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An Analysis of the Neighborhood Impacts of the Mortgage Assistance Program in Dallas

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Abstract: Down-payment or closing cost assistance is a commonly used and effective program in addressing the wealth constraints of underserved homebuyers. This paper estimates the impact of the city of Dallas Mortgage Assistance Program (MAP) on neighborhood home values. We define neighborhoods for each sale based on distance from MAP properties, and estimate the difference-in-difference (DID) in home prices between neighborhoods with various numbers of MAP before and after MAP sales. We find that while MAP properties tend to locate in neighborhoods with generally lower property values, the infusion of MAP has no detrimental impact on neighboring property values overall.

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The views expressed are those of the individual authors and do not necessarily reflect official positions or the views of the Federal Reserve Bank of Dallas, the Federal Reserve system, or Networks Financial Institute. Please address questions regarding content to Wenhua Di at wenhua.di@dal.frb.org. Any errors or omissions are the responsibility of the authors. The authors acknowledge The City of Dallas and Enterprise Community Partners, Inc., who generously provided the database and helpful information on the Mortgage Assistance Program, which made this research possible. The authors would also like to thank Community Affairs staff at the Federal Reserve Bank of Dallas and participants of UT Dallas economics seminars for valuable comments and discussions.

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INTRODUCTION

Americans regard owning a home as a fundamental step to asset building. Since the Great Depression, the federal government has provided incentives for homeownership. In the 1930s, the government-backed Home Owner's Loan Corporation (HOLC) purchased defaulted mortgages and offered homeowners self-amortizing refinancing with fixed rates and long terms. The Federal Housing Administration (FHA) was created to support home financing with more flexible terms than conventional loans by offering mortgage insurance. The Federal National Mortgage Association (FNMA, or Fannie Mae) purchased mortgages, issued mortgage-backed securities and sold them in the secondary market. In 1965, the FHA became part of the new U.S. Department of Housing and Urban Development (HUD)—a federal agency established to address community development and housing issues. In addition to the FHA's insurance activities, HUD provides funding and oversight for numerous programs aimed at increasing homeownership opportunities. Government support, together with legislative efforts, technological and structural changes in the mortgage industry, and favorable economic conditions boosted the U.S. homeownership rate from approximately 48 percent in the 1930s to near 70 percent in 2005.

Homeownership generates financial and social benefits in the long term. Under right market conditions, homeowners may be able to save more and build equity in their homes. Homeowners tend to move less frequently than renters and are more likely to invest in the upkeep of their homes and contribute to local amenities (Rohe & Stewart, 1996). They may also be more involved in their communities (DiPasquale & Glaeser, 1999). Family and school stability helps homeowners' children build long-term supportive and informative relationships with teachers and fellow students. The result is often a positive impact on their academic performance and future job opportunities (Aaronson, 2000). Harkness & Newman (2002) found that a child who has always lived in a home owned by his parents attained approximately one half of a year of school more than a child whose parents did not own a home. In addition, a child whose parents owned a home was 10 percent more likely to graduate from high school and attend college.

Realizing the benefits of homeownership depends on whether owners can sustain ownership while retaining sufficient resources to support families and communities. The recent subprime turmoil suggests that some lenders and mortgage brokers, driven by excessive incentives to make and sell loans, engaged in unscrupulous practices, such as lending to borrowers with limited capacity to repay. Borrowers with limited income, credit and financial knowledge were especially attracted by the easy availability of mortgages with low initial payments. This phenomenon is troublesome because these borrowers have limited assets other than their homes and less flexibility in adjusting to changing economic circumstances (Haurin and Rosenthal, 2004 and 2005). The threat of foreclosure may devastate a household and offset any gains from homeownership.

There has not been much attention given to mortgages that are government-backed or originated with the assistance of public programs. The share of these loans in the mortgage market has declined substantially in recent years due to the increased availability of private loan products and escalating housing prices. However, the participants of these programs are typically low- and moderate-income households with higher credit risk; without public assistance, they might still be renting or have purchased homes with a subprime mortgage. A down-payment or closing cost assistance program has been one of the most common government-supported approaches to promoting homeownership. Combined with FHA or other government-backed affordable lending products, these programs have helped close the gap between the limited savings of lower income borrowers and the down-payment requirements for a prime mortgage. These mortgages taken by lower income borrowers are typically underwritten in a traditional way with lenders scrutinizing borrowers' information. Loan applicants are informed of mortgage requirements and homeowner responsibilities in mandatory homeowner education classes. As a result, creditworthy borrowers can achieve a lower loan-to-value ratio and build equity faster. There is potentially a lower risk for default because the loan approvals are based on careful assessment of borrowers' repayment ability. For lenders, there is also potentially a lower risk of prepayment associated with lower income borrowers (Deng & Gabriel, 2006), who are more likely to stay occupied for longer time due to program requirements or limited mobility.

