

“The Color of Money” Expanded: Geographically Contingent Mortgage Lending in Atlanta

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Abstract

“The Color of Money,” a series of articles published in the *Atlanta Journal-Constitution* in May 1988 (Dedman 1988), documented persistent barriers in access to mortgage credit in Atlanta’s African-American neighborhoods. Wyly and Holloway (1999) updated the original study with recent data and found that during the intervening decade traditional lenders still exhibited many of the same patterns that prompted concern in the 1980s. We extend the analysis here (1) by using applicant-level Home Mortgage Disclosure Act data not available for the original study and (2) by proposing and empirically examining a hypothesis about the geographically contingent influence of applicant race on loan application denial probabilities.

Probability models that explicitly incorporate cross-level interactions between neighborhood racial and income characteristics and an applicant-level racial identifier support the hypothesized effects. Results are at least partially consistent with traditional redlining arguments, arguments highlighting unintended effects of spatially targeted policy efforts to expand minority and low-income homeownership, and arguments that posit exclusionary discrimination by lenders in predominantly white suburban communities.

Keywords: Geographic contingency; Mortgage lending discrimination; Redlining

Introduction

“The Color of Money,” a four-part series of articles published in the *Atlanta Journal-Constitution* in May 1988 (Dedman 1988), documented persistent barriers to mortgage credit in Atlanta’s African-American neighborhoods. The series generated an immediate outcry in Atlanta, won the Pulitzer Prize for investigative reporting, and contributed to major efforts nationwide to limit and ameliorate lending discrimination.¹ Mortgage-lending markets under-

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¹ Federal agencies tightened regulation of the lending industry, community groups successfully challenged lending industry practices, and substantial sums of money were made available to minority and low- and moderate-income (LMI) neighborhoods.

went a series of broader changes² that many hoped would reduce neighborhood racial lending disparities. In a recent replication of “The Color of Money” in Atlanta, based on data from the early- to mid-1990s (Wily and Holloway 1999), we found small improvements in neighborhood racial lending disparities.³ Even so, the segment of the lending market of greatest theoretical and policy concern—the lending of conventional products by depository institutions—still exhibited patterns in the early- and mid-1990s that remained very similar to those observed in the 1980s (see also Torres, Bullard, and Johnson 2000). In this article we attempt to make sense of these durable inequalities by evaluating a hypothesis of geographically contingent lending with applicant-level loan denial probability models.

Most early studies of restricted credit flows to minority and disadvantaged neighborhoods (redlining), including the original “Color of Money,” used geographically aggregated data, largely because these were the only data available until the early 1990s (e.g., Listokin and Casey 1980; Shlay 1988). The replication (Wily and Holloway 1999) also used aggregated data to remain methodologically consistent with the original study (see Fitterman 1988 for details). These studies provide consistent evidence of geographic lending differences based on race: African-American neighborhoods receive fewer loans and less total mortgage capital than do white neighborhoods. Whether racial discrimination generated the racially patterned geographic disparities in mortgage lending, however, remains contested.⁴ The few recent studies that investigate geographical effects using applicant-level data now available through the expanded reporting requirements of the Home Mortgage Disclosure Act (HMDA) are either inconsistent or indicative of no redlining (Ross and Yinger 1999b; Schill and Wachter 1993; Tootell 1996).⁵

Most recent studies have not focused on geographic disparities in lending. Instead, most of this research, fueled by the availability of applicant-level HMDA data, focuses on the effect of racial and ethnic group membership on loan denial probabilities (see Turner and Skidmore 1999a; see especially Ross and Yinger 1999a and 1999b for recent reviews). These studies consistently show systematic racial differences in lending outcomes; for example, black mortgage applicants are more likely to be rejected, even after controlling for income, requested loan amount, and other relevant applicant characteristics. The issue of discrimination against applicants on the basis of group membership remains controversial (Ladd 1998; Turner and Skidmore 1999a), in part because the HMDA data do not contain all the information that lenders legitimately consider in the underwriting process. Even so, the most substantial evidence comes from the well-known study sponsored by the Boston Federal Reserve Bank (Munnell et al. 1992) that matched HMDA information with a full set of applicant data provided by cooperating lending institutions. This study and several replications that addressed

² The secondary mortgage market and government-sponsored enterprises (GSEs—Fannie Mae and Freddie Mac) now play a more pronounced role. In addition, interest rates dropped considerably through the 1990s, and a wide variety of new mortgage instruments—many designed to increase the supply of mortgage finance to LMI and minority borrowers—were introduced and marketed.

³ Independent and nondepository lending institutions not included in the original study exhibit lending patterns much more favorable to minority neighborhoods, especially when dealing with government-backed products.

⁴ Methodological and theoretical problems faced by redlining studies using aggregated data are well known and do not need to be repeated here.

⁵ Ross and Yinger (1999b) report an unpublished paper (Ross and Tootell 1998) that finds evidence of redlining in Boston, but only when minority applicants do not also apply for private mortgage insurance.

early criticisms (Carr and Megbolugbe 1993; Munnell et. al. 1996; Ross and Yinger 1999a) found a persistent race effect, even after controlling for a full set of underwriting criteria and addressing measurement error and model specification criticisms.

The Urban Institute’s extensive review of empirical research on mortgage lending discrimination (Turner and Skidmore 1999a) concludes that “a substantial body of objective and credible statistical evidence strongly indicates that discrimination persists” (p. 2). Even so, the editors highlight significant research gaps that allow the debate to rage on. We find especially relevant that as they call for continued nationwide statistical analysis of mortgage denials,⁶ Turner and Skidmore emphasize a scale distinction of conceptual and empirical importance:

[A]nalysis of discrimination in the loan approval process should attempt to distinguish discrimination based on the borrower’s race or ethnicity from discrimination based on the racial or ethnic composition of the neighborhood in which a property is located. (Turner and Skidmore 1999b, 20)

Turner and Skidmore highlight the importance of that distinction for policy, even while expressing doubt about the ability of empirical analysis to reveal it. We contend that the significance of this dichotomy is rooted in the history of housing market segregation and public policy. Until recently the two scales of discrimination (race- and place-based) were not distinguishable because most minority home buyers applying for mortgage financing did so primarily for properties located in traditional minority or racially transitional neighborhoods. Thus, redlining served the dual purpose of restricting the availability of mortgage credit to minorities (anywhere), and to minority neighborhoods (no matter who applied for loans there). More recently federal fair housing laws and civil rights efforts, combined with increased minority income (at least for some—see Wilson 1996), have resulted in greater proportions of minority home buyers seeking mortgage financing on properties located outside traditional minority neighborhoods. Thus, redlining and applicant-level racial discrimination are no longer necessarily coincident.

The research presented in this article moves beyond Turner and Skidmore’s call in two important ways. First and most important, we argue that drawing a simple distinction between discrimination against individuals and discrimination against neighborhoods does not go far enough. Indeed, we contend that models used to evaluate discrimination may be seriously misspecified because they do not incorporate the interaction of applicants’ racial and ethnic identity with the racial and ethnic composition of neighborhoods. We argue that these two targets of discrimination, although no longer necessarily coincident, are still related. The few studies that explicitly address a possible interaction (Holloway 1998; Reibel 2000; Schill and Wachter 1994) found that the experiences of minority and low- and moderate-income (LMI) applicants appear to vary considerably across neighborhoods.

Second, Atlanta presents an ideal case study that overcomes one of the empirical difficulties highlighted by Turner and Skidmore. In most metropolitan areas, neighborhood distributions of minorities and income are so similar that empirical analysis of the sort we suggest here becomes very difficult. Atlanta has a sizable black middle class that seeks to buy properties in predominantly white and higher-income neighborhoods in numbers large enough

⁶ We strongly support their call for an expanded multilocational replication of the Boston Fed study.

to sustain detailed empirical analysis. We hope to enlighten some of the bitter debate and confusion over the existence, magnitude, and nature of contemporary lending discrimination by considering explicitly the geographically contingent nature of the race–lending relationship in Atlanta.

