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Do mortgage rates vary by neighborhood? Implications for loan pricing and redlining

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Abstract

Using a nationally representative sample of conventional single-family mortgage loans that originated during 1992–1995 with detailed loan pricing information, this paper examines whether interest rates vary by neighborhood income and racial composition. The estimates suggest that borrowers financing homes in low- and moderate-income neighborhoods generally paid 2–4 basis points more for 30-year loans, but there was no difference for 15-year loans. Results by racial composition of the neighborhood were more mixed, with borrowers in predominately Hispanic and Asian neighborhoods paying slighting higher rates, while borrowers in predominately African–American neighborhoods occasionally paid slightly lower rates. Omitted variables could account for some of these differences. Overall, the small effects suggest that redlining is unlikely to be a factor, although no firm conclusions can be drawn.

1. Introduction

As recently as 1980, it was common to observe wide differences in mortgage interest rates across the US. Average interest rates across regions varied by as much as a percentage point, reflecting geographic imbalances in the

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supply and demand for mortgage funds. Interest rates differed by 30 basis points, on average, between 95% and 75% loan-to-value (LTV) loans, leading to intra-regional rate differentials as utilization of high-LTV loans varied by neighborhood.[1] The maturation of the secondary market and the mortgage insurance industry and rise of national lending organizations have substantially reduced differences in mortgage interest rates by geographic location or loan LTV. However, rate differentials may remain for both economic (e.g., differences in origination or servicing costs, credit risk, points paid, and borrowers' search behavior) and non-economic (discrimination) reasons.

Fears that lower-income neighborhoods were being "redlined," or subject to geographic discrimination, led to passage of the Home Mortgage Disclosure Act in 1975 and the Community Reinvestment Act (CRA) in 1977. The CRA directly addressed the policy concern that banks and thrifts may have been taking deposits from inner city neighborhoods, especially lower-income neighborhoods, yet lending those funds primarily elsewhere.[2] Specifically, the CRA's focus was to assure that borrowers in low- and moderate-income neighborhoods were not disadvantaged in terms of credit access because of their location. While it has been difficult to empirically document the effect of the CRA, research to date has been consistent with higher flows of lending in low- and moderate-income areas. For example, Schill and Wachter (1994) find evidence of loan concentration effects in lower-income neighborhoods, and Evanoff and Segal (1996) find increased application and origination flows in lower-income census tracts.

Most studies of neighborhood redlining have focused on differential rejection rates. Simple tabulations of rejection rates by census tract do show higher rejection rates in lower-income and higher minority tracts.[3] However, after controlling for other factors, such as borrower attributes, most of these studies have been inconclusive or have not found evidence of geographic discrimination. Munnell et al. (1996), for example, did not find any significant neighborhood effects on loan approval or denial in the Boston area, but found evidence that borrower race was a factor in these decisions.[4]

In a follow-up study, Munnell et al. (1993) explored the extent to which low origination rates were due to differential treatment based on neighborhood location. They found no evidence that lenders deny loans due to a high concentration of minorities in the neighborhood or because the neighborhood is

[1] These differentials were found in surveys of mortgage rate quotes for new commitments. See *Financing Homes in A Diverse America*, Freddie Mac (1995), Exhibit 1; and *Savings and Home Financing Source Book: 1980*, Federal Home Loan Bank Board (August 1981), Table 40A.

[2] See Garwood and Smith (1993) for background on the CRA and its evolution.

[3] See Canner and Gabriel (1992), Table 4.

[4] Horne (1997) suggests that the statistically significant race effects found in the Boston Fed study (Munnell et al., 1993) are sensitive to differences in model specification, particularly in terms of the proxies used to measure credit risk.

poor or 'run down.' Schill and Wachter (1993) estimate accept/reject models for Boston and Philadelphia and do not find evidence of redlining when proxies for neighborhood risk are added. Avery et al. (1994) arrive at similar conclusions, although reporting some effect of tract income for the poorest tracts. Holmes and Horvitz (1994) examine the flow of conventional mortgage loans in the Houston area and do not find any effect of the racial composition or income of census tracts, once risk variables are incorporated.[5] These studies did not, however, have data on interest rate or other loan term differentials that could have affected the results.

Even though loan denial rates may not vary by neighborhood characteristic after controlling for borrower attributes, redlining may occur in more subtle forms, such as a variation in loan pricing by neighborhood. Redlining is generally defined to "include more subtle practices of restricting credit where the lender may...fix loan interest rates...or...closing costs in amounts higher than those set for all or most other mortgages in other areas...or...charge discount 'points' as a way of discouraging financing."[6]

Variation in mortgage interest rates and origination fees by the racial composition or relative income of a neighborhood may reflect legitimate economic considerations relating to credit risk, origination cost, or expected mortgage life. For example, this could reflect a correlation of the neighborhood's income or racial mix with legitimate risk-related factors such as high-LTV ratio, high payment-to-income ratios, poor credit-paying histories, or house value volatility.[7] Loans in these areas may be smaller, and due to fixed origination costs, fees may be higher relative to the loan principal amount.[8]

[5] Holmes and Horvitz (1994) include the default-to-mortgages-granted ratio by census tract as an additional explanatory variable and find it significant in all their models. Studies of mortgage flow generally find reduced application and origination rates in lower income and higher minority census tracts, but lack the direct measure of default rates; as an example, see Shear et al. (1995).

[6] HUD (1977), Part II, pp. 4–5.

[7] After controlling for a host of loan, borrower, and census tract characteristics, Berkovec et al. (1994) found a highly significant inverse relationship between the relative income of the tract and the likelihood of default on FHA-insured loans. However, a direct measure of credit history was unavailable, and the estimates may reflect a correlation of borrowers' creditworthiness with the relative income of the tract. Van Order et al. (1993) found evidence of higher risk and higher default in African–American neighborhoods, after controlling for LTV, borrower income, and house price appreciation. Van Order and Zorn (2000, 2001) found that defaults and loan losses were higher in low-income neighborhoods, after controlling for a variety of loan and property features.

[8] See Hendershott and Shilling (1989) and ICF (1989). In addition, the ICF study looked at the impact of minority status on the effective rate paid. ICF found that borrowers that took out low-balance loans (about $35,000) paid 10–30 basis points more than borrowers that took out loans for larger amounts (about $75,000). When loan size was interacted with minority status, ICF found that minority borrowers pay higher premiums than white borrowers on low-balance loans.