Studies show that among various affordable lending programs, down-payment or closing cost assistance is most effective in addressing the wealth constraints of underserved homebuyers (Listokin et al., 2001; Quercia et al., 2002; Feldman, 2004; Herbert & Tsen, 2005). Small amounts of assistance can stimulate fairly large numbers of renters to buy homes. Besides creating homeownership, these programs have consequences for both participants and communities. Empirical evidence shows that household income among new homeowners typically rises relatively rapidly (Haurin & Rosenthal, 2005). Lower income borrowers paying manageable housing expenses associated with a fixed and reasonably priced mortgage may save extra money for improving living conditions, investing in children's education and contributing to the community by keeping up maintenance and getting more actively involved in community services. Therefore, homes in proximity may appreciate more than homes without subsidized neighbors. However, for some low- and moderate-income home buyers, owing a home may not be the best choice. Mortgage payments and maintenance costs may exhaust their financial resources and leave them with no cushion in the event of a financial crisis. When distressed homeowners cannot maintain their homes properly, or default on their payment, the property values in their neighborhood may be adversely affected.

Previous literature has evaluated individual or neighborhood impacts of subsidized rental housing programs. For example, a number of studies compared the changes in health, social and economic opportunities, or kids' school performance of participants randomly assigned with housing voucher in the Moving to Opportunity demonstration with people without the voucher (Jacob 2003, Kling et al. 2007). There have also been studies of the community changes measured by neighborhood property appreciation near dispersed section-8 units or tax credit properties (Galster et al. 1999, Ezzet-Lofstrom & Murdoch, 2006). But there are only a few attempts evaluating the impacts of subsidized homeownership programs on individuals or neighborhoods. Calem (1993) showed evidence that the Delaware Valley Mortgage Plan was effective in broadening mortgage lender's reach to underserved neighborhoods, and the loan performance was not too bad because lenders' extensive underwriting process. Smith & Hevener (2005) and Schwartz et al. (2006) found that place-based revitalization projects have significant positive spillover effects on the surrounding neighborhood.

This paper extends the previous literature by integrating data from the city of Dallas Mortgage Assistance Program (MAP) with single-family home sales data in Dallas over a 17 year period in order to address the following question: how does subsidized homeownership affect participants' neighborhood? If the neighboring property values fall relative to similar neighborhoods without subsidized homeownership, then one may question if any individual benefits of homeownership are muted by local externalities. Otherwise, we have evidence that may suggest subsidizing down payments is a valid public lending instrument for increasing homeownership.

We first provide an overview of MAP by summarizing the characteristics of participants, properties and loan performance. Then, we define sliding neighborhoods for each single-family sale based on the distance from the location of MAP properties and compare the average differences in home value appreciation in homes that are close to MAP properties with homes without nearby MAP properties using a hedonic price model. We correct for spatial correlation in neighboring sales, and allow the treatment levels to vary when estimating the impact of MAP infusion on property values. We conclude with policy implications.

OVERVIEW OF THE CITY OF DALLAS MAP

Down-payment assistance programs can be implemented by state, county or city governments. The city of Dallas MAP was established in October 1991 and has been administered by Enterprise Community Partners, Inc. in Dallas (formerly known as the Enterprise Foundation). As of December 31, 2008, Enterprise had closed 6,623 MAP loans, and total subsidies had exceeded $63.4 million, the amount of leveraged private fund was nearly $460 million. It is one of the largest down-payment assistance programs in the nation primarily because Dallas has a large supply of housing within the price limits of the FHA 203B regulations—the maximum loan amount allowed for such programs.[1] The Dallas program is

[1] The FHA 203B limit is adjusted annually, and it is $200,160 for Dallas County in 2007 (U.S. Department of Housing and Urban Development).

funded for the most part with HUD block grants through three programs—HOME Investment Partnerships Program, Community Development Block Grant Program and American Dream Downpayment Initiative.

To qualify for a zero-interest, second-lien MAP loan, client households must be first-time homebuyers with total household income of less than 80 percent of the Dallas-area median. The first lien is a mortgage loan from a traditional lender, while the MAP loan assumes second-lien status. The current second-lien MAP loan has an eight-year recapture period. One-eighth of the loan is forgiven each year as long as no default occurs and the property remains the borrower's principal residence. MAP funds are used primarily for down-payment and closing cost assistance, although they may also cover some of the seller's repair costs. [2]

There are numerous requirements for both the borrowers and the properties.[3] In particular, borrowers must successfully complete a homeowner education course from an approved provider and apply for MAP funding through a city-approved lender. The property must pass Housing Quality Standards (HQS)[4] set by HUD and the city.

Table 1. Summary statistics of MAP

Variable	**No. of observations**	**Mean**	**Standard deviation**	**Minimum**	**Maximum**

[2] Approximately 4 percent of the participants received funding from resources other than MAP, such as the county down-payment assistance program, city bond program, Federal Home Loan Bank, Helping Hands, and lenders' programs. This study does not differentiate the impact of MAP from that of other funding because the fund has been used for similar purposes.

[3] The MAP manual for FY 2008–09 is available at www.dallasmap.org under "Exhibits and Forms." http://www.dallasmap.org/aefiles/00%20FY%2008-09%20MAP%20Manual%20Rev%2010-17-2008.pdf.

[4] Housing Quality Standards (HQS) was renamed Minimum Housing Standards (MHS) in 2007.