We develop a hypothesis of geographically contingent lending that anticipates both geographic variability in the impact of racial identity on loan denial probabilities, and geographic variability in the outcomes of the loan approval process. We argue that mortgage finance markets are functionally and by nature geographically contingent. Both the processes governing these markets and their outcomes vary across geographic contexts. If we are correct, the mixed evidence of the current literature will persist as long as the social practice of discrimination is treated as universal, uniform, and consistent in its empirical expression. Our empirical analysis using 1996 Atlanta HMDA data shows that the applicant-level race–denial relationship varies considerably across neighborhood contexts. Black applicants exhibit the highest conditional denial probabilities in predominantly white, high-income neighborhoods on Atlanta’s north side. White applicants exhibit their highest conditional denial probabilities in predominantly black, low-income neighborhoods in Atlanta’s south and southwest sections. Before detailing our hypotheses and analysis, we briefly review some lending concepts important to our arguments.

Discrimination in Mortgage Lending

Generally, academics and policy makers recognize two types of discrimination in mortgage lending (Interagency Regulatory Task Force 1994; Turner and Skidmore 1999a). Disparate treatment occurs when individuals are evaluated differently on the basis of their group status,⁷ involving, for example, the use of different thresholds when applicant creditworthiness is measured (see Longhofer 1996; Longhofer and Peters 1998a, 1998b). Disparate impacts are recognized when practices not directly related to business survival and supposedly neutral relative to group membership adversely and disproportionately affect one group over another. Distinguishing between the two forms of discrimination is notoriously difficult, even with the most complete data sets available (e.g., see the conclusions to the Ross and Yinger 1999a reanalysis of the Boston Fed data). We contend that both forms of discrimination are geographically contingent, that is, that the treatment of minority applicants depends on where the property is located, and that the impacts of lending institution actions are geographically variable in ways that affect applicants of different racial and ethnic groups differently.

An important part of this debate concerns the motivations behind discrimination. A fundamental distinction exists between discrimination based on noneconomic motives and discrimination based on economic motives.⁸ Noneconomic, or preference-based, discrimination requires that lenders forfeit some income or profit to satisfy a prejudicial taste (Becker 1971; Ladd 1998). Many industry defenders claim that the lending industry is too highly regulated

⁷ Protected group status is defined based on race or color, national origin, religion, sex, marital or family status, age, handicap, receipt of public assistance, and geographic location.

⁸ Longhofer and Peters (1998a, 1998b) prefer to use the labels “preference-based” and “belief-based” discrimination, arguing that even when lenders engage in preference-based discrimination, they are still behaving with economic rationality, just under (economically irrational) constraints.

and competitive for noneconomic discrimination to be prevalent.⁹ Critics counter that more subtle forms of preference-based discrimination (both disparate treatment and disparate impacts) have replaced overt discrimination.

Those making the argument for economically motivated discrimination, also referred to as statistical or belief-based, contend that discriminatory behavior can be economically rational (Arrow 1972). Straightforward arguments note that lenders must institutionally assess the risk of adverse future borrower behavior—that is, will the borrower default? Lending institutions and their officers understandably want to minimize the risk of making an inaccurate assessment, so they use every piece of information available to them. Discrimination occurs if lenders attribute aggregate characteristics of protected groups, or geographic locations, to individual applicants, even if that attribution reduces economic risk for the lender.

Cultural affinity is a more specific statistical discrimination argument claiming that loan officers can obtain and evaluate compensating information with less cost when they share a cultural affinity with a group of applicants.¹⁰ The most common version (e.g., Hunter and Walker 1995) suggests minority disadvantage when applicants do not automatically qualify for loans (i.e., do not meet the government-sponsored enterprise [GSE] requirements for loans to be sold on the secondary mortgage market or satisfy proprietary credit scoring thresholds). Because most loan officers are white, nonconforming white applicants are treated more flexibly than are nonconforming minority applicants. In other words, white applicants are encouraged to explain or compensate for credit blemishes, employment instability, and/or debt burdens, allowing them the chance to provide information that would justify a positive override of the initial rejection. Moreover, the same type of compensating information is either not gathered from minority applicants or not evaluated as favorably, presumably because lenders have had greater experience with white borrowers and are able to more accurately use this additional information to predict future borrower behavior. The bottom line is that lenders resort to group characteristics and hold minority applicants more rigidly to standard criteria because of the uncertainty involved with evaluating nonstandard minority applicant information.¹¹

We argue that both motivations for discrimination are geographically contingent. Preference-based discrimination is more pronounced in some neighborhoods than in others because of loan officers’ perceptions of the suitability of the “match” between applicants’ racial or ethnic identity and the nature of the neighborhood they seek to move in to. In addition, there are economic motivations for geographically differentiated treatment of minority applicants.

Scholars are increasingly aware that although empirical research has focused on loan approval, discrimination based on group membership or neighborhood location can occur in many of the several stages of the lending process, ranging from product advertising and outreach to

⁹ Some scholars working from this position rest their claim that discrimination does not exist on the observation that minorities exhibit higher default rates than do whites (e.g., Berkovec et al. 1994). Such arguments have received considerable criticism (Galster 1993, 1996; Ross 1996; Yinger 1996; see especially Ross and Yinger 1999c for a thorough treatment of the subject).

¹⁰ See Longhofer (1996) and Longhofer and Peters (1998a, 1998b) for detailed and cautious theoretical and empirical treatments of the cultural affinity arguments.

¹¹ Turner and Skidmore (1999a) note that the behavior we describe here can also be a subtle form of preference-based discrimination, that is, loan officers simply being more helpful and flexible with co-cultural applicants.

the administration of the loan.¹² Moreover, discrimination in mortgage lending (wherever it occurs in the process) is only one of the many forms of discrimination that occur in housing markets (Galster 1992; Yinger 1995). Indeed, discriminatory effects in one market are transmitted to other markets, and all forms of discrimination are subject to long-term feedback effects.¹³ These mutually reinforcing processes characterize both differential treatment and disparate impact discrimination. Our theoretical arguments and empirical analysis are focused on underwriting decisions in the primary mortgage market, thus not allowing us to directly consider debates about discrimination at other stages in the mortgage lending process or, more broadly, in other aspects of housing markets. Nonetheless, our work should not be interpreted as a suggestion that discrimination is any less important in those arenas. Indeed, we suspect that broader treatments of discrimination in housing will also benefit from our framework of geographic contingency.

Geographically Contingent Lending

The effects of neighborhood context are sufficiently important that we have developed a hypothesis of geographic contingency in mortgage discrimination. The focus of the hypothesis is on the race-denial relationship: Does it vary across neighborhood contexts and, if so, why? Almost none of the existing research considers that possibility, either conceptually or empirically. Our discussion in this section of the article is designed to provide a conceptual foundation—that is, why should we look for evidence of contingency in the race-denial relationship?

Our use of the term contingency (the Latin *contingere*, “to touch”) is explicit and deliberate, and the term should not be interpreted simply as a residual, or leftover, variability remaining after the explanation provided by theories of economic rationality. We do not wish to minimize or naturalize the term or phenomenon of discrimination by considering the inherent variability in its geographic expression. Indeed, we contend that analysis and antidiscrimination policy can be strengthened considerably through explicit attention to contingency. Our concern with geographic contingency reflects contemporary debates in the social sciences generally and in human geography more specifically. First, note that most social sciences ignore, or at best treat superficially, issues of location and geographic context. Second, within the discipline of geography, two distinct and conflicting approaches to the study of human society dominated for several decades following World War II. Some studied geographic processes thought to be universal, such as “laws” of spatial organization and spatial interaction (e.g., Schaefer 1953). Often these approaches overstated the importance of trivial aspects of location—sometimes slipping into forms of geographic determinism. Others studied particular or unique phenomena, such as the distinctive features of a country, region, or

¹² Turner and Skidmore (1999a, especially exhibit 1, p. 6) provide a thorough treatment of the stages of the mortgage lending process. Members of protected groups are protected from discrimination in all of these stages by federal civil rights legislation.