Borrowers in such communities may be less mobile, reducing the likelihood of early prepayment and causing lenders to price mortgage credit accordingly,[9] or may shop for loans less intensively. It is also possible that there are fewer lenders operating in these areas, resulting in less price competition. Finally, it may be the case that lenders discriminate by overtly or inadvertently charging higher rates based on borrower or neighborhood characteristics that are unrelated to lending costs.

Few studies of discrimination and redlining in mortgage markets have looked at differential loan terms, generally because details on loan pricing have been lacking. For example, Schafer's (1978) study was confounded by the existence of usury laws in New York state, which disallowed discount points on most mortgages. Benston and Horsky (1992) tested the hypothesis that people in redlined areas face harsher mortgage terms, including higher interest rates, than in non-redlined areas. In an analysis of survey data from homeowners in three central cities, these authors found no evidence that borrowers in areas allegedly redlined faced higher interest rates than borrowers in other areas (Benston and Horsky, 1979, 1992).

Crawford and Rosenblatt (1999) found no evidence of racial differences in conventional home mortgage interest rates for a sample of loans originated by one lender, after controlling for relevant factors, including LTV, housing-expense and debt-to-income ratios, and loan size. In addition, they found no significant effects of race on interest rate charges relative to the lender's daily market rates, or on rate movements between lock-in and closing dates; their analysis, however, did not include any neighborhood variables. Similarly, Courchane and Nickerson (1997), using data from three banks, examined racial differences in overage charges, or premiums paid by borrowers when lenders charge more than their minimum stated interest rate. These authors found that in some cases minority borrowers are charged higher overages, but that this is often due to changes in lock dates or closing dates rather than because of lender intentions.

The present study differs from the existing literature in its use of a nationally representative sample of conventional single-family loans with detailed loan origination data for the years 1992–1995. These data are used to determine whether interest rates on fixed-rate loans vary by the income and racial composition of the neighborhood.

This paper is structured as follows. The next section describes the data and methodology used in the analysis. The section thereafter presents the results. A concluding section summarizes the analysis and suggests future work.

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[9] See Rosenthal and Zorn (1993) and Van Order and Zorn (2001). Van Order and Zorn find lower prepayment rates in lower-income neighborhoods, after controlling for a variety of loan, borrower, and locational characteristics.

2. Data and analysis

This analysis is based on data from the Federal Housing Finance Board's Mortgage Interest Rate Survey (MIRS) for the 1992, 1993, 1994, and 1995 origination years. It is a survey of conventional, fully amortizing, purchase-money first mortgage originations secured by one-family, non-farm homes and includes all major types of lenders (commercial banks, savings banks, savings and loan associations, and mortgage companies) across the United States. Each institution surveyed reports all loans closed during the last five work days of each month and reports the loan principal amount, interest rate, points and fees charged, the type of originating institution, the loan term, the product type (fixed- or adjustable-rate), whether the home has been previously occupied, and the five-digit ZIP code location of the property.[10] For this paper's research, each loan was matched to data on the characteristics of the ZIP code area based on data collected as part of the 1990 Census of Population and Housing; the census data include the racial composition, median income, and housing stock characteristics for 29,228 residential ZIP codes. After merging both the MIRS and census datasets, and limiting the sample to loans with principal amounts that make them eligible for sale to Freddie Mac and Fannie Mae,[11] the final sample includes 228,076 30-year fixed-rate conforming loans and 58,530 15-year fixed-rate conforming loans in 15,883 ZIP codes; while this represents 54% of all valid ZIP codes, these codes comprise an area that includes 89% of the 1990 US population.[12]

This paper tests the hypothesis that mortgage rates are higher in lower-income and minority areas relative to high-income or low-minority areas after controlling for loan, property, and lender differences. To test these

[10] The Federal Housing Finance Board began collection of the five-digit ZIP code on all loans in November 1991. Prior to that month, the ZIP code was only collected for properties in New England.

[11] "Conforming" loans have original principal amounts below the Congressional loan limits of Freddie Mac and Fannie Mae. In 1992 this limit was $202,300 and in 1993–1995 was $203,150, with limits 50% higher in certain high-cost areas (Alaska, Hawaii, and Guam for 1992–1995 and the US Virgin Islands for 1993–1995).

[12] A relatively small number of loans with unusually high or low interest rates or with high fees were deleted from the analysis. Hendershott and Shilling (1989), ICF (1990), and Cotterman and Pearce (1996) have identified reporting errors, especially the misreporting of ARMs as fixed-rate loans. For 30-year loans, loans with an interest rate below 6.5% or above 9.5% were deleted; for 15-year loans, loans with a rate below 6.0% or above 9.0% were excluded. In addition, loans with more than four points were deleted. The deletions reduced the analytic sample by less than 5%. In comparison, Freddie Mac's Primary Mortgage Market Survey reported that rates on new commitments for 30-year loans varied between 6.7 and 9.3%, and for 15-year loans from 6.3 and 8.8%, over a comparable period. Furthermore, the average number of points was reduced only from 1.30 in the full dataset (before any exclusions) to 1.24 (after all exclusions).

relationships, multiple-regression models are estimated with either the mortgage interest rate or fees as the dependent variable. The independent variables are intended to capture the effects of neighborhood characteristics (ZIP code racial composition, ZIP code income relative to that of the local area, and ZIP code housing characteristics) while controlling for differences in LTV, loan product, type of originating institution, state location of property, and week of origination. A list of model variables including a brief description is included in Table 1; the origination-week dummies appear