Total subsidy ($)*	5,389	11,015	4,408	990	38,504
Second lien amount ($)*	5,066	9,796	4,407	501	38,504
First lien amount ($)	4,091	73,734	21,380	12,240	158,646
Appraised value ($)	4,045	84,232	20,606	8,000	168,000
Sales price ($)	4,091	81,931	20,218	17,500	159,900
Front-end ratio	3,553	0.30	0.06	0.1	1
Back-end ratio	3,543	0.36	0.08	0.1	0.99
Mortgage interest rate (%)	3,881	7.08	0.97	4.63	11.99
Household size	4,081	3.31	1.52	1	9
Number of bedrooms	4,042	2.97	0.50	1	6

Note:
Only nonzero amount is summarized because zeros are not separable in the database from missing values.
All data are from 1997-2006 except the lien amount and subsidy amount, which are from 1991-2006.

We obtained the MAP database from Enterprise Community Partners, Inc. in Dallas. Approximately 85 percent of the geocoded MAP properties were located in HUD low- and moderate-income census tracts. Table 1 presents summary information on the MAP properties from the Enterprise database as of the end of 2006. Before 1997, borrowers' characteristics and loan features were not recorded in the database. On average, MAP participants received a total subsidy of $11,015, which includes assistance for closing or repair costs and the second-lien (down-payment assistance) amount of almost $9,800. The appraised values of MAP properties ranged from $8,000 to $168,000, with an average of $84,232 and a median of $83,000. The sales prices ranged from $17,500 to $159,900, with an average of $81,931; this is lower than the average appraised value, as MAP requires appraisal to be at or above sales price. The average mortgage size is $73,734. A typical MAP property is a three-bedroom single family house for a household of three to four.

All program participants were low- or moderate-income households. Among the MAP participants for the years 1997 to 2006, 1,918 (46.9 percent) fell into an income range below 50 percent of area median income, 1,480 (36.2 percent) fell between 50 percent and 67 percent, and only 693 (17.0 percent) fell between 68 percent and 80 percent. In terms of race and ethnicity, 2,413 (59 percent) were Hispanic, 1,534 (37.5 percent) were African American and 128 (3 percent) were white. Approximately 29 percent of the households were headed by females, 30 percent by single parents and 16 percent by single mothers.

Among the loans made from 1997 to 2006, 74.5 percent were FHA loans and 24.5 percent were conventional loans. Approximately 94 percent of the loans were 30-year, fixed-term loans. The mortgage interest rate on MAP properties ranged from 4.63 percent to 11.99 percent, with mean and median both around 7 percent, which suggests that these loans were made to eligible borrowers at reasonable prices. The front-end ratio of MAP loans, or the ratio derived by dividing housing expenses by monthly gross income, was available in the database for 3,553 MAP participants; the average was 30 percent. Only seven (or 0.2 percent) of MAP participants have a severe housing cost burden, spending 50 percent or more of income on housing. While the city's percentage of low- and moderate-income households with severe housing cost burdens in 2000 was 23.1 percent, the MAP underwriting process has prevented applicants from borrowing more than they can afford. For those listed in the database, the average back-end ratio, or, the ratio derived by dividing total monthly debt by monthly gross income, was 36 percent.

Di et al. (2007) analyzed the experience of Dallas MAP's participants in numerous dimensions. The MAP default rate was 4.8 percentage points lower than the default rate on subprime loans in Texas—the likely best alternative for low-income households. Similarly, the foreclosure rate was 4.3 percentage points lower than that for subprime loans in Texas. For MAP participants who sold their homes, the average length of tenure was 6.7 years and the average equity gain was more than $33,000. They concluded that the overall impact on the individual participating households was beneficial because it facilitated homeownership in low-income households with the accompanying gain in wealth without the financial risk that can come with homeownership. MAP households were not as likely to purchase a house that was too expensive in relation to their income.

IMPACTS OF MAP ON NEIGHBORHOODS

The benefits and costs of a program like Dallas MAP may extend beyond the individual participants into surrounding neighborhoods. Homeowners have an incentive—preserving equity—to maintain their homes, providing positive external benefits to neighboring properties. Homeowners may also have a stake in their community to help foster neighborhood safety and school quality. However, MAP makes homeownership accessible to an income group that, without the program, would be unlikely to obtain affordable mortgages. To the extent that MAP properties cluster in specific neighborhoods, the program has the potential to produce clusters of poverty—or at least reduced incomes—in neighborhoods that might not otherwise have as many lower-income families. The myriad of potential social problems associated with concentrations of poverty and lower levels of income (see, for example, Brooks-Gunn et al., 1997 and Jargowsky, 1997) could cause either a perceived or real change in neighborhood quality and, therefore, generate external costs on neighboring properties. To test the existence of these neighborhood impacts, we compare changes in sale prices of homes with MAP properties nearby (either 500 feet or 1000 feet) to sales of homes without MAP neighbors before and after the infusion of MAP. In theory, community changes are highly correlated with changes in property values, and numerous previous studies have used housing prices or property values to measure changes in neighborhood quality (see, for examples, Ding & Knaap, 2003; Smith & Hevener, 2005; Ezzet-Loftstrom & Murdoch, 2006).