¹³ For example, discrimination in housing and mortgage markets (whether disparate treatment or disparate impact) limits opportunities for minority homeownership, asset accumulation, and access to the educational and employment benefits of desirable residential neighborhoods. In turn, long-term reductions in wealth, education, and occupational achievement reinforce racial disparities even in the absence of discrimination. “Lower educational credentials and occupational attainment, less stable employment histories and incomes, and minimal accumulations of wealth conspire to render minority applicants more risky mortgage loan applicants, even by objective, evenhandedly applied criteria” (Galster 1992, 5).

city (Hart 1982; Jones and Hanham 1995; Livingstone 1992). Many geographers in recent decades, however, sought to bridge that dichotomy by distinguishing between necessary and contingent relations (Sayer 1992). Necessary relations constitute the underlying structure of social relations or social practice. The concept of renter, for example, necessarily requires the concept of landlord, and both terms are given meaning only by an understanding of how property rights are defined, maintained, and enforced. A contingent relation, by contrast, is “any process that mediates between the operation of a general, necessary mechanism and a particular context” (Jones and Hanham 1995, 195).

Mortgage capital markets are subject to relations that we consider necessary in the national context of the United States. For example, there must be social, political, and economic acceptance of the idea of homeownership and private property. There also must be social, political, and economic acceptance and support for long-term debt. We contend that mortgage capital markets are embedded, necessarily, in the broader land and capital markets of the United States, which have been shaped dramatically by racial conflicts and inequalities emerging from generations of discrimination and violence. Specifically, it simply is not possible to understand U.S. housing and credit markets without explicitly considering the role of race and racial identity. Those general and necessary processes are mediated, however, by contextual mechanisms operating at many different scales. Examples include state and local policies, broader regional variations in demographic conditions affecting the meaning of majority and minority group status, and contrasts between cities in the historical legacy of housing choices and racial conflicts.

Our analysis centers on neighborhood-scale contextual mechanisms that mediate the race–lending relationship, which typically is treated as spatially invariant. We specifically draw from our theoretical discussion of motivations for discrimination in mortgage lending and detail two related but distinct sets of reasons that the race–lending relationship may vary systematically across neighborhood contexts. First, underwriting decision making may directly consider the match between the applicant’s racial identity and the neighborhood of the property—we term these possibilities contingent processes. We suspect that lenders are very aware of local residential geography,¹⁴ even though such awareness is not necessary for processes to operate in contingent ways. Moreover, geographic variability may be introduced into the race–lending relationship by processes that do not directly vary across neighborhoods—we term these possibilities contingent outcomes. As we outline our arguments, we pay explicit attention to two aspects of the potential results of our empirical analysis presented below. First, what are the intraracial patterns across space¹⁵—that is, how and to what extent do loan denial probabilities vary across neighborhoods for applicants of a given race? Second, what are the interracial patterns—that is, how do white applicants and black applicants compare across different types of neighborhoods, and where do apparent racial disparities in denial probabilities reach their highest and lowest points?

¹⁴ Lenders’ perceptions of local residential geography are complex and remarkably underresearched, yet they most certainly cannot be ignored. Lending institution case studies (e.g., Listokin et al. 1998; Rohe et al. 1998; Squires 1992) demonstrate that lenders’ geographic perceptions are shaped by appraisal and real estate agent referral networks. Moreover, these perceptions are affected by branch locations, decisions on *where* loan applications are accepted, and mergers that displace underwriting decisions to other cities or states.

¹⁵ A reviewer suggested this phrasing.

Mortgage Lending as a Geographically Contingent Process

We start with the traditional concern of the redlining literature: inner-city minority and low-income neighborhoods. Ross and Yinger (1999b) distinguish between process-based redlining and outcome-based redlining (i.e., the focus of early community activism and redlining research that compared the flow of mortgage funds to minority and comparable majority neighborhoods). Process-based redlining posits that applicants are treated differently if the property they seek to purchase is in an LMI or minority neighborhood. We argue that process-based redlining is one form of a geographically contingent process. Specifically, if institutions continue to restrict credit to minority and/or LMI neighborhoods, perhaps because there are still too few housing transactions in some of these neighborhoods to generate adequate appraisals,¹⁶ all applicants in these places will exhibit higher denial probabilities than in other neighborhoods. Whether there is a denial probability difference between white and minority applicants in these neighborhoods depends on many factors, including the degree to which noncontingent discrimination further disadvantages minorities, and the extent to which omitted variables bias the empirical results.

Second, we suggest that policies and programs designed to increase minority and low-income homeownership inadvertently may have created geographically limited “spaces” of opportunities for minorities in what are now termed underserved neighborhoods.¹⁷ Schill and Wachter (1994) discuss a racial “concentration effect” of public policies that channel minority homeowners to low-income, racially segregated neighborhoods. Given that redlining has been the focus of much legislation and community activism, several of the most prominent mortgage market innovations and policies aimed at increasing homeownership during the past several decades are either explicitly or implicitly spatially targeted. The Federal Housing Administration (FHA) program, for example, which has become a significant source of lending to minorities, prohibits lending on higher-value properties more commonly found in predominantly high-income neighborhoods. To meet federally mandated goals of acquiring an increased share of loans from underserved neighborhoods, GSEs have participated in the innovation of conventional loan products with lenient debt-to-income ratio and flexible loan-to-value (LTV) requirements. Some lenders, acting alone or in consortia, have provided loan products, independently of GSE activities, designed to increase lending to underserved communities and populations. Many of these programs have spatial targets. Indeed, spatial targeting was an essential goal of the Atlanta Mortgage Consortium (as well as other nationally prominent industry responses to the community reinvestment movement) and constitutes a key element of federal urban policy in the empowerment zone/enterprise community legislation.

Empirically, if spatially targeted policies introduce geographic variability into the race–lending relationship, we expect denial probabilities to be lower in spatially targeted neighborhoods, all else being equal. The implications of spatially targeted policies on relative racial differences

¹⁶ An anonymous reviewer suggested this reasoning. Listokin et al. (1998) relate a story of the first new market-rate single-family housing built in Detroit since World War II: To secure comparable sales data, appraisers based their evaluations on property transactions several miles away in the suburbs. This economic motive does not preclude preference-based interpretations, however.

¹⁷ According to current federal rules, neighborhoods qualify as underserved for GSE purposes if a metropolitan area census tract meets one of two conditions. Median household income in the tract must be either less than 90 percent of the metropolitan area median or less than 120 percent of the metropolitan area median with a minority population share greater than 30 percent. In the Atlanta study area described later in the article, 65 percent of tracts qualify under those criteria. Forty percent of loan applications come from those tracts.

in denial probabilities are unclear. On one hand, the programs do not encourage discrimination against white applicants. Applicants of both races should benefit from the programs; racial differences in denial probabilities in targeted neighborhoods should be limited. On the other hand, minorities will constitute a disproportionate share of applicants taking advantage of these programs. There also may be racial differences in the degree to which these programs are marketed. Holloway (1998) found that denial probabilities for whites exceeded those for blacks in predominantly black neighborhoods, but did not examine the impact of neighborhood income.

Most of our discussion has so far focused on minority and low-income neighborhoods. Geographically contingent lending may characterize other types of neighborhoods also. We argue specifically that often preference-based acts of discrimination are stimulated by perceptions of geographic transgression—that is, minorities attempting to enter, use, or occupy places where it is thought they do not belong. To the extent that black applicants attempting to purchase homes in predominantly white and/or high-income neighborhoods are perceived to be out of place, lending institutions may be motivated to resist with preference-based disparate treatment discrimination. Note that the interaction of race with place constitutes a core concern of much of the housing market discrimination research. When real estate agent steering is documented (e.g., Turner 1992; Turner, Struyk, and Yinger 1991; Yinger 1995), the concern is that minority home seekers encounter differential treatment in the range of housing choices presented. Minorities are shown different (and often fewer) places than are identical whites. Similarly, the events stimulating some of the worst urban unrest in our history involve minorities either moving into, or using facilities in, the wrong place—that is, places where they were not wanted, and where current majority-group occupants felt threatened (Hirsch 1983; Philpott 1991). Lenders’ preference-based discrimination may be triggered by the attempts of minority home buyers to purchase housing in predominantly white neighborhoods, especially high-income white neighborhoods. Ethnographic evidence documents that some middle-class black home buyers perceive the treatment they receive from lenders when they attempt to purchase homes in traditionally white neighborhoods to be potentially discriminatory and different from the treatment they receive when they attempt to purchase homes in traditionally black neighborhoods (Feagin and Sikes 1994). To the extent that geographically contingent preference-based discrimination characterizes the lending market, we suspect that black applicants experience higher denial probabilities in predominantly white than in traditionally black neighborhoods.