Table 1
Variable definitions

Variable name	Description
ZIP code variables	
MINPCT	Percent of ZIP code population that is African–American, Hispanic, or Asian
MIN1029	1 if minority share between 0.10 and 0.29, 0 otherwise
MIN3049	1 if minority share between 0.30 and 0.49, 0 otherwise
MIN50	1 if minority share equals 0.50 or greater, 0 otherwise
BLKPCT	African–American share of ZIP code population
BLK1029	1 if African–American share between 0.10 and 0.29, 0 otherwise
BLK30	1 if African–American share 0.30 or greater, 0 otherwise
HISPCT	Hispanic share of ZIP code population
HIS1029	1 if Hispanic share between 0.10 and 0.29, 0 otherwise
HIS30	1 if Hispanic share 0.30 or greater, 0 otherwise
ASNPCT	Asian share of ZIP code population
ASN1029	1 if Asian share between 0.10 and 0.29, 0 otherwise
ASN30	1 if Asian share 0.30 or greater, 0 otherwise
MFIAREA	Ratio of ZIP code to area (MSA or county) median family income
LOWINC	1 if ZIP to area income ratio $\leqslant 0.80$, 0 otherwise
LOWMOD	1 if ZIP to area income ratio between 0.81 and 1.0, 0 otherwise
MIDINC	1 if ZIP to area income ratio between 1.01 and 1.2, 0 otherwise
RENTPCT	Rental share of total housing units in ZIP
VACANT	Vacancy rate of ZIP code
Loan-related variables	
RATEBASE	Interest rate without discount or buydown
EFF_RATE	Effective interest rate incorporating FEES
FEES	Fees, discounts, or points as a percent of principal amount
JAN92...NOV95	0, 1 dummy for origination month
HILTV	1 for LTV > 0.90, 0 otherwise
NOPMI	1 for LTV $\leqslant 0.80$, 0 otherwise
COMMBANK	1 if originated by commercial bank, 0 otherwise
SAIFSAV	1 if originated by SAIF-insured S&L or savings bank, 0 otherwise
BIFSAV	1 if originated by BIF-insured savings bank, 0 otherwise
MORTCO	1 if originated by mortgage company, 0 otherwise
LOAN	Log of the loan principal amount
BUYDOWN	1 if temporary discount or buydown, 0 otherwise
NEWHOME	1 if new home, 0 if previously occupied
State variables	0, 1 dummy if located in specified state
METRO	1 if ZIP code located within MSA, 0 otherwise

labeled by month, because the MIRS collects data only on loans closed during the last week of the month.

Two alternative interest rates are used as the dependent variable. One is the basic interest rate, or the initial rate paid by the borrower as specified in the loan contract, excluding the effects of temporary buydowns or discounts (RATEBASE).[13] When this is used as the dependent variable, an independent variable representing fees, which include discount 'points' paid by the borrower, is included in the model. The second is the effective interest rate (EFF_RATE), which is computed by the Federal Housing Finance Board and includes the amortization of fees over an assumed 10-year life; over 1992–1995, the effective rate is generally about 20 basis points greater than the base interest rate for 30-year fixed-rate mortgages.

We control for a number of risk-related factors that could affect the price of a mortgage. These independent variables can be divided into three categories: characteristics of the mortgage loan, characteristics of the property, and characteristics of the neighborhood, including racial and income composition of the ZIP code.

2.1. Loan characteristics

A number of studies have found that high-LTV loans have a significantly higher risk of default than others (Berkovec et al., 1994; Van Order et al., 1993; Van Order and Zorn, 2000, 2001). We include two variables related to the loan-to-value (LTV) ratio. The first (HILTV) is a binary dummy for LTVs above 90%. The second (NOPMI) is a binary dummy for loans with LTVs at or below 80%; conventional mortgages in this category do not require primary mortgage insurance coverage. We control for the size of the loan by including the log of the loan principal amount (LOAN). The rationale is that fixed costs of origination may result in higher rates or fees on smaller balance loans (Hendershott and Shilling, 1989). A set of dummies for the type of lending institution was included to capture pricing differences that may reflect portfolio versus secondary market lending activity, or CRA coverage (mortgage companies in the MIRS will not generally be covered by the CRA). We control for loan product by estimating separate models for 30-year fixed-rate and 15-year fixed-rate mortgages. We also include a set of

[13] A buydown is a type of financing where the borrower typically pays extra points up front in return for a temporarily lower interest rate. The most common are "2-1" and "3-2-1" buydowns. A "2-1" buydown means that the interest rate is two percentage points below the "base" rate the first year, then one percentage point below the second year, and then equals the base rate thereafter; a "3-2-1" buydown has a similar progression spanning the first three years of the mortgage contract.

dummies for the week in which the loan was closed to control for the temporal movement of rates. Finally, we include a dummy to indicate whether the loan rate has a temporary discount or buydown (BUYDOWN).

2.2. Property characteristics

The sample universe of the MIRS already limits the type of property to a fairly homogeneous group: one-unit, non-farm homes, excluding mobile homes. Thus, the second category of independent variables consists of a dummy for loans on new versus existing homes to control for any differences in default risk (NEWHOME), and dummies for state and metropolitan location. Existing homes may face higher maintenance and repair costs than new homes, and as such may pose a greater default risk. The state dummies capture any state-specific loan pricing differentials, perhaps related in part to variation in state foreclosure laws (Clauretie and Herzog, 1989) or regional mobility or appreciation patterns (Rosenthal and Zorn, 1993). The dummy for location within a metropolitan statistical area (METRO) controls for differential loan pricing, if any, between urban and rural locations.

2.3. Neighborhood characteristics

We include the percentage of housing units in the ZIP code that are occupied by renters (RENTPCT). The existence of large shares of rental properties may be an indication of below-average house price appreciation, or possibly high turnover, which could affect both default risk and the lender's rate of return on a mortgage. In addition, we control for the percentage of homes in the ZIP code that are vacant (VACANCY) to capture house price appreciation, turnover, or other local economy effects. The relative income of the ZIP code (MFIAREA) is measured as the ratio of the median family income of the ZIP to the median family income of the MSA (for loans in metropolitan areas) or of the county (for loans outside metropolitan areas).[14] In an alternate specification, we include dummy variables representing those ZIP codes where this ratio is at or below 80% of the area (MSA or county) median, between 81 and 100% of the area median, and between 101 and 120% of the area median (LOWINC, LOWMOD, and MIDINC). The first of these dummies, LOWINC, approximates the neighborhood geography that is a special focus of the CRA.

