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Simultaneity bias in mortgage lending: A test of simultaneous equations models on bank-specific data

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Abstract

This study uses simultaneous equations models and single-equation models to test for simultaneity bias in mortgage refinance data compiled by a regional bank. The purpose of the study is to assess the claim that single-equation models of the lending decision produce biased and inconsistent parameter estimates of endogenous mortgage terms. Bank-specific data are analyzed to avoid bias resulting from uncontrolled policy, training, or underwriting differences across banks. Importantly, the data contain *all variables* the regional bank identified as important factors in explaining its loan disposition results. After controlling for applicants' debt, income, credit history, and requested loan term, I find that the race coefficient in single-equation models is biased upward, while the loan-to-value ratio coefficient is biased downward, although both biases are insignificant. Overall, the results suggest that simultaneous equations models are preferable to single-equation models in tests for discrimination, and can be used to determine the extent of race coefficient and loan-to-value ratio coefficient bias in single-equation models.

JEL classification: G21; J71

Keywords: Lending discrimination; Mortgage discrimination; Simultaneous equations

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1. Introduction

When Home Mortgage Disclosure Act (HMDA) based studies showing racial disparities in mortgage approval and denial rates after controlling for income were first published, "the lending industry's response was that the disparities could be explained by missing variables" (Browne and Tootell, 1995, p. 59). [1] To substantiate this claim the Federal Reserve Bank of Boston (BFR) collected data intended to account and control for all variables Boston-area lenders identified as important when surveyed. The data were initially analyzed by Munnell et al. (1992). [2] The BFR staff assumed Munnell et al.'s (1992) results would demonstrate that race was not a determining factor in loan decisions, and were stunned when race was identified as a significant influence in lending decisions (Goering and Wienk, 1996, p. 15).

Munnell et al. (1992) use single-equation logistic regression models to analyze the BFR data. Studies criticizing the use of single-equation models soon followed. For example, Rachlis and Yezer (1993), Yezer et al. (1994), and Phillips and Yezer (1996) argue that single-equation models of the lending decision are flawed as a test for discrimination. [3] Specifically, they argue that in a world of imperfect information, simultaneous equations bias arises since mortgage terms (i.e., loan-to-value (LTV) ratio, loan term (TERM), and back-end ratio (BER)) are not exogenous to the lending decision. As a result, single-equation models of the lending decision produce biased and inconsistent parameter estimates of the endogenous mortgage terms. [4] They also argue that single-equation models are subject to self-selection bias since only submitted applications are considered (i.e., potential applicants likely to be denied self-select not to apply for a mortgage loan). Rachlis and Yezer "conclude that unbiased tests for discrimination require, at a minimum, multiple-equation models estimated by econometric techniques capable of dealing with simultaneous equations or sequential selectivity with limited dependent variables" (p. 315).

[1] HMDA reports detail loan disposition for each Metropolitan Statistical Area (MSA) in the US by race, income, and gender. HMDA reports have five loan disposition categories (originations/approved, approved but not accepted, denied, withdrawn by applicant, and file closed for incompleteness), six race categories (Native American, Asian or Pacific Islander, Black, Hispanic, White, and Other), four income categories ($<$ 80% of MSA, 80–99% of MSA, 100–120% of MSA, and $>$ 120% of MSA), and two gender categories (male and female).

[2] The final version of this paper is Munnell et al. (1996), the results of which are consistent with those originally reported in Munnell et al. (1992).

[3] Other criticisms of Munnell et al. (1992) include Day and Liebowitz (1993), Horne (1994, 1997), Liebowitz (1993), and Zandi (1993), who argue that Munnell et al., did not correct coding errors in the data and exclude important variables correlated with race. Detailed responses to criticisms of the Federal Reserve study appear in Browne and Tootell (1995), Munnell et al. (1996), Tootell (1993), Tootell (1996), and Yinger (1996). Subsequent studies use the Federal Reserve data and attempt to improve the deficiencies of Munnell et al.'s (1992) research design (e.g., Bostic, 1994; Carr and Megbolugbe, 1993; Glennon and Stengel, 1994; Hunter and Walker, 1996; LaCour-Little, 1996; Munnell et al., 1996), and generally obtain results supportive of the original findings.

[4] Researchers disagree as to whether mortgage terms are endogenous or exogenous. Section 5 provides a general discussion of this issue.

This study uses simultaneous equations models and single-equation models of loan disposition (i.e., approved or denied) to test for simultaneity bias in mortgage loan data. It therefore is not subject to the simultaneous equations bias criticisms leveled against other single-equation mortgage discrimination studies by Rachlis and Yezer (1993), Yezer et al. (1994), and Phillips and Yezer (1996). The single-equation model's results are compared to the simultaneous equations model's results with respect to Yezer et al.'s (1994) claim that the race coefficient in single-equation models is biased upward, while the LTV ratio coefficient is biased downward. I thus assess Yezer et al.'s statement that "a positive and significant coefficient for a minority dummy variable in a single-equation rejection model may simply reflect the upward bias in estimates of β_M and cannot serve as a test for discrimination based on differential treatment as is commonly asserted in the literature" (p. 206).

The analysis is based on bank-specific loan file data compiled from mortgage refinance loan applications in response to a lending discrimination lawsuit, *and would not be available if not for the lawsuit*. A regional bank operating in the southeast US compiled the data. [5] I am aware of only three published bank-specific studies similar to this study, and each analyzes uniquely acquired bank-specific data (Siskin and Cupingood, 1996; Rosenblatt, 1997; Stengel and Glennon, 1999). [6] The bank-specific loan file data analyzed in Siskin and Cupingood (1996) were available to the authors only because Decatur Federal was under investigation by the Department of Justice, and the department asked them to analyze Decatur Federal's mortgage loan applications for evidence of lending discrimination. [7] Likewise, the bank-specific loan file data analyzed in Rosenblatt (1997) were available to the author only because he was Director of Credit Policy at Fannie Mae. [8] Similarly, the bank-specific loan file data analyzed in Stengel and Glennon (1999) were available to the authors only because they worked at the Office of the Comptroller of the Currency (OCC). [9]

This study analyzes bank-specific loan file data since Avery et al. (1993, 1994) and Stengel and Glennon (1999) raise concerns with regard to using aggregated loan file data in lending discrimination research. Specifically, they demonstrate that approval rates for minority applicants differ across lenders, and that little consistency exists between lenders with respect to their actions toward minorities. These authors concerns with using aggregated loan file data are supported by Horne (1997), who notes that analysis of data containing loan file information from multiple lenders

[5] The regional bank had total assets in excess of $40 billion as of 31 December 1993.