Benchmark Hedonic Model

We implement "sliding" neighborhood approach (Dubin, 1992) by defining treatment and comparison neighborhoods by distance rings around each MAP home. Sales within certain distance are considered in the treatment neighborhood, and sales beyond that distance are in the comparison neighborhood. As we move from one MAP home to another, the neighborhood definition slides; that is, each MAP house under consideration has potentially different treatment and comparison neighborhoods. The advantage of this approach over the commonly used neighborhood definition based on census tract or census block group is that it gives us a better chance of controlling for the unobserved changes in neighborhoods over time—the treatment and control groups are defined simply by distance from observed sales and the treatment area is much smaller.

For most social programs, the treatment or intervention is not randomly assigned. Neighborhoods with no MAP participants may be affluent areas without housing stock within the price range of MAP, or at the other extreme, so depressed that they are unattractive to potential MAP participants due to a lack of housing that passes the required housing quality standards. We try to limit the variability between the treatment and comparison groups by using only the sales of homes in the 485 census block groups with one or more MAP properties in 2006. That way we are certain that the census block group is a potential candidate for MAP properties. This allows us to control for unobserved factors such as neighborhood demographics, location to employment centers and school quality that may differ substantially between block groups with and without MAP homes.

Consider a home sold in year 2000 in one of these block groups. We define two areas around the home—for example, within 1,000 feet and beyond 1,000 feet.[5] If MAP matters, we expect to find that MAP properties within 1,000 feet, as of year 2000, have a greater impact on selling price (positive or negative) than MAP properties beyond 1,000 feet. In other words, we use geography to set up treatment and comparison groups—homes sold with MAP properties within 1,000 feet are defined as the treatment group, and homes sold with MAP properties beyond 1,000 feet are defined as the comparison group.

We obtain the estimates of neighborhood effects in a linear regression model:

$$\log(Price_i) = \alpha_0 + \beta X_i + \xi Z_i + \gamma T_i + \alpha_1 MAP_i + \alpha_2 POSTMAP_i + \varepsilon_{\mathrm{i}} \quad (1)$$

In (1), the dependent variable is the natural logarithm of selling price. X_i is a vector of characteristics that are traditionally considered to influence the selling price, such as living area, number of bathrooms, and condition of the house. T_i is time. MAP_i is a dummy variable indicating whether the house is within 1,000 feet of MAP properties at the time of sale or in the future. $POSTMAP_i$ is a dummy variable indicating whether the house is within 1,000 feet of MAP properties at the time of the sale. For homes that do not ever fall within 1,000 feet of MAP properties, the conditional mean is α_0. The pretreatment difference in conditional mean prices is α_1. Controlling for the appreciation trend, the pre- and post-treatment difference in difference

[5] 1,000 feet is somewhat arbitrary. For most Dallas lot sizes it will be approximately 20 to24 lots. We also consider 500 feet below.

(DID) between MAP and non-MAP neighborhoods is α_2.[6] A positive α_2 means that MAP has a positive influence on sales of properties with MAP within 1,000 feet.

We use Multiple Listing Service data on 59,335 single family home sales within the city of Dallas from 1990 to 2006 to estimate model (1). The data are geo-referenced and include measurements on a wide array of characteristics. Because the majority of initial sales of MAP properties are not captured in our sales transaction database, the hedonic estimations use only the location and transaction time of MAP and do not examine the impact of MAP on the sale prices of MAP properties. Table 2 displays descriptions and summary statistics about the property sales data. We continue to restrict the sales to those in census block groups with one or more MAP properties in 2006 so the comparison neighborhoods would not be substantially different than the treatment neighborhoods. Even though the sample contains one home that sold for $3,375,000, the average home has a selling price of just under $88,112, with 1,490 square feet of living area and 1.7 bathrooms, is about 38 years old and, probably, has central air conditioning and is a single story structure. It is representative of low- and moderate-income single-family housing in Dallas. Sales in each year account for approximately 4 to 8 percent of the sample except 2006 where the data only include sales in the first two quarters.

[6] This derivation relies on correctly controlling for the trend.

Table 2. Variable definitions and summary statistics (59,335 sales in MLS data)

Variable	Description	Mean	Minimum	Maximum
PRICE	Sales price ($)	88,112	1,000	3,375,000
LIVAREA	Square feet of living area	1,490	358	11,882
AGE	Age of the house in years	37.81	0	103
BATHS	Number of bathrooms	1.71	0	10
POOL	Existence of a pool	0.05	0	1
FIREPLACE	Number of fireplaces	0.45	0	10
QUARTER1	Sold in first quarter	0.23	0	1
QUARTER2	Sold in second quarter	0.29	0	1
QUARTER3	Sold in third quarter	0.26	0	1
CENTRALAIR	Existence of central air conditioning	0.74	0	1
MAP	Home within 1000 feet of any MAP	0.84	0	1
POSTMAP	Home within 1000 feet of any MAP—Sold after MAP	0.58	0	1
MAP1	Home within 1000 feet of just 1 MAP	0.34	0	1
POSTMAP1	Home within 1000 feet of just 1 MAP—sold after MAP	0.15	0	1
MAP2	Home within 1000 feet of just 2 MAP	0.10	0	1
POSTMAP2	Home within 1000 feet of just 2 MAP—sold after MAP	0.09	0	1
MAP3_4	Home within 1000 feet of just 3 or 4 MAP	0.14	0	1
POSTMAP3_4	Home within 1000 feet of just 3 or 4 MAP—sold after MAP	0.13	0	1
MAP5_9	Home within 1000 feet of 5-9 MAP	0.17	0	1
POSTMAP5_9	Home within 1000 feet of 5-9 MAP—sold after MAP	0.14	0	1
MAP10	Home within 1000 feet of 10 or more MAP	0.09	0	1
POSTMAP10	Home within 1000 feet of 10 or more MAP—sold after MAP	0.07	0	1
MINORITY	Proportion of population minority in block group	0.48	0.01	1
MHVALUE	Median home value in block group	74,799	12,095	450,800
PCINCOME	Per capita income in block group	14,836	3,301	85,693