Different combinations of continuous or dummy variables are used to capture the racial composition of the neighborhood. The racial composition

[14] Comparison with the county median differs slightly from an analogous calculation done by banking regulators. For monitoring compliance with CRA mandates, regulators measure the median income of a non-metro census tract relative to the median income for the entire non-metro portion of a state.

of the ZIP code is captured as the minority percentage of the population, including African–American, Hispanic, and Asian residents (MINPCT). In an alternate specification, we include the percentage of the population that is African–American, Hispanic, or Asian, to determine the extent to which rates vary for different minority groups (BLKPCT, HISPCT, and ASNPCT). In a third version of the model, we include dummy variables for ZIP codes where the minority share is between 10 and 29%, 30 and 49%, and above 50% (MIN1029, MIN3049, and MIN50). The fourth variation of the model includes dummy variables for each racial/ethnic category representing between 10 and 29% of the population or 30% or more of the population (BLK1029, BLK30, HIS1029, HIS30, ASN1029, and HIS30).[15]

Table 2 presents the mean and standard deviation for each variable in the 30-year and 15-year fixed-rate datasets. A simple comparison of the means shows that 15-year loans carried a rate that was about 0.4% points below 30-year loans during this period. Furthermore, 15-year loans have far lower LTVs; the average LTV on 15-year loans in the sample was 66%, compared to 81% for 30-year product. Likewise, even though both products financed the purchase of similarly valued homes, the average loan size for 15-year loans ($79,400) was substantially smaller than for 30-year loans ($100,200). Fifteen-year loans were also used less to finance the purchase of a newly built home and were more likely to be used in non-metropolitan locations.

3. Results

The MIRS data allow a unique opportunity to examine how conventional loan features vary by the relative income and minority share of neighborhoods. No other recent dataset contains LTV or loan product (ARM versus fixed-rate) combined with neighborhood information for a nationally representative sample. For example, the annual Home Mortgage Disclosure Act datasets lack LTV, term, or ARM indicators, while the metropolitan American Housing Survey datasets cover only a limited number of MSAs and identify only subareas of about 100,000 in population; both datasets exclude loan origination date on the public-use files.

Table 3 compares the LTV distribution and the ARM share for conforming loans made during 1994 based on the income and minority composition of the ZIP code. The selection of 1994 loan originations was arbitrary and

[15] We also computed the relative home value of the ZIP, measured as the median home value of the ZIP divided by the median home value of the metropolitan area or the non-metropolitan county. However, this variable was highly correlated with other ZIP variables, such as MFIAREA, and led to multicollinearity and poor model specification. We excluded this variable from the models reported in this paper.

Table 2
Descriptive statistics for 30-year and 15-year fixed-rate model variables

Variable name	Thirty-year fixed-rate mean (standard deviation)	Fifteen-year fixed-rate mean (standard deviation)
ZIP code variables		
MINPCT	0.16 (0.18)	0.14 (0.16)
MIN1029	0.32 (0.47)	0.29 (0.46)
MIN3049	0.08 (0.27)	0.07 (0.25)
MIN50	0.06 (0.24)	0.05 (0.22)
BLKPCT	0.07 (0.13)	0.06 (0.12)
BLK1029	0.13 (0.34)	0.13 (0.33)
BLK30	0.05 (0.22)	0.05 (0.22)
HISPCT	0.06 (0.10)	0.05 (0.10)
HIS1029	0.11 (0.31)	0.09 (0.28)
HIS30	0.04 (0.19)	0.03 (0.17)
ASNPCT	0.03 (0.05)	0.02 (0.04)
ASN1029	0.03 (0.18)	0.03 (0.16)
ASN30	0.01 (0.08)	0.004 (0.06)
MFIAREA	1.06 (0.25)	1.05 (0.26)
LOWINC	0.12 (0.32)	0.13 (0.33)
LOWMOD	0.31 (0.46)	0.33 (0.47)
MIDINC	0.33 (0.47)	0.31 (0.46)
RENTPCT	0.27 (0.13)	0.27 (0.13)
VACANT	0.04 (0.02)	0.04 (0.03)
Loan-related variables		
RATEBASE	7.92 (0.67)	7.52 (0.67)
EFF_RATE	8.12 (0.68)	7.75 (0.69)
FEES	1.23 (1.09)	1.26 (1.10)
JAN92…NOV95	0.01–0.03 (0.08–0.17)	0.004–0.04 (0.06–0.19)
HILTV	0.37 (0.48)	0.09 (0.29)
NOPMI	0.51 (0.50)	0.85 (0.35)
COMMBANK	0.03 (0.18)	0.04 (0.19)
SAIFSAV	0.41 (0.49)	0.46 (0.50)
BIFSAV	0.03 (0.18)	0.05 (0.21)
MORTCO	0.53 (0.50)	0.45 (0.50)
LOAN	11.4 (0.46)	11.1 (0.56)
BUYDOWN	0.01 (0.08)	0.002 (0.05)
NEWHOME	0.15 (0.36)	0.11 (0.31)
State variables	0.001(AK)–0.08(CA) (0.01–0.27)	0.001(DC)–0.11(OH) (0.02–0.32)
METRO	0.91 (0.28)	0.85 (0.36)

the 1994 distribution is similar to that during the other years in our sample. The upper panel contains the LTV distribution and ARM share within each relative income bucket. The share of high-LTV loans decreases as the relative income of the neighborhood increases. For example, the group with the highest proportion of high LTV loans (above 90%) was the low-income ZIP-code group (at or below 80% of the MSA or county median). Twenty-seven percent of loans in high-income ZIPs had LTVs above 90%, compared to 51% in the lowest income areas. At the same time, ARM usage appears

Table 3
ZIP code demographic characteristics and distribution of 1994 originations by LTV and ARM share

ZIP code characterеristic	LTV			ARM share
	⩾80%	81–90%	Above 90%	
Relative income				
⩽80%	31.3	17.5	51.2	30.5
81–100%	39.3	18.1	42.6	36.3
101–120%	45.9	19.9	34.2	40.8
>120%	54.2	18.5	27.3	45.0
All	43.3	18.7	38.0	39.0
Minority percent				
<10%	48.6	19.7	31.7	40.1
10–29%	42.6	18.0	39.4	39.9
30–49%	32.9	17.5	49.6	34.8
⩾50%	28.8	17.6	53.7	32.8
All	43.3	18.7	38.0	39.0

Source. 1990 Census and 1994 MIRS (conforming fixed-rate and adjustable-rate 30-year mortgages).

to increase with neighborhood income. In low-income areas, 30% of conventional mortgages were ARMs, compared to 45% of loans in high-income areas.