[6] Holmes and Horvitz (1997) is also a bank-specific study. However, it investigates lending discrimination from a redlining perspective and thus differs from Siskin and Cupingood (1996), Rosenblatt (1997), Stengel and Glennon (1999), and this study.

[7] Decatur Federal Savings and Loan was an Atlanta, GA lender that eventually was purchased by First Union National Bank.

[8] Rosenblatt's (1997) loan file data came from City Federal Savings Bank, a national mortgage lender based in New Jersey.

[9] The data used in Stengel and Glennon (1999) were gathered by OCC staff from three nationally chartered banks.

introduces aggregation bias since underwriting criteria vary across lenders. [10] Horne (1997) and Stengel and Glennon (1999) both note that parameter estimates from models based on aggregated data potentially obscure differences in lending practices across institutions (i.e., policy, training, and underwriting differences).

An important sample issue in using data compiled from mortgage refinance loan applications in tests for simultaneity bias is whether mortgage refinance loans are appropriate since the loan file samples of almost all prior lending discrimination studies consist solely of original mortgage loans. [11] Five lending discrimination studies that include mortgage refinance loans as part of their sample are useful for addressing this issue. Schill and Wachter (1993) and Holmes and Horvitz (1997) provide the most compelling evidence supporting the appropriateness of using mortgage refinance loans in simultaneity bias tests since both studies use the same independent variables to model mortgage refinance loans and the other loan types examined. Rosenblatt (1997) and Berkovec et al. (1998) also support using mortgage refinance loans in simultaneity bias tests by documenting significant negative changes in mortgage refinance applicants' credit profiles and likelihood of default, which shows that many such borrowers financial position has deteriorated since the original mortgage loan. Additionally, Kelly (1995) supports using mortgage refinance loans in simultaneity bias tests by documenting a substantially lower prepayment rate for black borrowers relative to white borrowers. Kelly also finds that black borrowers are less sensitive to interest rate differences than white borrowers, leading him to conclude that lending to black borrowers may be more profitable than lending to white borrowers. [12]

LaCour-Little's (1999) review of the mortgage lending discrimination literature identifies several recommendations for future research. This study is consistent with each recommendation. First, it uses simultaneous equations models of the mortgage lending process to explicitly consider potential endogeneity of loan term variables. Second, it limits the use of variables in single-equation rejection probability models to significant variables identified by the simultaneous equations models to minimize simultaneity and omitted variable bias. Third, it analyzes mortgage refinance loans from a single regional lender, thus avoiding concerns resulting from aggregating data from "lenders with different products, clientele, pricing, and underwriting standards" (p. 41).

After controlling for applicants' debt, income, credit history, and requested loan term, I find that this study's results support Yezer et al.'s (1994) claim that the race coefficient in single-equation models is biased upward, while the LTV ratio coefficient is biased downward, although both biases are insignificant. Overall, the results suggest that simultaneous equations models are preferable to single-equation models

[10] For example, the FHA data set contains over 220,000 records on mortgages originated by 70 FDIC-insured lenders operating in nearly 300 different metropolitan areas, while the BFR data set contains over 2,900 records from 131 Boston-area lenders.

[11] I thank a referee for raising this issue.

[12] This assumes that black borrowers lower prepayment risk more than offsets any higher credit risk relative to white borrowers.

in tests for discrimination, and can be used to determine the extent of race coefficient and LTV ratio coefficient bias in single-equation models.

The remainder of this paper is organized as follows: Section 2 details the loan file sample, Section 3 presents the variables, Section 4 presents descriptive statistics, Section 5 presents the research method and empirical results, Section 6 presents limitations, and Section 7 provides a summary and concluding remarks.

2. Loan file sample

A regional bank compiled a data file containing individual summaries of mortgage refinance loan applications in response to a lending discrimination lawsuit. Loans included in the sample met the following criteria:

(a) Loan for the purpose of refinancing a residential property.
(b) Loan application submitted between September 1991 and August 1993.
(c) Loan application submitted to one of the regional bank's branches in Tallahassee, FL. [13]
(d) Loan applicants either white or black. [14]
(e) Mortgage refinance application either approved or denied.

A total of 488 mortgage refinance loan applications met the above criteria. The classification of these 488 mortgage refinance loan files by loan disposition and race appears in Panel A of Table 1.

Since sample loans are restricted to mortgage refinance loans submitted between September 1991 and August 1993, an estimate of the regional bank's reported HMDA data for this period appears in Panel B of Table 1. [15] The HMDA estimates in Panel B are derived by taking 33% of the HMDA data from 1991 (representing September–December), 100% of the HMDA data from 1992 (representing January–December), 67% of the HMDA data from 1993 (representing January–August), summing and rounding to the nearest integer. The four entries in Panel B marked with a (*) should approximately coincide with the four inner entries in Panel A, and they do. This validity check suggests that the data provided by the regional bank used in this study are consistent with the data the bank reported to the government under the HMDA guidelines.

Panel A of Table 1 reveals that the approval rate for black applicants $(10/18 = 55.6\%)$ is much smaller than the approval rate for white applicants

[13] The Tallahassee, FL branches of the regional bank had total assets in excess of $190 million as of 31 December 1993.

[14] Since whites and blacks comprised 95% of the racial composition of Tallahassee, FL in 1990 (65.9% White, 29.1% Black, 0.2% American Indian, 1.8% Asian, and 3.0% Hispanic), insufficient mortgage refinance application data exists to separately analyze racial groups other than white and black.

[15] Five HMDA loan disposition categories (originations/approved, approved but not accepted, denied, withdrawn by applicant, and file closed for incompleteness) and three race categories (white, black, and other) are presented in Panel B. Only the first and third of the disposition categories, and only races white and black are considered in this study.