The mean of *MAP* is 0.84, meaning that 84 percent of the sample (49,650 sales) falls within 1,000 feet of at least one MAP property. The mean of *POSTMAP* (0.58) indicates that 58 percent (34,465 observations) of the sample is composed of sales of homes within 1,000 feet of at least one existing MAP property; that is, they are in the treatment group and after treatment.

Moreover, 15,639 (26.4 percent) of the observations are sales in the treatment group, before treatment, and 9,685 (16.3 percent) are in the comparison group. The numbers of sales in treatment and comparison groups are listed in Table 3.

Table 3. Treatment and comparison group sizes for various rings and levels of treatment
Total observations: 59,335 sales

Treatment with MAP within 1000 feet:

Treatment level	**Comparison group**	**Treatment group**	
		Pretreatment	*Post treatment*
Any MAP homes	9,685	15,185	34,465
Just 1 MAP home	38,890	11,736	8,709
Just 2 MAP homes	53,611	252	5,472
3-4 MAP homes	51,120	738	7,477
5-9 MAP homes	49,400	1,444	8,491
10 or more MAP homes	54,004	1,015	4,316

Treatment with MAP within 500 feet:

Treatment level	**Comparison group**	**Treatment group**	
		Pretreatment	*Post treatment*
Any MAP homes	22,266	15,639	21,430
Just 1 MAP home	35,476	13,670	10,189
Just 2 MAP homes	53,759	674	4,902
3-4 MAP homes	54,597	785	3,953
5-9 MAP homes	55,382	441	1,690
10 or more MAP homes	58,658	88	677

Table 4 displays the results of estimating clustered standard error (CSE) linear regression model (1). We assume that errors are correlated within block groups but independent across block groups. The standard errors in the “clustered” regression are computed based on the aggregated prices for each of the 485 block groups with one or more MAP properties, assuming these block group level aggregates are independent. The set of variables in *X* includes the natural logarithm of the square footage of living area, age of the home, number of bathrooms, a dummy variable denoting the existence of a pool, number of fireplaces, a dummy variable denoting the existence of central air conditioning, several dummy variables denoting the condition of the home (from “fair” to “excellent” with “poor” being the left-out category) and a dummy variable denoting whether the house is single story. We use annual and quarterly dummy variables to control for the time trend (*T*). All of these are significant and of the anticipated signs.

The main coefficients of interest are those on the variables *MAP* and *POSTMAP*. The estimate on *MAP* is negative and significant indicating that MAP properties tend to appear in areas with relatively low property values; that is, all else equal, the homes within 1,000 feet of future MAP properties were sold for approximately 30.3 percent less than similar homes that were more than 1,000 feet from future MAP even before MAP participants move in. This is because MAP participants are limited by income and thus limited to relatively low-cost housing options.

The DID estimate of the coefficient on *POSTMAP*, however, is positive and significant, indicating that houses near existing MAP properties are actually sold at higher prices than houses without MAP around. All else equal, the prices of homes that sell within 1,000 feet of existing MAP properties are approximately 23.9 percent (-30.3 percent + 6.4 percent) less than similar homes that are more than 1,000 feet from MAP. This finding would indicate that MAP has positive spillover effects on the neighborhood property values.