The lower panel of Table 3 shows the variation in the LTV distribution and ARM share based on ZIP code minority composition. Here, the share of high-LTV loans increases with minority concentration. Over half of loans in areas where at least 30% of the population are minorities have high LTVs (LTV above 90%). For areas where the minority share is less than 10%, only 32% of loans have high LTVs. This pattern is most likely due to the fact that minorities have disproportionately lower wealth and are more likely to be first-time homebuyers. In addition, areas with high minority concentrations have a smaller ARM share. For areas where at least half of the population is minority, 33% of loans were ARMs. For areas with less than 10% minority population, the ARM share was 40%. The variation in ARM share by relative income and minority share of the neighborhood is striking, since most studies of mortgage loan choice conclude that the relative price of fixed- versus adjustable-rate credit is the crucial determinant, with borrower attributes having, at best, a small effect on loan choice (Berkovec et al., 2001; Berkovec and Nothaft, 1997).

The regression analysis examines two homogeneous loan product types: 30- and 15-year fixed-rate conforming mortgages. These two products represent the bulk of loans reported on the MIRS. ARMs are excluded from the analysis because of the greater difficulty in controlling for variation in pricing across loans. "Jumbo" loans—those with a principal that exceeds

Table 4
Distribution of 1992–1995 originations by income and racial composition of ZIP code

ZIP code characterisitic	Thirty-year fixed-rate		Fifteen-year fixed-rate	
	Loans	Percent	Loans	Percent
Relative income				
⩽80%	26,448	11.6	7347	12.6
81–100%	71,428	31.3	19,417	33.2
101–120%	75,331	33.0	18,284	31.2
>120%	54,869	24.1	13,482	23.0
Minority percent				
<10%	119,548	52.4	33,760	57.7
10–29%	75,041	32.9	17,535	30.0
30–49%	19,018	8.3	4195	7.2
⩾50%	14,469	6.3	3040	5.2
All	228,076	100.0	58,530	100.0

the allowable limits for purchase by Freddie Mac and Fannie Mae—are also excluded, since they carry substantially higher interest rates (Cotterman and Pearce, 1996; Hendershott and Shilling, 1989). The sample sizes and distribution of loans by relative income and minority share of the neighborhood are shown in Table 4. The distributions are comparable to those reported by Canner and Passmore (1995) for loans approved during 1993.[16]

Four alternative model specifications were estimated, varying by the type of neighborhood relative income and racial composition variables used as regressors. Model 1 estimates the effects of the minority share and the neighborhood relative income (both measured in continuous form) on the basic interest rate (RATEBASE), the effective interest rate (EFF_RATE), and on fees paid (FEES). Model 2 replaces the minority percentage in Model 1 with the percentage of the population in each of the three separate racial/ethnic categories, also measured in continuous form. Model 3 replaces the continuous minority share and income variables with dummy variables for each of the three minority share and income buckets. Finally, Model 4 includes dummy variables for individual minority groups along with dummies for income categories.

[16] Based on conventional home purchase applications reported in 1993 Home Mortgage Disclosure Act data, Canner and Passmore's (1995) tables indicate that 57.5% of approved applications were in census tracts with minority population less than 10%, 35.7% were in tracts with a minority population of 10–49%, and 6.8% were in tracts with a minority population of 50% or more; by relative income, 10.1% were in tracts with income below 80% of area median, 48.2% were in tracts with relative income of 80–119%, and 41.7% were in tracts with income of 120% or more (Tables A-4 and A-9). These distributions are very similar to those shown in Table 4, considering that Canner and Passmore include jumbo loans and other loan products, such as ARMs and balloons, and use different neighborhood groupings (tract versus ZIP).

The four years of data were pooled together to estimate each model. To test for structural homogeneity, the sample was then cut into two by separating 1992 and 1993 from 1994 and 1995. The resulting F tests showed that the model was not homogeneous across the four years at a 99% significance level. As a result, the models were estimated separately for the first two sample years and for the last two years.

Estimates of Model 1 for the 30- and the 15-year loans are shown in Tables 5 and 6, respectively. In addition to the listed variables, the models included 23 monthly dummies (DEC93 and DEC95 were excluded) and 50 state dummies (CA excluded but DC included); the monthly dummies generally were highly significant and the state dummies as a group were significant at the 99% level. As shown in Tables 5 and 6, loans secured by homes in a metropolitan area had mortgage rates that were consistently 5–7 basis points lower in 1992 and 1993, and 10–12 basis points lower in 1994 and 1995. Evidence of pricing by credit risk is evident in the LTV variables. For 30-year loans, loans with an LTV above 90% (HILTV) cost borrowers 2–5 basis points more, while 15-year loans with an LTV of 80% or less (NOPMI) cost about 5 basis points less in 1992 and 1993. This difference was insignificant (albeit negative) in 1994 and 1995. The principal amount variable (LOAN) is strongly negative in all regressions, consistent with evidence that average fixed costs of originating and servicing loans decline with loan size. Loans with a rate buydown (BUYDOWN) carry a lower interest rate initially, but the effective rate is higher (and generally significant). The fee variable is inversely related to the contract interest rate, as expected, although the size of the FEES coefficient is unusually small, implying about 10 basis points to buydown the contract rate one percentage point.[17]

Because the parameter estimates change very little over the estimation of the four alternative models, the full regression estimates for Models 2, 3, and 4 are not shown. Instead, Tables 7 and 8 summarize the effect of alternative specifications of the neighborhood relative income and racial composition regressors for 30- and 15-year loans, respectively. The regressions show that borrowers in low- and moderate-income neighborhoods generally pay about 2–4 basis points more in interest rates on 30-year fixed-rate loans, after controlling for loan features, some property attributes, and other neighborhood characteristics. For example, the MFIAREA variable could serve as a proxy

[17] The coefficient on FEES may be biased toward zero to the extent that there is some joint determination of mortgage rates and points. Nonetheless, if the rate-point tradeoff is constant, then only the coefficient on FEES will be biased while the other coefficients will be unbiased. In other words, the other coefficients are estimated conditional on holding the rate-points tradeoff constant. One alternative is to convert the points into yield to incorporate the joint dependence; this is what is done in our models with EFF_RATE as a regressand, and the results are largely the same, suggesting that the other coefficients in the RATEBASE model are unbiased. Jud and Epley (1991) choose to treat rates and points as endogenous and estimate a two-stage least squares model, although the variables chosen as instruments lack intuitive appeal.