The impact of neighborhood income levels on preference-based discrimination presents an interesting point to consider. A reviewer of an earlier version of this article suggested that black applicants seeking to move into any predominantly white neighborhood would trigger preference-based discrimination, regardless of neighborhood income. Historically, some of the most aggressive and violent resistance to blacks moving into white neighborhoods occurred in working-class neighborhoods bordering black ghettos, especially in periods when alternative housing choices for working-class whites were constrained (see Hirsch 1983 for the example of post-World War II Chicago). At the same time, high-income inner-city neighborhoods also effectively resisted black in-movement, but with different means. Specifically, these neighborhoods tended to use violence less frequently, and mobilized local housing institutions more effectively (Hirsch 1983). Atlanta’s racial history contains examples of neighborhoods at a variety of income levels resisting black in-movement (e.g., Bayor 2000; Silver and Moeser 1995). The implication for our empirical analysis is that preference-based discrimination contingent on the racial composition of neighborhoods should be evident at all neigh-

neighborhood income levels. Even so, we suspect that preference-based discrimination may also be contingent on the interaction of neighborhood racial composition with income levels. During the past three decades the predominant pattern of racial transition has been white flight triggered by relatively low levels of integration, especially in lower- and moderate-income neighborhoods. The general attitude has been to avoid resisting transition unless the neighborhood is considered valuable.¹⁸ In the context of preference-based discrimination triggered by “out-of-place” black applicants, we thus find it plausible that this type of discrimination may be restricted to higher-income white neighborhoods. Note in this regard that the programs and market forces that have the greatest potential to reduce discrimination are not found in high-income neighborhoods, but are restricted to LMI neighborhoods (for homeownership programs) or middle-income neighborhoods (for general GSE acquisitions because of upper limits on loan values).

Predominantly white, high-income neighborhoods may be the locale of disparate treatment for another reason. Lenders are likely to realize economic motivations to discriminate against minority applicants in these neighborhoods if they are perceived to be vulnerable to the threat of future racial transition. Because whites almost universally equate racial transition with neighborhood decline, typically real estate markets respond with stagnant or downward trending appreciation rates.¹⁹ Thus, often the entry of minorities into a neighborhood is assumed to be detrimental to local house values. Historically, these expectations were codified in FHA appraisal standards. More recently, with increasing income and wealth holdings of minorities and increases in housing availability for minorities, the number of neighborhoods completely devoid of minorities has been greatly reduced. Nonetheless, based on “tipping point” notions (Schelling 1972), we suspect that homeowners, appraisers, real estate agents, and lending institutions continue to respond to an implicit threshold. If lenders have substantial portfolio holdings in a set of neighborhoods, future racial transition beyond that threshold may be perceived as a considerable risk to the collateral on outstanding mortgages.

The problem involves lenders acting in anticipation of consumer discrimination in the housing market. Lenders may, however, misjudge the extent or severity of consumer discrimination. As LaCour-Little expresses it,

If lenders believe that minority occupancy reduces property values, they might avoid lending to minorities seeking to purchase properties in predominantly white neighborhoods for fear of damaging the collateral value on loans they have already extended in the neighborhood. Likewise, lenders may face a type of “prisoner’s dilemma,” in that they do not wish to make loans in neighborhoods in which other lenders do not also make loans. (LaCour-Little 1999, 23)

That risk will be greatest in the neighborhoods in which lenders are most likely to retain their loans in portfolio—wealthy neighborhoods in which loan amounts often are too large to be sold on the secondary market. Based on the geography of that potential risk, we expect denial probabilities in high-income, predominantly white neighborhoods to increase substantially

¹⁸ Buckhead, a high-income white neighborhood in Atlanta’s northern section, has experienced rising racial tensions owing to the popularity of its commercial district among young African Americans.

¹⁹ Sometimes home values briefly spike in association with rapid racial transition. The pattern soon reverts to stagnation.

for black applicants, and to remain level or decrease for white applicants.²⁰ Denial probabilities should be higher for black than for white applicants.

Noncontingent Reasons for Geographically Variable Outcomes

So far we have made the argument that the lending process is contingent, or geographically variable, in its operation. We also recognize that the race–lending relationship can vary empirically across neighborhoods even when the processes generating it are not spatially variable in their operation. We consider two possibilities.

First, much of the criticism of lending discrimination research has focused on forms of missing-variable bias—that is, most often analysts do not have access to all the information lending institutions have, and even when they can gain access, it is only for a limited set of institutions (Ross and Yinger 1999b). The lack of credit histories or credit scores has been particularly problematic, but missing information on LTV ratios, debt-to-income ratios, and cash-to-close, among other factors, is also troubling. It is possible that an increase in denial probabilities for black applicants in high-income white neighborhoods could result from asset constraints.²¹ Wealth holdings are lower for blacks than whites at all income levels. In higher-income neighborhoods where purchase prices are higher, asset requirements will also be higher, especially without the ameliorating effect of homeownership programs available in other neighborhoods. Thus, higher black denial probabilities in high-income neighborhoods may reflect those accentuated asset constraints. Given that the HMDA data do not include purchase price or wealth information, our empirical analysis cannot rule out that possibility. Counter to that expectation however, the HMDA data for our study area indicate that 3.2 percent of black applicants in high-income neighborhoods²² were denied for insufficient cash, whereas 6.7 percent of white applicants in the same neighborhoods were denied for insufficient cash. Also, this version of the omitted variable bias hypothesis requires the assumption that the highest-income black applicants in the best neighborhoods have greater asset deficiencies relative to the purchase price of the home than do black applicants in other neighborhoods—an assumption that we find premature and potentially unreasonable without further research.

Second, discrimination, especially disparate treatment, may be triggered by applications for nonconforming loans that exceed GSE maximums, wherever the homes are located. Given that institutions are more likely to hold jumbo loans in portfolio and thus bear the risk, preference- and economically motivated discrimination against minority applicants may be accentuated. A geographic expression of that form of discrimination may result simply from the underlying distribution of properties that require a jumbo loan. If jumbo loan applications are predominantly located in high-income white neighborhoods, we will not be able to distinguish empirically resultant geographic patterns from those created by a geographically contingent process.

²⁰ The pattern for white applicants depends on whether institutions show a positive preference for white applicants as neighborhood income rises, or just a negative preference against black applicants in higher-income neighborhoods.

²¹ A reviewer of an earlier version of this article made that suggestion.

²² We selected tracts with median household income greater than 120 percent of the metropolitan area median income.

In sum, we bring to our empirical analysis the following expectations. First, we expect black denial probabilities to be high in predominantly white, high-income neighborhoods and decrease through “average” neighborhoods in which underwriting practices are most likely to be standardized. Moderate-income, predominantly white neighborhoods may or may not show higher denial probabilities. Black denial probabilities will then increase in LMI and minority neighborhoods according to the redlining hypothesis, or decrease according to the spatially targeted policy hypothesis. White denial probabilities may decrease in high-income neighborhoods if lenders exhibit positive preference for white applicants. The redlining hypothesis suggests that white applicants’ denial probabilities will increase in LMI neighborhoods, whereas the spatially targeted policy hypothesis suggests that white denial probabilities will decrease. We expect that black applicants will show higher denial probabilities than whites in high-income neighborhoods; we expect relative racial parity in the middle. Interracial patterns in low-income and minority neighborhoods depend on whether the redlining or policy hypothesis receives stronger support. All our expectations regarding interracial patterns in particular kinds of neighborhoods depend a great deal on the ability of the empirical analysis to provide an accurate assessment of the base level of discrimination throughout the study area. In particular, the issue of omitted variables plagues the empirical analysis and prevents us from presenting definitive results regarding interracial patterns. We are more confident about the intraracial patterns across neighborhoods, but note here too that data limitations prevent us from being definitive. Nonetheless, our empirical results are very suggestive.