Table 4. Benchmark estimates of MAP impacts on neighborhood property values

Treatment: MAP within 1000 feet

Dependent variable: log (sales price) Linear regression with clustered standard errors at block group level			
LOG (LIVING AREA)	0.829*** (0.033)	*YEAR 1993*	-0.190*** (0.013)
AGE	0.002*** (0.001)	*YEAR 1994*	-0.180*** (0.015)
BATHROOMS	0.076*** (0.017)	*YEAR 1995*	-0.099*** (0.015)
POOL	0.164*** (0.015)	*YEAR 1996*	-0.057*** (0.016)
FIREPLACE	0.071*** (0.013)	*YEAR 1997*	-0.024 (0.016)
QUARTER1	-0.026*** (0.005)	*YEAR 1998*	0.065*** (0.018)
QUARTER2	0.023*** (0.005)	*YEAR 1999*	0.146*** (0.019)
QUARTER3	0.015*** (0.005)	*YEAR 2000*	0.248*** (0.018)
CENTRAL AIR CONDITIONING	0.199*** (0.018)	*YEAR 2001*	0.318*** (0.018)
FAIR	0.351*** (0.019)	*YEAR 2002*	0.378*** (0.020)
AVERAGE	0.579*** (0.022)	*YEAR 2003*	0.391*** (0.020)
GOOD	0.677*** (0.023)	*YEAR 2004*	0.312*** (0.022)
VERY GOOD	0.788*** (0.023)	*YEAR 2005*	0.330*** (0.022)
EXCELLENT	0.807*** (0.022)	*YEAR 2006*	0.391*** (0.023)
ONE STORY	0.015 (0.023)	*MAP*	-0.303*** (0.033)
YEAR 1991	-0.081*** (0.011)	*POSTMAP*	0.064*** (0.016)
YEAR 1992	-0.159*** (0.012)	*Constant*	4.177*** (0.254)
		Observations	59335
		R-squared	0.71

Standard errors in parentheses; *** significant at 1 percent

Correction for Spatial Correlation

We could augment model (1) with either block group dummies or a random effect for each block group. However, including block group fixed effects overspecifies the variation across block groups because we have already confined our analysis to block groups with one or more MAP participants in order to limit the variation in block group attributes. A post random-effects estimation Hausman test indicates a rejection of the assumptions that the random effects are uncorrelated with any of the explanatory variables so random effects is not a good choice either.

A better alternative to addressing correlated errors in this context is a spatial econometric model wherein any unmeasured neighborhood effects cause spatial dependence in the error terms; that is, the errors at one location are formally modeled to be dependent on the errors at neighboring locations. Instead of defining neighbors as sales in large block group as we used in CSE regression and would need to if using random- and fixed-effects models, we follow the spatial econometrics tradition (Anselin 1988) by specifying neighbors with a spatial weights matrix (W). Each element in W (w_{ij}) gives the strength of the influence between observation i and observation j. If the weight is greater than zero, then the two observations are neighbors. The spatial weights formulation gives so much flexibility to the modeling of neighborhood relationships that it can be difficult to decide how to specify the matrix. In our application, we use a nearest-neighbor algorithm to define neighbors. Since each observation is a market sale, it seems likely that any unmeasured neighborhood effects would also influence the sales of nearby homes. For each observation, we first find the four nearest neighbors, then, for the nearest neighbors within 1,000 feet, w_{ij}=1, and for the nearest neighbors beyond 1,000 feet, w_{ij}=0.25. For all other pairs of observations that are not nearest neighbors, w_{ij}=0. Our W matrix is 55,097 by 55,097.

This algorithm has three advantages. First, it reflects the way real estate markets operate. When negotiating prices, people tend to form judgments about whether a price is too high or too low for the neighborhood by looking at transactions of nearest neighbors. Second, the algorithm gives the most weight to observations within the sliding neighborhoods that are in the treatment group. Thus, it helps control for unobserved neighborhood effects. And, third, it produces a sparse weight matrix thereby facilitating manipulation and estimation.[7]

A slight complication in our application is that we have 17 years of data. After eliminating trends in the data, errors from homes sold in different time periods may not influence each other. Thus, we apply the nearest-neighbor algorithm year by year, and the resulting W matrix is block diagonal with the individual years' relationships on the diagonal blocks and zeros in the rest of the elements.

The spatial error model (SEM) is

(2) $$\log(Price_i) = \alpha_0 + \beta X_i + \xi Z_i + \gamma T_i + \alpha_1 MAP_i + \alpha_2 POSTMAP_i + \lambda \sum_1^J w_{\mathrm{ij}}\, \epsilon_{\mathrm{ij}} + \phi_{\mathrm{i}}$$

In model (2) we add an error term and one fixed effect. The fixed effect (λ) is the estimate of the spatial autocorrelation in the original error term. Thus, the SEM contains elements of both random and fixed effects.[8]

The second column in Table 5 shows the CSE estimates of the key variables from Table 4. The third column displays the results for the key variables after correction for spatial

[7] Sparsity makes it possible to just use the nonzero elements of the weights matrix in many of the operations. This improves the speed of estimations significantly.

[8] Other spatial error models are possible. For example, one could include the neighborhood values of other sales prices (a simultaneous model—or spatial lag) and neighborhood values of any or all of the X variables. Our focus on the SEM is driven by our theoretical concern with omitted neighborhood effects.

correlation by model (2).[9] The SEM estimates of the coefficients on *MAP* and *POSTMAP* are substantially smaller than the CSE estimates but still statistically significant. All else equal, the homes within 1,000 feet of future MAP properties were sold for approximately 24.7 percent less than similar homes that were more than 1,000 feet from future MAP even before MAP participants move in. The prices of homes that sell within 1,000 feet of existing MAP properties are approximately 23.4 percent (-24.7 percent + 1.3 percent) less than similar homes that are more than 1,000 feet from MAP. The estimate of *LAMBDA* is also significant, which indicates the presence of spatial autocorrelation.