Table 5
OLS estimates of the determinants of the interest rate and fees on 30-year fixed-rate conforming mortgages

Regressand:	RATEBASE		EFF_RATE		FEES	
Period:	1992–1993	1994–1995	1992–1993	1994–1995	1992–1993	1994–1995
Regressors:						
constant	8.510	9.022	8.642	9.040	11.303	7.022
	(222.4)	(178.8)	(222.0)	(177.5)	(79.18)	(50.06)
ZIP code variables						
MINPCT	0.021	0.009	0.034	0.016	0.244	0.195
	(2.68)	(0.93)	(4.11)	(1.60)	(10.83)	(8.78)
MFIAREA	−0.056	−0.046	−0.061	−0.048	−0.086	−0.028
	(11.32)	(6.87)	(11.93)	(7.09)	(6.10)	(1.86)
RENTPCT	−0.028	−0.022	−0.058	−0.036	−0.399	−0.211
	(2.10)	(1.26)	(4.34)	(2.04)	(10.74)	(5.44)
VACANT	−0.041	−0.202	−0.102	−0.217	−0.266	0.100
	(0.57)	(2.32)	(1.39)	(2.46)	(1.30)	(0.52)
Loan-related variables						
NEWHOME	0.001	−0.053	0.016	−0.020	0.121	0.171
	(0.31)	(9.88)	(5.66)	(5.01)	(10.33)	(14.36)
METRO	−0.069	−0.102	−0.054	−0.098	0.154	−0.004
	(11.55)	(15.04)	(8.91)	(14.33)	(9.16)	(0.29)
HILTV	0.052	0.027	0.046	0.023	−0.075	−0.132
	(10.64)	(4.08)	(9.28)	(3.48)	(5.48)	(9.07)
NOPMI	0.003	−0.008	0.016	0.002	0.147	0.121
	(0.59)	(1.17)	(3.40)	(0.34)	(11.47)	(8.48)
COMMBANK	−0.022	−0.050	−0.053	−0.052	−0.367	−0.059
	(2.31)	(5.16)	(5.60)	(5.33)	(13.95)	(2.76)
SAIFSAV	0.047	−0.024	0.037	−0.027	−0.043	0.040
	(14.60)	(5.53)	(11.29)	(5.93)	(4.77)	(4.14)
BIFSAV	0.006	−0.066	−0.023	−0.027	−0.350	0.052
	(0.56)	(4.79)	(2.20)	(5.93)	(12.26)	(1.70)
LOAN	−0.077	−0.099	−0.088	−0.104	−0.198	−0.080
	(21.55)	(22.12)	(24.45)	(22.97)	(19.79)	(8.04)
BUYDOWN	−0.690	−1.272	0.319	0.175	−0.084	−0.721
	(26.22)	(52.48)	(11.86)	(7.14)	(1.13)	(13.19)
FEES	−0.078	−0.095	—	—	—	—
	(56.68)	(51.34)				
RATEBASE	—	—	—	—	−0.522	−0.435
					(50.34)	(49.75)
Adjusted R^2	0.7346	0.5888	0.7491	0.5734	0.2340	0.1856

Note. Absolute value of t statistic appears in parenthesis beneath the estimated coefficient. Regressions also include 23 monthly dummies and 50 state dummies. Sample sizes are 122,316 and 105,760 for 1992–1993 and 1994–1995, respectively.

for declining property values, crime, school quality, and other omitted characteristics. The effects are more muted for 15-year fixed-rate loans but are generally in the same direction.

Table 6
OLS estimates of the determinants of the interest rate and fees on 15-year fixed-rate conforming mortgages

Regressand:	RATEBASE		EFF_RATE		FEES	
Period:	1992–1993	1994–1995	1992–1993	1994–1995	1992–1993	1994–1995
Regressors:						
constant	8.547	9.464	8.776	9.531	11.270	9.016
	(149.1)	(107.7)	(151.5)	(107.3)	(52.47)	(30.97)
ZIP code variables						
MINPCT	0.096	−0.006	0.116	0.005	0.376	0.150
	(6.43)	(0.25)	(7.62)	(0.20)	(9.04)	(2.90)
MFIAREA	−0.010	−0.015	−0.011	−0.016	−0.014	0.011
	(1.24)	(1.13)	(1.25)	(1.13)	(0.61)	(0.34)
RENTPCT	0.017	0.107	0.001	0.110	−0.198	0.051
	(0.73)	(3.01)	(0.03)	(3.05)	(2.93)	(0.61)
VACANCY	0.423	0.196	0.450	0.227	0.599	0.736
	(3.28)	(1.13)	(3.41)	(1.29)	(1.66)	(1.81)
Loan-related variables						
HILTV	0.024	0.008	0.021	0.012	−0.011	−0.007
	(1.60)	(0.40)	(1.36)	(0.55)	(0.26)	(0.14)
NOPMI	−0.056	−0.021	−0.049	−0.005	0.063	0.167
	(4.65)	(1.16)	(3.94)	(0.28)	(1.87)	(3.98)
COMMBANK	0.090	−0.008	0.065	−0.007	−0.274	0.060
	(5.80)	(0.45)	(4.10)	(0.38)	(6.29)	(1.41)
SAIFSAV	0.043	−0.007	0.042	−0.005	0.018	0.078
	(7.09)	(0.77)	(6.80)	(0.56)	(1.04)	(3.64)
BIFSAV	0.062	−0.155	0.054	−0.180	−0.100	−0.224
	(4.04)	(7.83)	(3.46)	(9.00)	(2.34)	(4.81)
LOAN	−0.116	−0.130	−0.137	−0.142	−0.289	−0.177
	(21.81)	(17.59)	(25.41)	(18.95)	(26.14)	(10.05)
BUYDOWN	−0.094	−0.427	0.080	0.314	−0.007	0.035
	(1.42)	(3.76)	(1.18)	(2.72)	(0.04)	(0.13)
NEWHOME	0.072	−0.048	0.065	−0.002	0.144	0.167
	(8.02)	(4.07)	(10.29)	(0.23)	(5.71)	(6.07)
METRO	−0.072	−0.121	−0.056	−0.112	0.145	0.041
	(8.42)	(10.88)	(6.42)	(9.96)	(6.04)	(1.56)
FEES	−0.118	−0.100	—	—	—	—
	(46.48)	(26.54)				
RATEBASE	—	—	—	—	−0.951	−0.557
					(46.34)	(26.48)
Adjusted R^2	0.7384	0.6423	0.7541	0.6360	0.2672	0.1774

Note. Absolute value of t statistic appears in parenthesis beneath the estimated coefficient. Regressions also include 23 monthly dummies and 50 state dummies. Sample sizes are 37,249 and 21,281 for 1992–1993 and 1994–1995, respectively.