Data and Methods

To examine denial patterns for mortgage loan applicants, we used data from 1996 HMDA loan applicant records (Federal Financial Institutions Examination Council [FFIEC] 1997) for the seven-county Atlanta urbanized region described in Wylly and Holloway (1999). We used 1996 data because at the time of the analysis they were the most current data available. A single year of data provided ample observations for analysis. To clarify our focus, we restricted our sample to applications for the purchase of owner-occupied dwellings; although important work remains to be done on refinancing and home improvement lending (e.g., Scriber 2000), it is beyond the scope of our project. We focused our study on the initial underwriting decision, and thus excluded records that were purchased by the reporting institution. We applied additional cleaning criteria to maximize the utility of our data. Table 1 summarizes these procedures, showing that out of 180,606 original observations, we are left with 59,910.²³ Note that many observations were excluded from the analysis sample for more than one reason.

Denial Probability Logistic Regression Models

We estimated a series of logistic regression models with applicant- and tract-level data for the seven-county Atlanta region to sort out the relations between individual- and neighbor-

²³ We used part of this sample (N = 29,960) to estimate the parameters of a credit history instrument described later, and the remaining part (N = 29,950) to estimate the parameters of the denial probability models. The split sample approach to creating an instrument avoids the possibility of introducing tautology into the analysis.

Table 1. Summary of Cleaning Procedures Applied to the 1996 HMDA Data Analyzed

Reason Excluded from Data	Number	Percentage
Total observations	180,606	100.00
Loan not for purchase	76,519	42.37
Property not owner-occupied	10,606	5.87
Failed FFIEC quality or validity edit	17,088	9.46
Loan purchased by institution	38,155	21.13
Loan type Farmers Home Administration	99	0.05
Very low income (< \$10,000)	511	0.28
Very high income (> \$1,000,000)	60	0.03
Applicant income missing	36,635	20.28
Tract < 500 owner-occupied housing units	7,527	4.17
Applicant sex information not provided	36,875	20.42
Cleaned observations remaining	59,910	33.17

Note: Percentages do not sum to 100 because many applicants were excluded for more than one reason.

hood-level factors in lending decisions. The first model allowed us to test for racial discrimination, and includes only applicant-level information:

$$\ln \frac{P}{1-P} = b_0 + b_1 R_i + \mathbf{b}'_2 \mathbf{A}_i + \mathbf{b}'_3 \mathbf{I}_i + e_i, \tag{1}$$

where R_i is the race of the applicant (coded 1 for blacks, 0 for whites), \mathbf{A}_i represents a vector of applicant financial characteristics, and \mathbf{I}_i is a set of controls for institutional-level variations measured with the surrogate of regulatory agency dummies. This specification mirrors the specification adopted in most accept/reject studies of lending discrimination. A positive and statistically significant estimate of b_1 indicates that black applicants have higher denial probabilities than do white applicants, net of the other variables in the model. This is interpreted as evidence of discrimination against black applicants, though it cannot differentiate between disparate treatment and disparate impact forms. A statistically significant race parameter may be generated by omitted-variable bias (see Ross and Yinger 1999b for an extensive discussion of this issue); we use an instrumental measure of applicant credit history, described below, to partially account for that possibility.

The second model adds percentage black (PB_j) as a measure of neighborhood racial composition, and a set of additional neighborhood risk attributes (\mathbf{N}_j):

$$\ln \frac{P}{1-P} = b_0 + b_1 R_i + \mathbf{b}'_2 \mathbf{A}_i + \mathbf{b}'_3 \mathbf{I}_i + b_4 PB_j + \mathbf{b}'_5 \mathbf{N}_j + e_i. \tag{2}$$

By including the percentage black, we test for redlining. A positive and statistically significant coefficient associated with the percentage black variable (b_4) indicates that the racial geography of neighborhoods exhibits an impact on denial probabilities independent from that of the racial identification of applicants. Including additional neighborhood-level variables describing average property appraisals and other factors associated with perceived property risk should boost the overall predictive power of the model and may also reduce the magni-

tude of the estimated effect of applicant race on loan disposition (Perle, Lynch, and Horner 1993).²⁴

The third model includes interaction terms:

$$\ln \frac{P}{1-P} = b_0 + b_1 R_i + \mathbf{b}'_2 \mathbf{A}_i + \mathbf{b}'_3 \mathbf{I}_i + b_4 PB_j + \mathbf{b}'_5 \mathbf{N}_j + b_6 (R_i * PB_j) + b_7 (R_i * INC_j) + b_8 (R_i * PB_j * INC_j) + e_i. \quad (3)$$

First, consider the interaction between applicant race and tract racial composition ($R_i * PB_j$). If b_6 is negative as we expect, the magnitude of the association between an applicant's black racial identity and higher denial probabilities (captured by a positive coefficient for b_1) is greatest in neighborhoods where the percentage black is lowest—predominantly white neighborhoods. Second, consider the interaction between applicant race and tract median household income ($R_i * INC_j$). If b_7 is positive, the magnitude of the race effect (i.e., the positive association between denial probabilities and black racial identity as captured by R_i) is amplified in the highest-income neighborhoods.²⁵ Third, consider the three-way interaction between applicant race, tract percentage black, and tract income ($R_i * PB_j * INC_j$), which we include to test for the possibility that racial disparities are most pronounced in the highest-income white neighborhoods. A positive estimate for b_8 is not consistent with our hypothesis—the impact of the race dummy variable is accentuated only when the neighborhood income and percentage black variables both take on large positive values.²⁶ If b_8 is negative, however, the impact of the race dummy variable is accentuated when neighborhood income and percentage black are in the opposite tails of their respective distributions, that is, when income is high and percentage black is small or when income is low and percentage black is large. A negative estimate, thus, is consistent with our suspicion that high-income, predominantly white neighborhoods present particular difficulties for black applicants.²⁷

The specification of the application denial probability models is limited by the variables included in the HMDA files and by indicators available at the census tract scale (see table 2).

²⁴ Including these neighborhood indicators might also eliminate the effect of race on loan denial probabilities. In such a scenario, however, it is crucial to limit and qualify the conclusions that can be drawn. The absence of a statistically significant effect of applicant race on the likelihood of loan rejection, though counter to theories of lender discrimination, does not rule out the possibility of lender discrimination in the guise of selective marketing/outreach or prescreening, and it tells us nothing about racial steering in housing search processes.

²⁵ The direct effect of median household income is also included in the models as one element of \mathbf{N}_j . We specify this effect as a nonlinear quadratic based on results of preliminary analysis.

²⁶ Given that we measure tract-level variables centered on their means (and thus have both positive and negative values), tracts with income and percentage black values substantially below the mean would also produce that result with a positive estimate for b_8 .

²⁷ We experimented with several alternative conditional-effects specifications, interacting race and neighborhood racial composition with housing value, population growth, and housing value appreciation. We also evaluated nonlinear direct and interactive effects for the neighborhood variables in the analysis. A specification including a nonlinear (quadratic) effect for tract income interacted with applicant race (without a three-way interaction term) performed in a very similar way to the one we report here. We chose to report the model with the three-way interaction term, primarily because it allowed us to explicitly test our third hypothesis.

