a dummy variable identifying Hispanic male borrowers (*MALE_H*). The equation was estimated using the sample of 682 borrowers for whom both TMS scores and HMDA data were obtained. We excluded tract variables from the model used for imputation, since they exhibited little relation to TMS and had no material effect on the estimation results when added to the regression equation.

The estimation results, shown in Table 10, indicate that single borrowers and borrowers obtaining loans backed by private mortgage insurance had higher scores. Relative to white male borrowers, black male borrowers and Hispanic female borrowers had lower scores. In addition, borrower income was positively related to TMS. Each of these relationships was statistically significant at the 5% level or better. The coefficient estimates also indicated higher scores for white female borrowers than for white male borrowers.

Table 10 ■ Imputation model regression results.

Variable	Estimated Coefficient	<i>t</i> -statistic
Intercept	615.3	41.5**
<i>YEAR94</i>	7.53	0.6
<i>YEAR93</i>	-13.93	1.9*
<i>YEAR91</i>	1.63	0.2
<i>YEAR90</i>	12.30	1.1
<i>INCOME</i>	1.63	3.8**
<i>INSURED</i>	37.53	2.7**
<i>SPECIAL</i>	24.55	1.8*
<i>SINGLE</i>	14.97	1.8*
<i>FEMALE_W</i>	18.94	1.7*
<i>FEMALE_B</i>	-1.73	0.2
<i>FEMALE_H</i>	-18.42	1.6*
<i>MALE_B</i>	-37.25	3.6**
<i>MALE_H</i>	2.46	0.3
No. of observations	652	
<i>R</i> ²	0.1	

The dependent variable is borrower credit score (TMS).

**Statistically significant at the 5% level or better

*Statistically significant at the 10% level.

Appendix B

Sample Selection Equation for the Two-Stage Probit Procedure

The following independent variables were included in the first-stage sample selection equation associated with the results reported in Table 7, panel 2: year-of-origination dummy variables (*YEAR94*, *YEAR93*, etc.), *ACTIVITY*, the proportion of tract housing units that are rental properties (*PCTRENT*), the tract median house value (*MEDVALUE*) and a dummy variable identifying loans associated with “high-value rehabilitated properties” (*SPECIAL*). (No other loan or tract variables were found to exhibit a statistically significant relation to the dependent variable, and including additional variables had no material effect on the estimation results.) The equation was estimated using the sample of 1,614 borrowers whose loans were originated after October 1, 1989, since no credit scores were obtained for loans originated prior to this date.

The first-stage estimation results, presented in Table 11, indicate that scores are less likely to be available for loans originated in earlier years. Loans associated with “high-value rehabilitated properties” are more likely to have credit scores. The likelihood of obtaining a score also varies with Census-tract characteristics. Various interpretations of these relationships are possible. For instance, a relatively high proportion of borrowers who purchased properties in tracts with a high proportion of rental units may have been relocating within the same ZIP code, facilitating continuity in their credit records.

When the loan performance equation of Table 5, panel 1 was re-estimated using the two-stage procedure, borrower income and dummy variables controlling for female, single, black or Hispanic status were added to the first-stage sample selection equation. The results (not shown in a table) indicated that scores were more likely to be available for single borrowers, female borrowers and higher-income borrowers, and less likely to be available for Hispanic borrowers. With the exception of *ACTIVITY* (which lost statistical significance), relationships to other variables were similar to those reported in Table 11.

Table 11 ■ Bivariate probit estimation results for the sample selection equation.

Variable	Estimated Coefficient	Chi-Square Statistic
Intercept	-0.24	1.7
<i>YEAR94</i>	0.64	5.4**
<i>YEAR93</i>	-0.19	4.0**
<i>YEAR91</i>	-0.70	50.4**
<i>YEAR90</i>	0.46	18.6**
<i>ACTIVITY</i> ^a	-0.15	3.5*
<i>PCTRENT</i> ^b	2.24	12.3**
<i>MEDVALUE</i> ^c	0.70	2.0
<i>PCTPOOR</i> ^d	-1.23	4.0**
<i>SPECIAL</i> ^e	0.47	5.1**
No. of observations		1,614
Two-equation model chi-square		1,124.3

The dependent variable is a dummy variable equal to 1 if a credit score was retrieved, and 0 otherwise.

^a Number of mortgages originated during 1990–1993 per 10 owner-occupied units in the Census tract where the property is located.

^b Fraction of housing units that are rental units in the Census tract where the property is located.

^c Fraction of households earning less than \$15,000 per year in the Census tract where the property is located.

^d Median house value (units of \$100,000) in the Census tract where the property is located.

^e Dummy variable that equals 1 if the loan is associated with a “high-value rehabilitated property,” and equals 0 otherwise.

**Statistically significant at the 5% level or better.

*Statistically significant at the 10% level.