The results also suggest that borrowers in predominately minority neighborhoods (at least 50% minority) pay slightly higher rates—about 2–4 basis points for 30-year product and up to about 8 basis points at times for

Table 7
Thirty-year fixed-rate regression coefficients for race and income variables

ZIP code variables	Model 1						Model 2					
	RATEBASE		EFF_RATE		FEES		RATEBASE		EFF_RATE		FEES	
	1992–1993	1994–1995	1992–1993	1994–1995	1992–1993	1994–1995	1992–1993	1994–1995	1992–1993	1994–1995	1992–1993	1994–1995
MINPCT	0.02**	NS	0.03**	NS	0.24**	0.20**	—	—	—	—	—	—
BLKPCT	—	—	—	—	—	—	NS	−0.03*	NS	−0.03*	NS	NS
HISPCT	—	—	—	—	—	—	0.07**	0.09**	0.10**	0.10**	0.60**	0.48**
ASNPCT	—	—	—	—	—	—	0.08**	NS	0.09**	NS	0.30**	0.51**
MFIAREA	−0.06**	−0.05**	−0.06**	−0.05**	−0.09**	NS	−0.06**	−0.05**	−0.06**	−0.05**	−0.09**	−0.04*
Adjusted R^2	0.735	0.589	0.749	0.573	0.234	0.186	0.735	0.589	0.749	0.574	0.234	0.186
	Model 3						Model 4					
MIN1029	NS	NS	NS	NS	0.06**	0.05**	—	—	—	—	—	—
MIN3049	0.02**	NS	0.02**	NS	0.12**	0.08	—	—	—	—	—	—
MIN50	0.02**	0.03**	0.03**	0.04**	0.16**	0.15	—	—	—	—	—	—
BLK1029	—	—	—	—	—	—	NS	NS	NS	NS	0.03**	NS
BLK30	—	—	—	—	—	—	NS	NS	NS	NS	NS	NS
HIS1029	—	—	—	—	—	—	NS	NS	NS	NS	0.05**	NS
HIS30	—	—	—	—	—	—	0.04**	0.06**	0.05**	0.06**	0.23**	0.20**
ASN1029	—	—	—	—	—	—	0.01*	NS	0.01*	NS	NS	0.07**
ASN30	—	—	—	—	—	—	0.13**	0.08**	0.13**	0.08**	0.11*	0.19**
LOWINC	0.03**	0.02**	0.03**	0.02**	0.04**	NS	0.03**	0.02**	0.03**	0.02**	0.04**	NS
LOWMOD	0.03**	0.03**	0.04**	0.03**	0.04**	NS	0.04**	0.03**	0.04**	0.03**	0.04**	NS
MIDINC	0.02**	0.02**	0.02**	0.02**	0.04**	0.03**	0.02**	0.02**	0.03**	0.02**	0.05**	0.03**
Adjusted R^2	0.735	0.589	0.749	0.574	0.234	0.186	0.735	0.589	0.749	0.574	0.234	0.186

Note. NS indicates that the variable was "not significant" at a 95% level, an asterisk (*) indicates significance at a 95% level, a double asterisk (**) indicates significance at a 99% level, and a dash (—) denotes that the variable was not included in the specified model. Sample sizes are 122,316 for the models estimated over 1992–1993 and 105,760 for 1994–1995.

Table 8
Fifteen-year fixed-rate regression coefficients for race and income variables

ZIP code variables	Model 1						Model 2					
	RATEBASE		EFF_RATE		FEES		RATEBASE		EFF_RATE		FEES	
	1992–1993	1994–1995	1992–1993	1994–1995	1992–1993	1994–1995	1992–1993	1994–1995	1992–1993	1994–1995	1992–1993	1994–1995
MINPCT	0.10	NS	0.12	NS	.38	0.15	—	—	—	—	—	—
MFIAREA	NS	NS	NS	NS	NS	NS	−0.02*	NS	−0.02*	NS	NS	NS
BLKPCT	—	—	—	—	—	—	NS	NS	NS	NS	0.18	NS
HISPCT	—	—	—	—	—	—	0.19	NS	0.23	NS	0.69	0.28
ASNPCT	—	—	—	—	—	—	0.34	0.33	0.35	0.33	0.49	NS
Adjusted R^2	0.738	0.642	0.754	0.636	0.267	0.177	0.739	0.642	0.754	0.636	0.268	0.178
	Model 3						Model 4					
MIN1029	NS	NS	NS	NS	0.05	NS	—	—	—	—	—	—
MIN3049	0.03	NS	0.04	NS	0.16	NS	—	—	—	—	—	—
MIN50	0.06	NS	0.08	NS	0.25	NS	—	—	—	—	—	—
LOWINC	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS
LOWMOD	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS
MIDINC	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS
BLK1029	—	—	—	—	—	—	NS	NS	NS	NS	NS	NS
BLK30	—	—	—	—	—	—	NS	−0.03*	NS	NS	0.08	NS
HIS1029	—	—	—	—	—	—	NS	NS	NS	NS	0.05*	NS
HIS30	—	—	—	—	—	—	0.13	NS	0.14	NS	0.32	0.10*
ASN1029	—	—	—	—	—	—	0.08	0.06	0.08	0.06	0.08	NS
ASN30	—	—	—	—	—	—	0.09	0.13*	0.09	0.14*	NS	NS
Adjusted R^2	0.739	0.642	0.754	0.636	0.268	0.177	0.740	0.643	0.755	0.636	0.268	0.177

Note. NS indicates that the variable was "not significant" at a 95% level, an asterisk (*) indicates significance at a 95% level but not at a 99% level, a dash (—) denotes that the variable was not included in the specified model, and all other coefficients are significant at a 99% level. Sample sizes are 37,249 for the models estimated over 1992–1993 and 21,281 for 1994–1995.