Table 2. Descriptive Statistics for Applicant-, Institution-, and Neighborhood-Level Variables Included in Loan Denial Probability Logistic Regression Models

Variable	Mean	Median	Standard Deviation
Applicant and institution variables (N = 27,487)			
Applicant income (\$ thousands)	66.420	52.000	55.700
Applicant loan amount (\$ thousands)	117.010	100.000	77.710
Loan-to-income ratio > 3	0.094	—	—
Applicant non-single female	0.065	—	—
Applicant single female	0.226	—	—
Applicant traditional family	0.407	—	—
Bad credit instrument	0.036	0.098	0.047
Applicant black	0.226	—	—
Applicant other	0.078	—	—
Applicant race not reported	0.018	—	—
OCC	0.249	—	—
FRB	0.159	—	—
FDIC	0.071	—	—
OTS	0.087	—	—
NCUA	0.004	—	—
FHA or VA	0.242	—	—
Census tract variables (N = 299)			
% Δ, number of households, 1990–96	15.045	6.966	25.357
Median housing age, 1996	24.550	21.000	11.640
% population that did not move, 1985–90	46.420	46.615	12.497
Rent-to-value (\$ thousands)	6.415	6.635	2.049
Median household income, 1996	47.871	44.392	22.006
% vacant housing	8.647	7.547	4.460
% non-Hispanic black	30.373	14.229	33.888
Housing appreciation	13.302	13.277	3.258

Note: OCC = Office of the Comptroller of the Currency. FRB = Federal Reserve Board. FDIC = Federal Deposit Insurance Corporation. OTS = Office of Thrift Supervision. NCUA = National Credit Union Association. FHA = Federal Housing Administration. VA = U.S. Department of Veterans Affairs.

Applicant-level characteristics include variables for income (centered on the sample median), loan amount requested (centered on the sample median), and gender and family composition. We explicitly built in an interaction between gender and family type to examine the potential impact of single-female-headed households on the models. We also constructed an indicator for unusually large loan requests (greater than three times annual income). Neighborhood-level variables measure conditions in the local housing market and the perceived risk associated with appraisal and underwriting of the property. These variables were drawn from (1) updated and corrected estimates developed by the Atlanta Regional Commission (ARC) (1997) and (2) Claritas™ Real Estate Solutionseries™, a proprietary database that provides annual updates for a limited set of population, housing, and consumption measures (Claritas, Inc. 1998). Where possible, 1996 estimates were calculated using linear interpolation between 1990 and 1997 values. We expect loan rejection probability to increase in older, low-value neighborhoods with higher vacancy rates and a greater degree of resident turnover. Conversely, rejection probabilities may be reduced in suburban growth areas where builders, real estate agents, appraisers, and trade-up home buyers work together to arrange financing for homes in new subdivisions. All tract-level variables are centered on their means.

Bad Credit History Probability Instrument

Despite the care we used to specify the denial probability models, our use of HMDA data means that we could not directly control for applicant characteristics legitimately associated with denial probabilities, such as employment histories and marginal or unacceptable credit scores. The primary concern is that omitted variables available to underwriters, but not available to us, are correlated with race. Thus by not accounting for those factors, we bias our estimates of race effects. We adapted a procedure here suggested by Aboriotos et al. (1993) and used by Holloway (1998) to construct an instrument representing the probability that a lender will reject an application on the basis of credit history problems (a decision reported in the HMDA records). This instrument is a continuously varying measure calculated for every observation included in the sample used to estimate the denial probability models. For a random 50 percent sample of the 1996 HMDA applicant records ($N = 29,960$), we estimated a logistic regression model for the probability that an applicant was denied on the basis of bad credit history. This model included applicant- and tract-level indicators. We then took the estimated parameters of this model (table 3) to calculate the estimated probability of having a credit history bad enough to merit application denial for the remaining 50 percent sample of the data ($N = 29,950$). We included this variable (centered on the sample median) in all application denial probability models. Consistent with our expectations, this instrument is correlated with applicant race ($r = 0.29, p < 0.01$), applicant income ($r = -0.32, p < 0.01$), tract-level racial composition ($r = 0.28, p < 0.05$), and tract-level income ($r = -0.35, p < 0.05$).

The logic of this approach centers on our attempt to create a continuously varying instrumental variable correlated with the variables of interest to us in this article (i.e., applicant race, neighborhood racial composition, and neighborhood income) and correlated with the missing information. Reporting regulations allow lending institutions to indicate up to three reasons for denying an application. Figure 1 shows the primary reason for denial by racial category. Note that the main difference between races is “credit history” and “reason not reported”; “credit history” is indicated more often for black than for white applicants, as the literature suggests. Conversely, “no reason” is reported much less frequently for blacks than for any other racial group, perhaps because lending institutions are cautious about potential claims of discrimination.²⁸ We coded our dependent variable equal to 1 if credit history is indicated as any one of the three reasons for denial. Our sample includes all applicants. The model thus indicates the degree to which applicant and tract characteristics known to us in the HMDA data are predictive of applicant credit histories that are problematic enough to warrant, even partially, a negative decision by lending institutions.²⁹

The validity of this approach rests on several factors. First, lenders who report reasons for denying an application must choose between the reasons listed on the forms. Some observers suggest that lenders may attempt to “hide” disparate treatment discrimination by reporting

²⁸ Multinomial logit models predicting the first reported denial reason based on racial category (black, white, other) confirm the impressions drawn from figure 1: Black and white applicants differ statistically ($p < 0.05$) only in the probability that “no reason” is indicated and the probability that “credit history” is indicated. Nonwhite, nonblack applicants are statistically more likely than white or black applicants to have been denied for “employment history” and “unverifiable information” reasons.

²⁹ Note that if we were to limit this sample to denied applicants, our model would predict the conditional probability that credit history was the reason, relative to other indicated reasons. We seek to create, however, an instrument that captures the correlation between race, neighborhood racial composition, and the missing credit information for all applicants—we thus include all applicants in our credit history model.

Table 3. Logistic Regression Parameter Estimates Predicting the Probability of Having Bad Credit Based on a Randomly Selected Half of the Total Sample (N = 29,960)