Table 5. MAP impact on sales for various ring sizes and alternative specifications

	Dependent Variable: Log (sales price)			
	Treatment: MAP within 1000 feet		Treatment: MAP within 500 feet	
	CSE	**SEM-4**	**CSE**	**SEM-4**
MAP	-0.303	-0.247	-0.132	-0.098
	(0.033)***	(0.007)***	(0.022)***	(0.000)***
POSTMAP	0.064	0.013	0.022	-0.003
	(0.016)***	(0.004)***	(0.010)**	(0.42)
LAMBDA		0.576		0.585
		(0.000)***		(0.000)***
Constant	4.180	5.560	3.902	5.362
	(0.246)***	(0.000)***	(0.282)***	(0.055)***
Observations	59335	59335	59335	59335
R-squared	0.71	0.81	0.70	0.81

Standard errors in parentheses
** significant at 5 percent *** significant at 1 percent

[9] Regression reported in Table 5 and Table 4 includes the same set of variables in X and T.

Variation of Treatment Levels

So far, our examination of robustness has focused on the standard errors of the linear regression model. Now, we examine how the level of treatment affects the conclusions. In model (1), we only include a dummy variable that indicates the treatment; therefore, we only test whether property values are affected by the existence of MAP in the neighborhood. We do not know whether the impact was caused by one MAP property or several. A natural approach to measure the impact of every additional MAP property infusion is to include a continuous variable that measures the number of MAP in the neighborhood, and we can assume that the marginal impact of MAP is constant in a linear specification. However, MAP infusion took place over 15 years of time. Including a variable that indicates the total number of existing MAP in the ring to replace *POSTMAP* would only compare homes sold with various number of MAP in the neighborhood with homes sold without any MAP in the neighborhood. There is a lack of comparison of pretreatment groups for marginal impacts of MAP at different levels.

To address this issue, we instead divide the sample into five treatment groups and five comparison groups by constructing additional dummy variables as follows: *MAP1* (equals 1 if there is only one MAP property within 1,000 feet), *POSTMAP1* (equals 1 if there is only one MAP property and the sale is after the occurrence of the MAP), *MAP2* (equals 1 if there are two MAP properties within 1,000 feet of the sale), and *POSTMAP2* (equals 1 if there are just two MAP properties within 1,000 feet and the sale is after the occurrence of the two MAP properties). Similarly, we have *MAP3_4*, *POSTMAP3_4*, *MAP5_9*, *POSTMAP5_9*, *MAP10* and *POSTMAP10* to denote treatments of three or four, five to nine, and 10 or more MAP properties. This specification helps us identify the incremental effects of MAP on the neighborhoods.

As Table 2 shows, 34 percent of the observations are within 1,000 feet of just one MAP property, while 15 percent of the sample is within 1,000 feet of an existing MAP property. Therefore, 44 percent (0.15/0.34) of the data in the single MAP property treatment group are sales after the existence of MAP and 56 percent are sales before MAP infusion. However, the pretreatment groups become smaller for higher level treatment. The majority of sales took place after the existence of MAP in the neighborhood, which makes the difference between the number of observations in post treatment and pretreatment groups substantial. The pretreatment groups account for 4 percent, 9 percent, 15 percent and 19 percent in the comparisons for the treatment of two, three to four, five to nine and more than 10 MAP properties, respectively. The number of observations in some of these groups may not be adequate for drawing statistical inferences in the estimation of the DID.

The second and third columns of Table 6 reports the estimates of the CSE model and spatial error model using the specific treatment levels for treatment within 1,000 feet. As in the simple model of treatment presented in Table 5, the pretreatment MAP areas (*MAP1*, *MAP2*, etc.) still display relatively low conditional mean prices. The coefficients on the *MAP* dummies range from approximately -0.325 to -0.216, and are all statistically significant at conventional levels. The CSE estimates of *POSTMAP* coefficients are all positive but only statistically significant for *POSTMAP_1* and *POSTMAP_2*. The SEM coefficient estimate is positive and significant on *POSTMAP_1*, positive and not significant on *POSTMAP_2* and *POSTMAP_3_4*, and negative and significant for *POSTMAP_5_9* and *POSTMAP_10*. These findings make it difficult to conclude that concentrations of MAP properties do not harm neighboring properties. Clearly, scattered MAP properties do no damage but as concentrations rise, we have some evidence from the SEM that home values fall.