Table 1
Disposition of mortgage refinance loan applications submitted to a Regional Bank from September 1991 to August 1993, estimate of mortgage refinance loans reported in the Regional Bank's HMDA statements for September 1991–August 1993, and disposition of 435 applications containing a back-end ratio

Panel A: Disposition of mortgage refinance loan applications by race[a]

	White	Black	Total
Approved	453	10	463
Denied	17	8	25
Total	470	18	488

Panel B: Estimate of mortgage refinance loans reported on HMDA statements by race[b]

	White	Black	Other	Total
Applications	529	27	24	580
Originations/approved	443*	13*	16	472
Approved/not accepted.	2	0	1	3
Denied	17*	8*	2	27
Withdrawn	60	5	4	69
Closed – incomplete file	7	1	1	9

Panel C: Disposition of 435 applications containing a back-end ratio by race (subtracted values indicate loan files removed from analysis due to missing back-end ratio)[c]

	White	Black	Total
Approved	453 − 44 = 409	10 − 2 = 8	463 − 46 = 417
Denied	13 − 3 = 10	8 − 0 = 8	21 − 3 = 18
Total	466 − 47 = 419	18 − 2 = 16	484 − 49 = 435

[a] Panel A indicates the disposition of 488 sample loan applications that met the following criteria: (a) loan for the purpose of refinancing a residential property; (b) original loan application made between September 1991 and August 1993; (c) loan application made at one of the regional bank's branches; (d) applicant either white or black; and (e) application either approved or denied.

[b] Panel B reports an estimate of the regional bank's mortgage refinance applications and dispositions from September 1991 to August 1993 derived by taking 33% of the bank's HMDA data from 1991 (i.e., September–December), all of the bank's HMDA data for 1992, and 67% of the bank's HMDA data from 1993 (i.e., January–August), summing and rounding to the nearest integer ($N = 580$). The four entries in Panel B marked with a (*) closely approximate the four inner entries in Panel A, which suggests the data provided by the regional bank for this study (Panel A) are consistent with the HMDA data reported to the government for 1991–1993.

[c] Panel C reports the disposition of the 435 loan applications containing a back-end ratio [total monthly obligations/gross monthly income (in %)].

(453/470 = 96.4%). Assuming that unconditional analysis applies, a difference this large is unlikely to have arisen due to random variability if the regional bank were applying the same standards to black and white applicants. However, it is also unlikely that black and white applicants were equally qualified for the loans sought. Indeed, a criticism of statistical analyses applied to HMDA data is that there is no control for differences between blacks and whites concerning applicant qualifications other than income. Evidence suggests that black applicants are, on average, less qualified for loans than white applicants. For example, prior studies find that black applicants have less wealth, higher LTV ratios, and weaker credit histories than white applicants

(Berkovec et al., 1998; Carr and Megbolugbe, 1993; Day and Liebowitz, 1998; Horne, 1997; Kim and Squires, 1995; Munnell et al., 1996; Rosenblatt, 1997; Tootell, 1993). Not surprisingly, the debate in the literature concerning racial discrimination in residential loan underwriting largely concerns controls for other variables that might legitimately explain the disparity between black and white loan approval rates.

3. Variables

In response to the Plaintiff's intent to use the regional bank's HMDA data to document a statistically significant disparity between black and white mortgage refinance loan approval rates, the bank prepared loan summaries for the 488 cases presented in Table 1. Presumably, the goal was to show that if one looked at the relevant variables for individual loan files, one would find no evidence of racial bias. An expert witness hired by the regional bank identified the relevant variables that explained the mortgage refinance lending decisions at the regional bank for the period examined. Thus, I did not selectively decide what variables to analyze, but rather analyzed *all variables* the regional bank identified as important factors in explaining their loan disposition results.

Nevertheless, I must acknowledge and discuss some data limitations and my attempt to resolve them. The data set provided me by the bank did not contain any neighborhood or census tract information, even though these characteristics have often been found to be important in lending discrimination research. The data set also did not distinguish between different types of properties: condos, single-family, and multi-family units may have slightly different lending standards. Additionally, no information on private mortgage insurance (PMI) was provided in the data set, even though PMI is generally needed to sell loans in the secondary market if the LTV ratio exceeds 80%. I do know that the bank kept its adjustable-rate (ARM) loans in its portfolio, and sold its fixed-rate (FR) loans in the secondary market. However, I am unable to account for this treatment in the analysis since the bank did not provide a FR/ARM breakdown for the loans in the data set.

I understand the potential importance of these variables, and did collect detailed data from my review of the bank's mortgage refinance loan files to specifically address omitted-variable concerns. However, the bank obtained a protective order that precludes my discussing any results based on the loan file data I collected and analyzed. Thus, although my analysis of the detailed mortgage refinance loan file data I collected did not reveal evidence of correlated omitted variables, I can only report analysis of the variables the regional bank identified as relevant in explaining their loan disposition results.

It is worth noting that since the regional bank identified the relevant variables for the purpose of defending itself against lending discrimination charges, it was exculpatory for the bank to reveal any information that differed between black and white applicants in a way that would explain differences in its rejection rates. And given the magnitude of negative ramifications from potentially losing the lawsuit (i.e., compensatory and punitive damages, reputation losses, additional lawsuits, loss of individual and corporate business, employee turnover, etc.), failure to disclose all relevant variables under such circumstances is counter-intuitive. For these reasons this study is less subject to omitted or correlated variables criticisms, and this mortgage refinance data set potentially represents a "best-case" scenario for a situation void of omitted variables issues and bias. [16]

The regional bank identified the following variables as relevant for their mortgage loan disposition results:

Variable	Explanation
ID	Loan ID number
RACE	Race indicator (0 = white, 1 = black)
DEC	Decision Indicator (0 = approved, 1 = denied)
INC	Gross monthly income (in \$) for loan applicant(s)
BER	Back-end ratio (total monthly obligations/gross monthly income) (in %)
LTV	Loan-to-value ratio (loan amount/appraised value of property) (in %)
TERM	Term of loan (in months)
IC	Credit installment accounts
IP	Periodic installment accounts
IM	Minor installment account derogatories (# of < 60 days late pay over prior two years)
RC	Retail credit accounts
RMAJ	Major retail account derogatories (# of > 60 days late pay over prior two years)
RMIN	Minor retail account derogatories (# of < 60 days late pay over prior two years)
CINQ	Credit inquiries (# of credit bureau inquiries over prior two years)

Three variables (INC, BER, and LTV) measure applicants' financial status or position. Seven variables (IC, IP, IM, RC, RMAJ, RMIN, and CINQ) measure applicants' credit history. The variable TERM crudely approximates the incremental financial burden the refinance loan would place on applicants' current financial position. The regional bank also provided a loan ID variable, a RACE indicator variable (0 = white, 1 = black), and a DECision indicator variable (0 = approved, 1 = denied). All of the financial and credit history variables have previously been identified in lending discrimination literature as having some explanatory power in predicting loan approval/denial, although there is debate over the relative importance of each variable. [17]

[16] Since the regional bank had unlimited access to all of the mortgage refinance loan files, an omitted or correlated variables claim is akin to arguing that the regional bank's determination of relevant variables used in its underwriting process is invalid.