15-year product (in 1992 and 1993, although the estimate is insignificant for 1994 and 1995). The results are more muddled when viewed by individual race. Borrowers in predominately Hispanic and Asian neighborhoods pay 4–14 basis points more in interest rates, but borrowers in predominately African–American areas pay about the same rate for 15- and 30-year loans (although the sign is generally negative and occasionally significant).

The estimates for the FEES variable are consistent with those for loan rates. Fees paid by borrowers are consistently higher, albeit by a small amount, in higher-minority neighborhoods, with the largest effects in predominately Hispanic and Asian neighborhoods. Effects by neighborhood income are smaller and weaker than for neighborhood racial composition, but do suggest an inverse relationship between neighborhood income and fees charged to borrowers.

To explore the potential effect of the CRA on loan pricing in lower income neighborhoods, we interacted a dummy reflecting depository lenders (equal to one if the lender was a depository, zero if it were a mortgage company) with the MFIAREA and LOWINC variables, but the estimated coefficient was small, often insignificant, and generally reversed sign between the 1992–1993 and 1994–1995 samples.[18] CRA-covered lenders have other ways to reduce the effective credit cost for borrowers in lower-income areas, such as waiving any mortgage insurance requirement that they would normally have. However, MIRS does not collect a mortgage insurance indicator.

Thus, the estimates do demonstrate that mortgage rates do vary, albeit by small amounts, by the demographic makeup of the neighborhood. A separate question, which this study cannot address, is whether this represents legitimate pricing to compensate for variation in credit risk, economic returns by neighborhood, subtle forms of redlining, omitted variables, or differences in borrowers' search behavior. Avery et al. (1994) find higher denial rates in low- and moderate-income areas, even after controlling for a variety of borrower, loan, and neighborhood characteristics. One interpretation of their finding suggests that higher-credit risk applications are filed for loans in such areas and those loans that are approved and made may carry

[18] As a general rule, mortgage companies are exempt from the CRA. However, a mortgage company owned by a CRA-covered institution may be covered if the parent chooses so, under Regulation C. We do not know the identities of the individual mortgage companies, and ignored this coverage fact in constructing our CRA coverage dummy. If CRA-covered lenders generally priced their loans in lower income neighborhoods more favorably than other lenders, one would expect a positive coefficient on the MFIAREA–CRA interaction variable, or a negative coefficient on the LOWINC–CRA interaction variable. For the 30-year fixed-rate models, the MFIAREA–CRA variable was insignificant or a small positive in 1992–1993, but significantly negative in 1994–1995 (albeit a small coefficient). The LOWINC–CRA interaction was insignificant or had a small negative coefficient (1–2 basis points) in 1992–1993, but was significantly positive (3–4 basis points) in 1994–1995.

somewhat higher rates to compensate for the greater credit risk of loans in those areas. Alternatively, it could be evidence that redlining may occur in lower-income areas. This study, like theirs, cannot disentangle these effects.

4. Summary

With a competitive primary market and an elastic supply of credit available throughout the nation, one might expect that there would not be any variation in mortgage pricing by geographic location, after controlling for all relevant factors. This paper finds evidence of variation, albeit small, in loan pricing by the relative income and racial mix of a neighborhood, holding loan features, property type, and neighborhood characteristics constant. In particular, borrowers in low- and moderate-income areas pay 2–4 basis points more for 30-year fixed-rate loans, with a similar effect for borrowers in high minority areas.

Unfortunately, the MIRS dataset lacks information on relevant borrower characteristics—most notably income, race, and creditworthiness—and on whether the loan has mortgage insurance that could explain the differentials we observe. For example, Avery et al. (1996) show that for recently made conventional fixed-rate loans, the average credit score of borrowers increased slightly with the relative income of the ZIP code. This suggests that the inverse relationship between relative income and mortgage rates could reflect pricing for credit risk related to borrower creditworthiness.[19] Thus, it is impossible to conclude whether the differences found reflect pricing for economic factors (higher credit risk, longer expected loan life), differences in borrower search behavior, or a subtle form of redlining.

The findings by racial mix of the neighborhood are more difficult to interpret, especially the occasionally lower rates observed in predominately African–American areas, counter to the view of some community advocacy groups. It may be that the relatively large market share captured by the FHA and VA programs in such neighborhoods leaves only the most-quali-

[19] An earlier version of our models included average FICO credit bureau scores by ZIP code as a regressor. The purpose of this variable was to hold constant the possible effects of credit risk differences on mortgage rates. Matching the file containing mean credit scores by ZIP code with the MIRS dataset resulted in a considerable loss of data. In addition, this variable was not statistically significant in any version of the model. For these reasons we omitted this variable from subsequent analyses. Jud and Epley (1991) found conventional, 30-year mortgage rates to be unrelated to borrower age but, oddly, positively related to borrower income. The positive relationship between borrower income and mortgage rates may reflect the fact that jumbo loans—which carry higher interest rates and are disproportionately taken by higher-income borrowers—are included in their sample, and because their model lacks explicit time effects; during higher-rate periods, lower-income borrowers are less able to qualify for mortgage loans of a given size, and their estimates may be picking up this fact.

fied borrowers for the conventional market;[20] since these borrowers are the most qualified, ceteris paribus, lenders may lend at more favorable rates. Alternatively, African–Americans may be more suspicious of the lending system, as reported by Bradley and Zorn (1996) through analysis of focus groups with renters and first-time homebuyers. As a result, African–Americans may engage in more extensive shopping for a loan, which could result in lower observed interest rates in predominately African–American neighborhoods. Finally, aggressive CRA lending programs may overlap with predominately African–American neighborhoods, resulting in slightly lower observed interest rates in these neighborhoods; our BLKPCT and BLK30 variables are generally significant only in the 1994 and 1995 period, consistent with the view that lenders stepped up special lending programs after the early 1990s. However, this is only speculation, and this empirical result will require more analysis.

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[20] Canner and Gabriel (1992) reported that the conventional share of home-purchase loans was 76% in census tracts with less than 10% minority population and 69% in tracts with at least 80% minority population (p. 258). Canner et al. (1991) found that African–American and Hispanic borrowers were more likely to obtain an FHA loan over a conventional loan; however, after controlling for the borrower's race, there was no separate effect of the census tract's minority share of the population on FHA versus conventional loan choice.

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