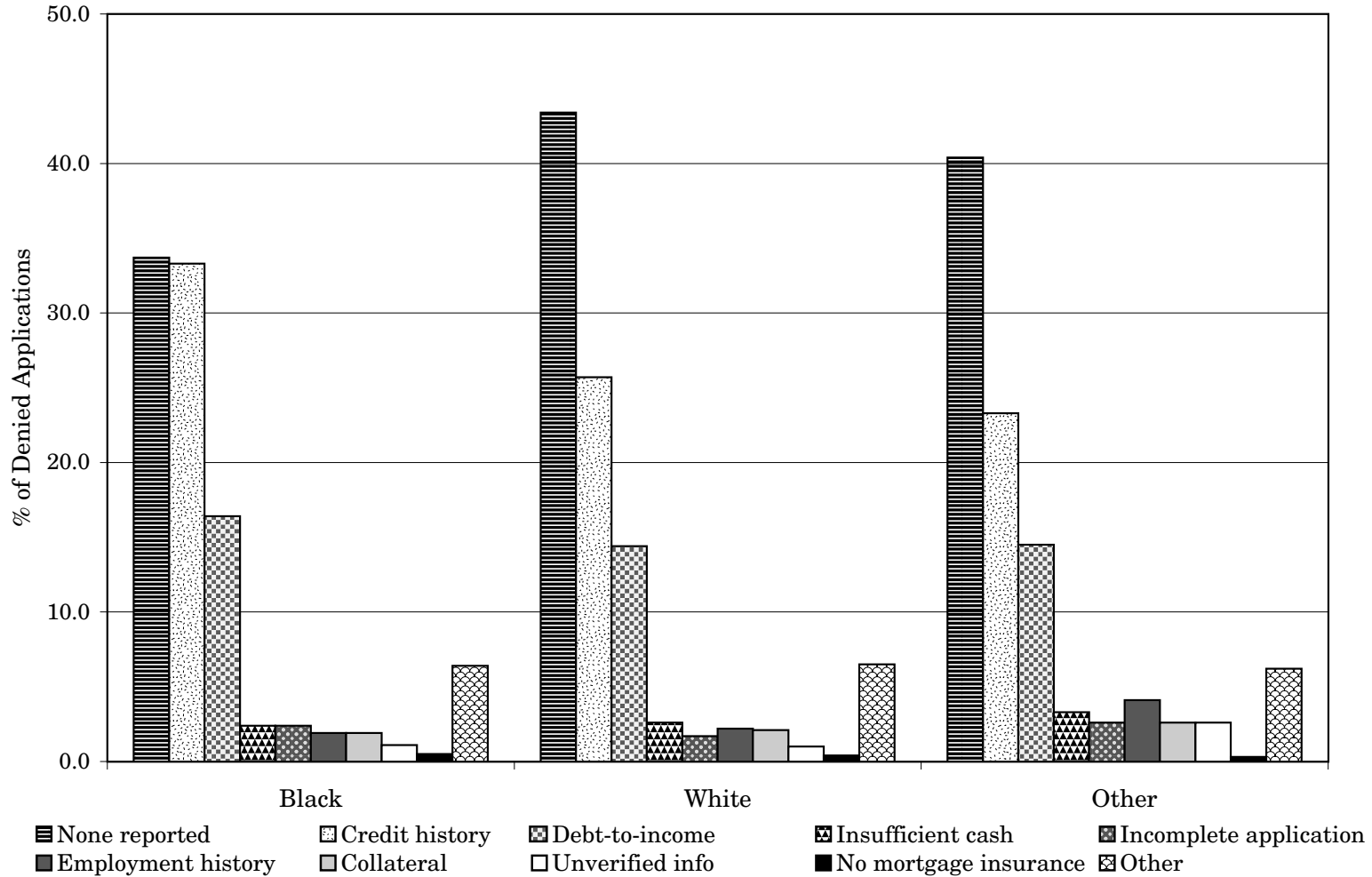
Variable	<i>b</i>	<i>e^b</i>
Income (\$ thousands)	-0.0072 **	0.9928
Loan amount (\$ thousands)	-0.0087 **	0.9913
Applicant female	-0.0994	0.9054
Applicant black (vs. white)	0.7191 *	2.0526
Applicant other (vs. white)	-0.1891 **	0.8277
Applicant race not reported (vs. white)	0.6189 **	1.8569
FHA (vs. conventional)	-0.6565 **	0.5187
VA (vs. conventional)	-0.7919 **	0.4530
OCC (vs. HUD)	1.5006 **	4.4844
FRB (vs. HUD)	0.5218 **	1.6851
FDIC (vs. HUD)	0.9354 **	2.5483
OTS (vs. HUD)	1.9414 **	6.9687
NCUA (vs. HUD)	0.3607	1.4344
Median household income (\$ thousands)	-0.0067	0.9933
% population with college degree, 1996	-0.0298 **	0.9706
% housing stock owner-occupied, 1996	-0.0026	0.9974
% non-Hispanic black, 1996	0.0026	1.0026
Median housing value, 1996 (\$ thousands)	0.0031 *	1.0031
Median gross rent, 1990	-0.0000	1.0000
Median age of housing stock, 1996	-0.0030	0.9970
Tract located in central city?	0.0158	1.0159
% labor force unemployed, 1996	0.0137	1.0138
% in poverty, 1990	-0.0168	0.9834
Constant	-2.0837 **	
-2LL	8039.455	
χ^2 versus null model	1350.431 **	

Note: Parameter estimates are used to generate our credit history instrument, which is used in subsequent models. FHA = Federal Housing Administration. VA = U.S. Department of Veterans Affairs. OCC = Office of the Comptroller of the Currency. HUD = U.S. Department of Housing and Urban Development. FRB = Federal Reserve Board. FDIC = Federal Deposit Insurance Corporation. OTS = Office of Thrift Supervision. NCUA = National Credit Union Association.

* $p < 0.05$. ** $p < 0.01$.

a superficially valid reason for denial. Given that poor credit history has been publicized as a significant problem for many minority applicants, such lenders may choose to report this particular reason more often than others do. To the degree that this lender behavior occurs, it makes our instrumental variable conservative—it artificially inflates the degree to which our instrument is correlated with race, and thus decreases the chances of finding a significant race effect in the denial probability models. Second, reporting the reason for denial is voluntary, and bias may be introduced if some institutions choose not to report reasons at all. Of the 59,910 total applications included in our analysis, 6,820 were denied. Of the denied applications, no reason was reported for 2,753 (40.4 percent of the total denied). Although this value is disturbingly large, almost half (1,294; 47.0 percent) of the no-reason denials came from a single institution that did not report reasons for any of its denied applications. We explored the impact of institutional variation in the propensity not to report a denial code on the credit history instrument by estimating the credit history model based on a variety of subsamples. For instance, we estimated one credit history model with a sample that excluded all institutions that fail to report a reason for more than half of their denied appli-

Figure 1. Reason for Loan Application Denial by Race



Note: Denial codes shown here are the first or primary reasons reported by lenders. Lenders may, but are not required to, report up to three reasons for denying a loan application.

cants, and another credit history model with a sample that excluded all applicants for whom a denial reason was not reported. The credit history instruments created from these various subsamples are extremely highly correlated ($r > 0.94$), suggesting that although institutional reporting behavior is problematic, it does not have a substantial impact on our attempt to create a credit history instrument.

Results

Parameter estimates for the logistic regression models are presented in table 4.³⁰ In model 1, the simple discrimination model, the coefficient for each of the race variables—black, other (nonwhite, nonblack), and race not reported—is statistically significant and positive, indicating higher denial probabilities than for white applicants, holding all other applicant and institutional characteristics constant. The credit history instrument is a very important variable, confirming its usefulness in this analysis as a control against overestimating the magnitude of direct racial discrimination.³¹ As expected and consistent with previous research (e.g., Holloway 1998), applicant income and loan amount requested are negatively related to denial probabilities, whereas a ratio of loan request to income over 3 is positively related to denial probabilities. Single female applicants (defined as female applicants without a male co-applicant) and traditional family applicants (defined as male applicants with a female co-applicant) are less likely to be denied than are male applicants lacking a female co-applicant. Female applicants with a co-applicant of either sex are more likely to be denied than are non-traditional male applicants. Applications for loans backed by FHA or the U.S. Department of Veterans Affairs (VA) are less likely to be denied. The regulatory agency dummies confirm that, in comparison with mortgage banks and after controlling for applicant-level characteristics, applicants to depositories are less likely to be denied.

Adding tract-level information to the model (model 2 in table 4) significantly improves the fit of the model, consistent with our expectations. Loan denial is less likely overall in rapidly growing, higher-income tracts, and in tracts with older housing stock.³² Note that we specify

³⁰ These models are estimated with a sample of 27,487 observations derived from the 50 percent subset ($N = 29,950$) of the original data that were *not* used to estimate the credit history model, by excluding 2,463 withdrawn or incomplete applications.

³¹ To further explore the importance of the credit history variable, we re-estimated each of the models reported in table 4, leaving the credit history instrument out of the specification. When the model does not control for credit history, the magnitude of the coefficients for the racial identity variables changes considerably. Relative to the coefficients reported in table 4, the coefficient comparing black applicants with white applicants is approximately 2.7 times larger, the coefficient comparing nonwhite, nonblack applicants to white applicants is approximately 0.6 times as large, and the coefficient comparing applicants with no racial information to white applicants is approximately 1.6 times larger. In addition, the coefficient comparing applicants reported by institutions regulated by the Office of Thrift Supervision with applicants reported by institutions regulated by U.S. Department of Housing and Urban Development (HUD) is only 0.1 times the coefficient reported in table 4, and the opposite sign. These coefficients, however, reflect the magnitude of the direct influence of racial identity on denial probability, which is not the main focus of this article. The estimated coefficients that constitute the core of our analysis—the interaction terms in table 4, model 3—are not substantially affected by the inclusion/exclusion of the credit history instrument. Moreover, the estimates of the models excluding our credit history instrument do not conform with the findings of previous research (e.g., Munnell et al. 1992, 1996; Tootell 1996), whereas the estimates reported in table 4 are of the same magnitude as those reported in studies using the Boston Federal Reserve Bank data, which include actual credit history information.