[17] A detailed explanation of the study variables, their relation to underwriting guidelines (Fannie Mae, 1996), and how they are used in the loan underwriting process is available from the author.

Some loan summaries had missing data. For example, the BER was missing from 10% (49 of 488) of the files. It is surprising that a loan decision would be made without calculating BER, but the regional bank was unable to find such a calculation in 10% of the mortgage refinance loan files. There does not appear to be any systematic pattern concerning RACE or DEC among the 49 missing cases (Panel C, Table 1). [18] The remaining analysis is restricted to the 439 mortgage refinance loan files with a BER, less four observations identified as outliers through analysis of the diagonal of the hat matrix and a DIFDEV analysis. [19] Thus, the final sample consists of 435 mortgage refinance loan files.

4. Descriptive statistics

Table 2 presents descriptive statistics and *t*-tests for differences by race on the 12 potential explanatory variables of the loan decision, DEC. Panels A, B, and C of Table 2 present results for the total sample of mortgage refinance loans, approved mortgage refinance loans, and denied mortgage refinance loans, respectively.

For the total sample (Panel A), black and white mortgage refinance applicants differ with respect to gross monthly income (INC), LTV ratio, BER, credit installment accounts (IC), and minor installment account derogatories (IM). On average, black applicants' gross monthly income is smaller than white applicants', while black applicants' LTV ratio, BER, and number of credit installment accounts is higher than white applicants'. The monthly income and LTV ratio results support prior findings that black applicants have less wealth and higher LTV ratios than white applicants (Berkovec et al., 1998; Carr and Megbolugbe, 1993; Day and Liebowitz, 1998; Horne, 1997; Kim and Squires, 1995; Munnell et al., 1996; Rosenblatt, 1997; Tootell, 1993). The minor installment account derogatories results indicate that black applicants have fewer minor installment account derogatories than white applicants. However, the other two derogatory credit variables in the data set, major retail account derogatories (RMAJ) and minor retail account derogatories (RMIN), suggest that black applicants may have a higher average level of derogatories than white applicants. [20]

For approved mortgage refinance loans (Panel B), black and white applicants differ with respect to gross monthly income (INC), LTV ratio, and minor installment

[18] An expert witness hired by the regional bank performed various computer checks, screened the data manually for unusual observations, and had the regional bank check unusual observations against the loan files. The expert witness reported an error rate of less than 1.5%. Data corrections were made based on expert witness testimony or documentation provided by the regional bank's employees.

[19] I thank a referee for suggesting this approach to outlier analysis. The empirical results and their interpretation are qualitatively consistent with the reported results when the four outliers are included in the analysis.

[20] RMAJ and RMIN do not differ significantly between the black and white applicants.

Table 2
Descriptive statistics and *t*-tests on the potential explanatory variables of the lending decision on 435 mortgage refinance loan applications containing a back-end ratio submitted to a Regional Bank from September 1991 to August 1993

Variable	Total sample		White applicants		Black applicants		Mean diff.	*t*-Stat.
	Mean	S.D.	Mean	S.D.	Mean	S.D.		
Panel A: Total sample								
DEC[a]	0.04	0.20	0.02	0.15	0.50	0.52	−0.48	−3.68***
RACE[b]	0.04	0.19	0.00	0.00	1.00	0.00	−1.00	N/A
INC[c]	6637	7631	6712	7726	4693	4215	2019	1.80*
LTV[d]	67.9	15.5	67.6	15.5	76.0	14.0	−8.4	−2.13**
BER[e]	29.9	10.1	29.6	9.9	38.4	12.2	−8.8	−3.46***
TERM[f]	245.0	90.6	245.2	90.8	240.0	87.8	5.2	0.22
IC[g]	1.43	1.66	1.40	1.64	2.19	2.10	−0.79	−1.86*
IP[h]	3.73	3.43	3.68	3.40	4.88	4.16	−1.20	−1.37
IM[i]	0.13	0.66	0.14	0.67	0.00	0.00	0.14	4.20***
RC[j]	4.27	3.55	4.31	3.57	3.25	3.02	1.06	1.17
RMAJ[k]	0.06	0.42	0.05	0.35	0.38	1.26	−0.33	−1.03
RMIN[l]	0.36	0.95	0.35	0.93	0.69	1.45	−0.34	−0.93
CINQ[m]	0.90	1.29	0.90	1.29	1.00	1.32	−0.10	−0.30
Panel B: Approved mortgage refinance loans								
RACE[b]	0.02	0.14	0.00	0.00	1.00	0.00	−1.00	N/A
INC[c]	6641	7716	6698	7778	3748	1443	2950	4.61***
LTV[d]	67.4	15.4	67.2	15.4	79.2	6.3	−12.0	−5.12***
BER[e]	29.6	9.8	29.6	9.9	31.3	8.9	−1.70	−0.50
TERM[f]	243.6	90.4	243.6	90.4	247.5	93.2	−3.90	−0.12
IC[g]	1.41	1.65	1.39	1.63	2.13	2.47	−0.74	−0.84
IP[h]	3.73	3.41	3.73	3.42	3.88	2.85	−0.15	−0.12
IM[i]	0.14	0.68	0.14	0.68	0.00	0.00	0.14	4.21***
RC[j]	4.33	3.58	4.33	3.59	3.88	3.60	0.45	0.36
RMAJ[k]	0.05	0.35	0.05	0.35	0.13	0.35	−0.08	−0.60
RMIN[l]	0.36	0.95	0.35	0.93	0.75	1.75	−0.40	−0.64
CINQ[m]	0.91	1.29	0.91	1.30	0.88	0.83	0.03	0.07
Panel C: Denied mortgage refinance loans								
RACE[b]	0.44	0.51	0.00	0.00	1.00	0.00	−1.00	N/A
INC[c]	6548	5492	7276	5408	5638	5826	1638	0.62
LTV[d]	78.7	14.7	83.4	8.4	72.7	18.9	10.7	1.49
BER[e]	36.4	14.1	29.2	12.0	45.4	11.4	−16.2	−2.91***
TERM[f]	281.3	92.2	320.0	79.4	231.4	87.8	88.6	2.11**
IC[g]	2.06	1.76	1.90	1.79	2.25	1.83	−0.35	−0.41
IP[h]	3.56	4.08	1.70	1.42	5.88	5.17	−4.18	−2.22*
IM[i]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	N/A
RC[j]	3.06	2.53	3.40	2.72	2.63	2.39	0.77	0.63
RMAJ[k]	0.33	1.19	0.10	0.32	0.63	1.77	−0.53	−0.83
RMIN[l]	0.45	1.01	0.00	0.00	0.63	1.19	−0.63	−1.49
CINQ[m]	0.78	1.26	0.50	0.71	1.13	1.73	−0.63	−0.96