Table 6. MAP impact on sales for various level of MAP infusion

	Dependent Variable: Log (sales price)			
	Treatment: MAP within 1000 feet		Treatment: MAP within 500 feet	
	CSE	**SEM-4**	**CSE**	**SEM-4**
MAP_1	-0.304	-0.245	-0.132	-0.097
	(0.033)***	(0.000)***	(0.022)***	(0.000)***
POSTMAP_1	0.076	0.020	0.035	0.007
	(0.018)***	(0.000)***	(0.010)***	(0.124)
MAP_2	-0.276	-0.230	-0.105	-0.083
	(0.039)***	(0.000)***	(0.025)***	(0.000)***
POSTMAP_2	0.034	0.002	0.008	-0.018
	(0.016)**	(0.855)	(0.014)	(0.067)*
MAP_3_4	-0.252	-0.216	-0.127	-0.093
	(0.036)***	(0.000)***	(0.029)***	(0.000)***
POSTMAP_3_4	0.016	0.013	0.015	-0.021
	(0.019)	(0.121)	(0.018)	(0.056)*
MAP_5_9	-0.265	-0.224	-0.174	-0.093
	(0.035)***	(0.000)***	(0.030)***	(0.000)***
POSTMAP_5_9	0.027	-0.022	0.019	-0.079
	(0.020)	(0.014)**	(0.022)	(0.000)**
MAP_10	-0.325	-0.237	-0.201	-0.123
	(0.036)***	(0.000)***	(0.040)***	(0.000)***
POSTMAP_10	0.027	-0.055	0.020	-0.119
	(0.029)	(0.000)***	(0.025)	(0.000)***
LAMBDA		0.574		0.5832
		(0.000)***		(0.000)***
Constant	4.246	5.565	3.974	5.565
	(0.243)***	(0.000)***	(0.278)***	(0.000)***
Observations	59335	59335	59335	59335
R-squared	0.71	0.81	0.70	0.81

Standard errors in parentheses
* significant at 10 percent; ** significant at 5 percent *** significant at 1 percent

Variation in ring size

By defining the treatment group as home sales with MAP within 1,000 feet ring, we assume that MAP homes could potentially affect roughly 20-24 single family homes on the same street in a residential neighborhood as well as some homes on nearby streets. This definition allows us to have treatment group of substantial sizes at higher levels of treatment (Table 3). However, unlike multi-unit subsidized rental housing or rehabilitation projects, single family home purchase may only have identifiable spillover effects on smaller neighborhood. We thus estimate the impact by narrowing the ring radius to 500 feet to MAP homes. The treatment group sizes shrink for higher levels of treatment (Table 3). The estimates for MAP existence are presented in the fourth and fifth columns in Table 5 and Table 6.

Again, the estimates on *MAP* for 500 feet ring are negative and significant in both the CSE and the SEM model; that is, the narrower ring does not change the results that MAP homes tend to locate in less expensive neighborhoods. The DID estimate of the coefficient on *POSTMAP* is positive and significant in the CSE model but not significantly different from zero in the SEM model. Again, this suggests that overall MAP does little harm to neighboring home values. When we incorporate dummy variables for different levels of MAP treatments, the CES coefficient estimates on all other *POSTMAP* variables are positive, but only *POSTMAP_1* is significant (column four and five in Table 6). The SEM coefficient estimate is positive but not significant on *POSTMAP_1*. SEM coefficient estimates on all other *POSTMAP* variables are negative and significant. The results are similar to those for higher concentration of MAP within 1,000 feet ring but even less positive, suggesting that proximity to clusters of MAP properties may adversely affect the property values, although MAP do not have detrimental impact on the neighborhood within 500 feet radius overall.

DISCUSSION

Realization of homeownership benefits is neither automatic nor immediate after purchase. As more and more low- and moderate-income households gain access to homeownership opportunities through a variety of innovative public or private home-financing products, many challenges arise. Borrowers that can barely afford mortgages are not likely to maintain their homes well, which may cause the decline of neighborhood property values. In recent years, foreclosures associated with the subprime mortgage fallout have been costly for almost all parties.

Rather than waiting for market forces to tighten up underwriting standards, lenders could have avoided or reduced losses by assessing more carefully borrowers' repayment ability and offering high-risk borrowers more suitable loans. For example, the Dallas MAP has provided up-front cost assistance to low- and moderate-income borrowers so that they obtain mortgages they can afford. To qualify for the program, applicants must verify their continuous and successful employment history, and the city-approved MAP lenders can only issue prime mortgages. Dallas MAP's mandatory pre-purchase homebuyer education also enables potential borrowers to make good choices to find suitable loans and build assets. These sound practices help explain the relatively good loan performance of MAP loans and MAP participants' potential beneficial external impacts on their communities.

We test the extent of the spillover effects of MAP on neighborhood home values. We define sliding neighborhoods for each home sale based on distance from the location of MAP properties. Using a hedonic price model with correction of spatial autocorrelation of neighboring home sales and allowing the level of MAP infusion and neighborhood ring radius to vary, we find that MAP has no detrimental impact on housing prices in their neighborhoods overall. When there are only a few MAP properties in the neighborhood, the spillover can be positive. However, if homes are close to a large number of MAP properties owned by low-income buyers, the sales price may be lower than similar homes without cluster of MAP homes nearby.

Many perceived homeownership benefits are associated with the mixed-income nature of neighborhoods, where residents can have a safe and diverse environment, better services and amenities, and upward mobility, especially for youth. Unlike low- and moderate- income renters in most public housing programs, participants in subsidized homeownership programs have more flexibility in choosing their homes' location and so are distributed in a more scattered pattern than subsidized renters. Although the majority of MAP participants still reside in low- and moderate-income census tracts where the affordable units are available, and home values are lower in areas where MAP participants choose to locate, our results show that to certain extent, and houses in MAP neighborhood were sold at higher prices than similar areas. Although the cluster of low-income MAP participants may have limited the homeownership gains for the participants and their neighborhoods, the program remains a reasonable public policy option for increasing and sustaining homeownership for lower-income population.

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