[a] DEC – decision indicator (0 = approved, 1 = denied).
[b] RACE – race indicator (0 = white, 1 = black).
[c] INC – gross monthly income (in $) for loan applicant(s).
[d] LTV – loan-to-value ratio (loan amount/appraised value of property) (in %).
[e] BER – back-end ratio (total monthly obligations/gross monthly income) (in %).

Table 2 (*continued*)
[f] TERM – term of loan (in months).
[g] IC – credit installment accounts.
[h] IP – periodic installment accounts.
[i] IM – minor installment account derogatories (# of $<$ 60 days late pay over prior two years).
[j] RC – retail credit accounts.
[k] RMAJ – major retail account derogatories (# of $>$ 60 days late pay over prior two years).
[l] RMIN – minor retail account derogatories (# of $<$ 60 days late pay over prior two years).
[m] CINQ – credit inquiries (#of credit bureau inquiries over prior two years).
*Significant at the 0.10 level (two-tailed).
**Significant at the 0.05 level (two-tailed).
***Significant at the 0.01 level (two-tailed).

account derogatories (IM). The monthly income and LTV ratio results reveal that black applicants receiving loan approval have less wealth and higher LTV ratios than white applicants, while the minor installment account derogatories results indicate that black applicants have fewer minor installment account derogatories than white applicants. As noted above, the other two derogatory credit variables in the data set, major retail account derogatories (RMAJ) and minor retail account derogatories (RMIN), suggest that black applicants may have a higher average level of derogatories than white applicants.

For denied mortgage refinance loans (Panel C), black and white applicants differ with respect to BER, TERM and periodic installment accounts (IP). Denied black mortgage refinance applicants have a significantly higher BER and have significantly more periodic installment accounts than denied white mortgage refinance applicants. Curiously, while loan term did not differ for approved mortgage refinance applicants, denied white mortgage refinance applicants applied for a significantly longer loan term than denied black mortgage refinance applicants. One explanation for this difference is coaching (e.g., encouraging white applicants to apply for a longer-term loan or to increase the term of the loan applied for to improve approval chances). Goldstein and Squires (1995), Hunter and Walker (1996), Yinger (1996), and Wachter (1997) provide additional discussion of coaching.

A similar analysis (not reported) reveals that approved white applicants differ from denied white applicants with respect to LTV ratio (LTV), TERM, IP, IM, and RMIN. Approved and denied black applicants differ only on the BER.

5. Research method and empirical results

5.1. Simultaneous equations models

Rachlis and Yezer (1993), Yezer et al. (1994), and Phillips and Yezer (1996) suggest that using single-equation models to model the lending decision provide flawed tests for discrimination. These authors argue that in a world of imperfect information, single-equation models of the lending decision suffer from simultaneous equations bias problems. The simultaneous equations bias arises since mortgage terms (i.e., LTV ratio, TERM, and BER) are not exogenous to the lending decision, resulting in biased and inconsistent parameter estimates in single-equation models. They argue that multiple-equation econometric models capable of dealing with simultaneous equations are needed for unbiased tests for discrimination.

LaCour-Little (1999) notes that a simultaneity argument assumes interaction between lenders and applicants with respect to loan terms throughout the application process. LaCour-Little also notes that this assumption generally does not hold:

> *While opportunity for such negotiation between borrower and lender clearly exists, such negotiation probably represents a very small fraction of the transactions in the residential home mortgage market. Rather than negotiate with a specific lender, home buyers and borrowers, often aided by real estate brokers who have an incentive to see financing occur so that the transaction can close and their commission be paid, choose loan terms that they believe likely to be accepted by the lender. The lender makes a decision based on requested loan amount and terms and negotiation terminates. Borrowers are free to contact other lenders if rejected by the first lender* (pp. 27–28, emphasis added). [21]

The reality of mortgage lending is that the industry strives for standardization, not customization, as it is too costly to negotiate with individual borrowers (LaCour-Little, 1999). [22] Even if one were to accept the assumption of continued interaction between borrower and lender, it may not hold for minority applicants since they frequently are not advised or "coached" with respect to changes needed to get their application approved as the application process unfolds. As previously noted, loan term did not differ for approved mortgage refinance applicants, while denied white mortgage refinance applicants applied for a significantly longer loan term than denied black mortgage refinance applicants (see Table 2). This result is consistent with lender coaching of white applicants (i.e., encouraging white applicants to apply for a longer-term loan or to increase the term of the loan applied for to improve approval chances). [23]

To assess whether simultaneous equations bias produces biased and inconsistent parameter estimates on this study's data, I test two simultaneous equations models of the bank's lending decision. The simultaneous equations models' results are then compared to results from two single-equation models. Both simultaneous equations

[21] LaCour-Little (1999) suggests the relationship between mortgage refinance applicants and lenders is recursive, not simultaneous (i.e., applicants make LTV and loan term adjustments prior to submitting the mortgage refinance application). Rosenblatt (1997) espouses a similar view by suggesting that lenders underwrite loan applications twice: at the prescreening stage (i.e., preunderwriting), and at the formal underwriting stage. He states that "Under this framework, endogeneity is minimal, because the formal approve/deny decision has little to do with assessing underwriting risk, default risk, or choice of loan terms" (p. 110).

[22] A noted exception is jumbo market loans since secondary market guidelines are not relevant for these loans (LaCour-Little, 1999).

[23] See Goldstein and Squires (1995), Hunter and Walker (1996), Yinger (1996), and Wachter (1997) for additional discussion of coaching.

models tested consist of two-equations where one endogenous variable is continuous and the other endogenous variable is discrete (i.e., loan approved or denied). The Heckman–Maddala method of estimation described in Heckman (1977) and Maddala (1983) is used. [24]

Rachlis and Yezer (1993) and Yezer et al. (1994) view the LTV ratio, monthly payments-to-income (BER), and TERM as endogenous variables. [25] I chose LTV as the first continuous variable to be tested for endogeneity since LaCour-Little (1999) and Quercia and Stegman (1993) note that it is the most important choice of loan term items borrowers select. Thus, the first simultaneous equations model tested has LTV as the continuous endogenous variable and DEC as the discrete endogenous variable.

Panel A of Table 3 presents the second stage regression analysis of LTV and ordinary least square (OLS) regression analysis of LTV for comparison purposes. INC, BER, TERM, RACE, and PREDDEC are used as predictor variables of LTV in the simultaneous equations model. The R^2 for the second stage regression analysis of LTV is 8.19%, while the OLS R^2 is 8.08%. Thus, the second stage regression analysis of LTV has a higher R^2 than the comparative OLS regression analysis of LTV even though no variables are significant in the second stage model and three variables are significant in the OLS model (INC, TERM, and RACE).

Panel B of Table 3 presents the second stage probit analysis of DEC and OLS regression analysis of DEC for comparison purposes. BER, RMAJ, RMIN, RACE, and PREDLTV are used as predictor variables of DEC in the simultaneous equations model. The pseudo-R^2 for the second stage probit analysis of DEC is 25.60%, while the OLS R^2 is 22.39%. Thus, the second stage probit analysis of DEC (LTV endogenous) has a higher R^2 than the comparative OLS regression analysis of DEC, and both models have two significant variables (LTV and RACE) and one marginally significant variable (RMAJ).

Rachlis and Yezer (1993) and Yezer et al. (1994) also view monthly payments-to-income (BER) and TERM as endogenous variables. These variables are related since borrowers can alter the BER by changing the TERM requested. I chose BER as the second continuous variable to be tested for endogeneity since underwriters consider a satisfactory BER critical for loan approval, and most loan officers (or real estate agents or brokers) calculate a "preliminary" BER when advising a borrower what TERM to apply for. Thus, the second simultaneous equations model tested has BER as the continuous endogenous variable, and DEC as the discrete endogenous variable.

Panel A of Table 4 presents the second stage regression analysis of BER and OLS regression analysis of BER for comparison purposes. INC, LTV, TERM, RACE, and PREDDEC are used as predictor variables of BER in the simultaneous

[24] The Heckman–Maddala method of estimation is consistent with Maddala and Trost (1982). Special thanks are extended to Kenneth Gaver for use of the simultaneous equations programs utilized in Copley et al. (1995), and programming assistance converting them for use on this study's data.

[25] They also view down payment and use of a cosigner as endogenous variables. Down payment and use of a cosigner are not represented in this study's data set.

Table 3
Simultaneous equations models and parameter estimates for 435 mortgage refinance loan applications submitted to a Regional Bank from September 1991 to August 1993

Variable	Parameter estimate	Z-stat	P-value
Panel A: Second stage regression analysis of LTV (LTV is endogenous)			
Intercept	61.1590	1.7748	0.0759
INC	−0.0003	−1.0033	0.3157
BER	−0.0057	−0.0247	0.9803
TERM	0.0355	0.8180	0.4134
RACE	15.0767	0.7054	0.4806
PREDDEC	−14.4614	−1.4792	0.1391
$R^2 = 8.19\%$			
		T-stat	P-value
Ordinary least squares (for comparison purposes)			
Intercept	61.9208	19.6290	0.0001
INC	−0.0003	−3.1150	0.0020
BER	−0.0154	−0.2050	0.8373
TERM	0.0327	4.0060	0.0001
RACE	8.6218	2.1790	0.0299
$R^2 = 8.08\%$			
		Z-stat	P-value
Panel B: Second stage probit analysis of DEC (LTV is endogenous)			
Intercept	−6.3773	−3.2713	0.0011
BER	0.0077	0.5531	0.5802
RMAJ	0.3903	1.7321	0.0832
RMIN	−0.1109	−0.6155	0.5382
RACE	1.3591	2.8481	0.0044
PREDLTV	0.0601	2.0954	0.0361
Pseudo-$R^2 = 25.60\%$		$-2 * \text{log-likelihood} = 101.60$	
		T-stat	P-value
Ordinary least squares (for comparison purposes)			
Intercept	−1.0973	−24.3970	0.0001
BER	0.0012	1.4350	0.1521
RMAJ	0.0378	1.8530	0.0646
RMIN	−0.0103	−1.1450	0.2528
RACE	0.4459	9.6050	0.0001
LTV	0.0013	2.3130	0.0212
$R^2 = 22.39\%$			

DEC (PREDDEC) – decision (i.e., loan approved or denied), INC – gross monthly income, BER – back-end ratio, TERM – term of loan, RACE – race (black or white), RMAJ – # of major retail account derogatories over prior two years, RMIN – # of minor retail account derogatories over prior two years, PREDLTV – loan-to-value ratio.
In Panel A INC, BER, TERM, RACE, and PREDDEC are used as predictor variables of LTV. In Panel B BER, RMAJ, RMIN, RACE, and PREDLTV or LTV are used as predictor variables of DEC.
P-values are two-tailed.

equations model. The R^2 for the second stage regression analysis of BER is 8.28%, while the OLS R^2 is 8.07%. Thus, the second stage regression analysis of BER has a higher R^2 than the comparative OLS regression analysis of BER even though no

Table 4
Simultaneous equations models and parameter estimates for 435 mortgage refinance loan applications submitted to a Regional Bank from September 1991 to August 1993

Variable	Parameter estimate	*Z*-stat	*P*-value
Panel A: Second stage regression analysis of BER (BER is endogenous)			
Intercept	29.8997	0.7991	0.4242
INC	−0.0003	−1.0801	0.2801
LTV	−0.0183	−0.0710	0.9434
TERM	0.0101	0.3707	0.7109
RACE	2.4751	0.1788	0.8581
PREDDEC	10.3100	1.6434	0.1003
$R^2 = 8.28\%$			
		T-stat	*P*-value
Ordinary least squares (for comparison purposes)			
Intercept	28.8460	11.7710	0.0001
INC	−0.0003	−4.3270	0.0001
LTV	−0.0065	−0.2050	0.8373
TERM	0.0117	2.1920	0.0289
RACE	7.0661	2.7670	0.0059
$R^2 = 8.07\%$			
		Z-stat	*P*-value
Panel B: Second stage probit analysis of DEC (BER is endogenous)			
Intercept	−5.3783	−3.1519	0.0016
LTV	0.0366	2.5865	0.0097
RMAJ	0.3613	1.7415	0.0816
RMIN	−0.1358	−0.7291	0.4660
RACE	1.6990	3.0457	0.0023
PREDBER	0.0213	0.3792	0.7045
Pseudo-$R^2 = 30.52\%$		$-2 * \text{log-likelihood} = 94.89$	
		T-stat	*P*-value
Ordinary least squares (for comparison purposes)			
Intercept	−1.0973	−24.3970	0.0001
LTV	0.0013	2.3130	0.0212
RMAJ	0.0378	1.8530	0.0646
RMIN	−0.0103	−1.1450	0.2528
RACE	0.4459	9.6050	0.0001
BER	0.0012	1.4350	0.1521
$R^2 = 22.39\%$			

DEC (PREDDEC) – decision (i.e., loan approved or denied), INC – gross monthly income, LTV – loan-to-value ratio, TERM – term of loan, RACE – race (black or white), RMAJ – # of major retail account derogatories over prior two years, RMIN – # of minor retail account derogatories over prior two years, and PREDBER – back-end ratio.

In Panel A INC, LTV, TERM, RACE, and PREDDEC are used as predictor variables of BER. In Panel B LTV, RMAJ, RMIN, RACE, and PREDBER or BER are used as predictor variables of DEC.

P-values are two-tailed.

variables are significant in the second stage model and three variables are significant in the OLS model (INC, TERM, and RACE).

Panel B of Table 4 presents the second stage probit analysis of DEC and OLS regression analysis of DEC for comparison purposes. LTV, RMAJ, RMIN, RACE, and PREDBER are used as predictor variables of DEC in the simultaneous equations model. The pseudo-R^2 for the second stage probit analysis of DEC is 30.52%, while the OLS R^2 is 22.39%. Thus, the second stage probit analysis of DEC (BER endogenous) has a higher R^2 than the comparative OLS regression analysis of DEC, and both models have two significant variables (LTV and RACE) and one marginally significant variable (RMAJ). [26]

Both simultaneous equations model's results are consistent (i.e., LTV (or PREDLTV) and RACE significant, RMAJ marginally significant), with each simultaneous equations model indicating that RACE appears to be the most important variable in explaining loan disposition. The lower $-2 *$ log-likelihood ratio for the model with BER as the endogenous variable (94.89 versus 101.60) indicates that this model provides a better fit of the regional bank's loan file data.

5.2. Probit regression models

Next, probit regression was run on the variables from the simultaneous equations models (i.e., BER, LTV, RMAJ, RMIN, and RACE). The results are presented in Table 5. For comparison purposes, the first model includes only BER, LTV, RMAJ, and RMIN, while the second model adds RACE. The lower $-2 *$ log-likelihood ratio for the model that includes RACE as an explanatory variable (103.34 versus 126.82) indicates that this model provides a significantly better fit of the regional bank's loan file data. BER, LTV, and RMAJ are significant in the first model, while LTV and RACE are significant in the second model and RMAJ is not significant. The second probit model's results are generally consistent with the simultaneous equations models' results (LTV and BER endogenous) in that LTV and RACE are significant, while RMAJ is marginally significant in the simultaneous equations models and not significant in the probit model. For both the simultaneous equations models (LTV and BER endogenous) and the probit model, RACE appears to be the most significant variable in explaining loan disposition at this regional bank.

5.3. Comparison of results from simultaneous equation and probit regression models

Yezer et al. (1994) use Monte Carlo experiments to argue that the race coefficient in single-equation rejection models is biased upward, while the LTV ratio coefficient is biased downward. They suggest that "a positive and significant coefficient for a minority dummy variable in a single-equation rejection model may simply reflect the upward bias in estimates of β_{M} and cannot serve as a test for discrimination based on differential treatment. . ." (p. 206). They further state that another sign of single-equation rejection model bias is the failure to find large and significant ef-

[26] LTV and RACE remain significant if RACE is removed as a predictor variable for the continuous endogenous variables (i.e., LTV and BER). The results are available from the author upon request.

fects of loan terms. This study assesses both claims by using simultaneous equations and probit regression to model a regional bank's lending decisions.

Yezer et al.'s (1994) first claim is that using single-equation rejection models biases the RACE coefficient upward, and the LTV coefficient downward. The following $-2 * \text{log-likelihood}$ ratios and parameter estimates from Tables 3–5 shed light on the validity of this claim (P-values in parentheses):

	RACE	LTV	BER	RMAJ
SE model (LTV endogenous)	1.3591	0.0601	0.0077	0.3903
[$-2 * \text{log-likelihood} = 101.60$]	(0.0044)	(0.0361)	(0.5802)	(0.0832)
SE model (BER endogenous)	1.6990	0.0366	0.0213	0.3613
[$-2 * \text{log-likelihood} = 94.89$]	(0.0023)	(0.0097)	(0.7045)	(0.0816)
Probit regression model	1.8412	0.0350	0.0108	0.3243
[$-2 * \text{log-likelihood} = 103.34$]	(0.0001)	(0.0062)	(0.4296)	(0.1416)

The $-2 * \text{log-likelihood}$ ratios for the simultaneous equations models with LTV endogenous and BER endogenous indicate that the model with BER endogenous provides a better fit of the data. Importantly, the $-2 * \text{log-likelihood}$ ratios also indicate that both simultaneous equations models provide a better data fit than the probit regression model.

Table 5
Probit regression models and parameter estimates for 435 mortgage refinance loan applications containing a back-end ratio which were submitted to a Regional Bank from September 1991 to August 1993

Variable	Parameter estimate	Z-stat	P-value
Probit regression on BER, LTV, RMAJ, RMIN, and RACE			
Intercept	−5.1896	−4.9260	0.0001
BER	0.0289	2.1706	0.0300
LTV	0.0337	2.8581	0.0043
RMAJ	0.4276	2.1649	0.0304
RMIN	−0.0238	−0.1576	0.8748
$-2 * \text{log-likelihood} = 126.82$			
Intercept	−4.9039	−4.4914	0.0001
BER	0.0108	0.7886	0.4303
LTV	0.0350	2.7365	0.0062
RMAJ	0.3243	1.4711	0.1413
RMIN	−0.1510	−0.8171	0.4139
RACE	1.8412	4.8505	0.0001
$-2 * \text{log-likelihood} = 103.34$			

DEC – decision (i.e., loan approved or denied), BER – back-end ratio, LTV – loan-to-value ratio, RMAJ – # of major retail account derogatories over prior two years, RMIN – # of minor retail account derogatories over prior two years, and RACE – race (black or white).
P-values are two-tailed.

As evident from column 1, the RACE coefficient appears to be biased upward in the probit regression model relative to the simultaneous equations models since the probit regression coefficient on RACE (1.8412) is greater than both simultaneous equations coefficients on RACE (1.3591 and 1.6990). This result is consistent with Yezer et al. (1994). However, the RACE coefficient bias appears to be insignificant, so the column 1 RACE results provide minimal support for their contention that a positive and significant coefficient for a minority dummy variable in a single-equation rejection model cannot serve as a test for discrimination since it may simply reflect the upward bias in estimates of β_M. The upward bias makes the RACE coefficient appear more significant in the single-equation model than indicated by the simultaneous equations models. The column 1 results thus suggest that simultaneous equations models are preferable to single-equation models, and can be used to confirm positive and significant RACE coefficients in single-equation rejection models if concern over coefficient bias exists. [27]

With respect to the LTV coefficient (column 2), it appears to be biased downward as a result of using a single-equation rejection model since the probit regression coefficient on LTV (0.0350) is less than both simultaneous equations coefficients on LTV (0.0601 and 0.0366). This result is consistent with Yezer et al. (1994). However, like the RACE coefficient bias, the LTV bias also appears to be insignificant. Yezer et al.'s (1994) second claim is that single-equation rejection models are biased because they fail to find large and significant effects of loan terms. As evident from columns 2 and 4, LTV is significant in both the probit regression and simultaneous equations models, while RMAJ is marginally significant in the simultaneous equations models and not significant in the probit model. Thus, this study's results are mixed with respect to the claim that single-equation rejection models are biased because they fail to find large and significant effects of loan terms. Additionally, the coefficient on RMAJ (column 4) indicates that it may be understated in the probit regression model relative to the simultaneous equations models, but the downward bias in the coefficient appears to be offset by downward bias in the level of significance.

6. Limitations

Given this study's limited sample size, the results and conclusions must be viewed as tentative and preliminary. Additional research in this area is needed before we can reach a general conclusion that single-equation models are (insignificantly) biased for this data, in particular, and across lenders, in general. Several other limitations must also be noted for this study. First, given the limited representation of minority applicants, this study's results may be sample specific. More bank-specific studies using data with a much larger percentage of minority applicants are needed to assess

[27] Rachlis and Yezer (1993) conclude that simultaneous equations models are needed for unbiased tests for discrimination.

this possibility. Hopefully, the results of this study will encourage banks to give researchers access to their loan file data to investigate the robustness of this study's results.

Second, the number of denied mortgage refinance loans in the sample is relatively small (18/439 or 4.1%), giving rise to the possibility that a few applicants with idiosyncratic credit profiles may be unduly influencing the statistical results. To assess this possibility I conducted DIFDEV and DIFCHISQ diagnostic tests, and found no evidence supporting undue influence for any denied mortgage refinance applicant. Although reassuring, the diagnostic tests do not completely eliminate the possibility of undue influence. Third, logit and probit models are less reliable when the number of "events" (e.g., mortgage refinance loan denials in this study) is less than 10%. Given that the percentage of denied mortgage refinance loans is 4.1% in this study, additional analysis is needed of loan file data that includes a larger percentage of denials. Lastly, additional simultaneous equations modeling is needed on both original mortgage loan data and mortgage refinance data to further assess the suitability of using mortgage refinance data to assess lending discrimination.

7. Summary and conclusions

When HMDA-based studies showing racial disparities in approval and denial rates after controlling for income were first published (e.g., Dedman, 1988), "the lending industry's response was that the disparities could be explained by missing variables, most particularly loan-to-value and obligation ratios and applicants' credit histories" (Browne and Tootell, 1995, p. 59). This study controls for these variables in mortgage refinance data files compiled by a regional bank. Unlike other lending discrimination studies, the regional bank determined the relevant variables in their loan files that explained its mortgage lending decisions, and I analyzed *all* of these variables.

Results from comparing simultaneous equations and probit regression models of the regional bank's lending decisions show that the race coefficient in single-equation models is biased upward, while the LTV ratio coefficient is biased downward, although both biases are insignificant. Overall, the results suggest that simultaneous equations models are preferable to single-equation models in tests for discrimination, and can be used to determine the extent of race coefficient and LTV ratio coefficient bias in single-equation models.

LaCour-Little's (1999) review of the mortgage lending discrimination literature identifies several recommendations for future research. This study is consistent with each recommendation. It uses simultaneous equations models of the mortgage lending process to explicitly consider potential endogeneity of loan term variables. It limits the use of variables in single-equation rejection probability models to significant variables identified by the simultaneous equations models to minimize simultaneity and omitted variable bias. Lastly, it analyzes mortgage refinance loans from a single regional lender, thus avoiding concerns resulting from aggregating data from "lenders with different products, clientele, pricing, and underwriting standards" (p. 41).

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