³² Lower denial probabilities in older neighborhoods may reflect institutional efforts to facilitate neighborhood upgrading (gentrification) in in-town neighborhoods such as Virginia Highlands, or it may reflect lower black denial probabilities in predominantly black neighborhoods that we describe later in the analysis.

Table 4. Logistic Regression Parameter Estimates Predicting the Probability of Loan Application Denial (N = 27,487)

Variable	Model 1 Discrimination Model		Model 2 Redlining Model		Model 3 Contingent Effects Model	
	<i>b</i>	<i>e^b</i>	<i>b</i>	<i>e^b</i>	<i>b</i>	<i>e^b</i>
Applicant-level variables						
Applicant income (\$ thousands)	-0.0026 **	0.9974	-0.0028 **	0.9972	-0.0026 **	0.9974
Applicant loan amount (\$ thousands)	-0.0072 **	0.9928	-0.0070 **	0.9930	-0.0067 **	0.9933
Loan-to-income ratio > 3	0.4585 **	1.5817	0.4668 **	1.5948	0.4752 **	1.6084
Applicant non-single female	0.2234 **	1.2503	0.2285 **	1.2567	0.2289 **	1.2572
Applicant single female	-0.2140 **	0.8073	-0.2129 **	0.8083	-0.2036 **	0.8158
Applicant traditional family	-0.2177 **	0.8043	-0.2042 **	0.8153	-0.1960 **	0.8220
Bad credit instrument	8.4808 **	4821.4149	7.9489 **	2832.5405	8.5884 **	5369.0132
Applicant black (vs. white)	0.2329 **	1.2622	0.2400 **	1.2713	0.1820 **	1.1997
Applicant other	0.2132 **	1.2377	0.2121 **	1.2363	0.1940 **	1.2141
Applicant race not reported	0.3566 **	1.4284	0.3860 **	1.4710	0.2762 *	1.3182
FHA or VA (vs. conventional)	-0.8007 **	0.4490	-0.8151 **	0.4426	-0.7834 **	0.4568
Institution-level identifiers						
OCC (vs. HUD)	-0.8825 **	0.4137	-0.8462 **	0.4290	-0.8841 **	0.4131
FRB (vs. HUD)	-0.6486 **	0.5228	-0.6439 **	0.5253	-0.6452 **	0.5245
FDIC (vs. HUD)	-0.7406 **	0.4768	-0.7240 **	0.4848	-0.7305 **	0.4817
OTS (vs. HUD)	-0.9924 **	0.3707	-0.9329 **	0.3934	-1.0051 **	0.3660
NCUA (vs. HUD)	-0.6167 *	0.5397	-0.6129 *	0.5418	-0.6112 *	0.5427
Neighborhood-level variables						
% Δ, number of households, 1990–96			-0.0029 **	0.9972	-0.0027 **	0.9973
Median housing age, 1996			-0.0096 **	0.9904	-0.0115 **	0.9885
% population that did not move, 1985–90			0.0096 **	1.0097	0.0111 **	1.0112
Rent-to-value			-0.0370 **	0.9637	-0.0378 **	0.9629
Median household income, 1996			-0.0068 **	0.9932	-0.0085 **	0.9915
(Median household income) ²			0.0001 **	1.0001	0.0001 **	1.0001
% vacant housing			0.0150 *	1.0151	0.0148 *	1.0149
% non-Hispanic black			-0.0001	0.9999	0.0057 **	1.0057
Housing appreciation			0.0284 **	1.0288	0.0260 **	1.0264
Black * % black					-0.0083 **	0.9917
Black * med. household income					0.0208 **	1.0210
Black * med. HH inc. * % black					-0.0003 **	0.9997

Table 4. Logistic Regression Parameter Estimates Predicting the Probability of Loan Application Denial (N = 27,487) (continued)

Variable	Model 1 Discrimination Model		Model 2 Redlining Model		Model 3 Contingent Effects Model	
	<i>b</i>	<i>e^b</i>	<i>b</i>	<i>e^b</i>	<i>b</i>	<i>e^b</i>
Constant		-1.5882 **		-1.5331 **		-1.5136 **
-2LL	18335.839		18263.179		18187.474	
χ^2 vs. null model	2228.843 **		2301.503 **		2377.208 **	
χ^2 vs. model 1			72.660 **		148.365 **	
χ^2 vs. model 2					75.705 **	

Note: The sample is the half not used to predict the probability of having bad credit. OCC = Office of the Comptroller of the Currency. HUD = U.S. Department of Housing and Urban Development. FRB = Federal Reserve Board. FDIC = Federal Deposit Insurance Corporation. OTS = Office of Thrift Supervision. NCUA = National Credit Union Association.

* $p < 0.05$. ** $p < 0.01$.

the tract income variable as a quadratic to capture potential nonlinear effects of tract income on loan denial probabilities. The quadratic term is significant and positive, indicating that denial probabilities start to increase with increasing neighborhood affluence toward the upper end of the income distribution. Loan denial probabilities are higher in residentially stable neighborhoods and in neighborhoods with proportionally high vacancy rates. Surprisingly, denial probabilities are also higher in neighborhoods that are appreciating rapidly. Contrary to outcome-based redlining expectations, the percentage black variable has the wrong sign (negative) and is not statistically significant in model 2.

Adding the interaction terms improves the fit of the model by a substantial margin (model 3 in table 4). Consistent with our expectations, the coefficient on the race–racial composition interaction term is negative, which suggests that the impact of race is reduced in predominantly minority neighborhoods relative to predominantly white neighborhoods. This finding is consistent with Holloway’s (1998) findings for Columbus, OH. The direct effect of tract percentage black in model 3 is positive and statistically significant, consistent with redlining expectations, whereas it was not in model 2. This relationship applies uniformly to white applicants. For black applicants, however, the effect of tract percentage black is negative ($-0.0026 = 0.0057 - 0.0083$) and statistically insignificant at the average neighborhood income level (\$44,400). The coefficient is positive and significant in low-income neighborhoods ($< \$25,000$), and is positive and not significant in neighborhoods between \$25,000 and \$36,000. The coefficient turns positive at about \$36,000, but does not reach statistical significance except in neighborhoods with greater than \$47,000 median income. In addition, the tract income interaction terms are statistically significant. This suggests that the effect of black racial identity on the probability of loan denial is accentuated in high-income neighborhoods, and that the degree of accentuation increases dramatically in the highest-income neighborhoods.

To explore the implications of the cross-level interaction variables on the empirical race–lending relationship, we calculated values of the parameter estimate associated with the black racial identity dummy variable at various settings of the tract income and percentage black variables (table 5). Tracts inside the box qualify as underserved according to current GSE standards; shading represents combinations of tract income level and percentage black values present in the Atlanta data set. Boldface type represents values for the parameter estimate that statistically differ from zero ($p < 0.05$). Note that the value of this parameter estimate captures the extent to which loan denial probabilities differ between black and white applicants, net of the other applicant-, institution-, and tract-level variables included in the model. Positive values indicate tracts where the probability of denial is significantly higher for black than for white applicants. Several findings stand out. First, denial probabilities are statistically greater for black than for white applicants in every tract that does not qualify for underserved status under GSE guidelines—that is, every neighborhood that is not low- or moderate-income or predominantly occupied by minorities. Second, there are tracts where denial probabilities are significantly lower for black than for white applicants—in this case the lowest-income tracts with the largest minority populations.³³ Third, not all targeted neighborhoods show empirical advantage for black applicants. Fourth, the degree of racial difference

³³ Although it might be tempting to interpret such a result as “reverse discrimination,” we must exercise caution. What appear to be minority advantages in targeted neighborhoods likely result from unobserved characteristics. Indeed, ethnographic and case study research strongly suggest that inner-city homeownership programs certainly demand an extraordinary degree of self-selection on the basis of endurance and patience, given the complexity of public/private/nonprofit partnerships, multilayered subsidies, counseling requirements, and bureaucratic delays. Put simply, we might be comparing average working-class whites with extremely motivated black applicants.

Table 5. Coefficients for the Black Dummy Variable Varying across Neighborhood Types

% Black	Neighborhood Income (\$ thousands)										
	10	20	30	40	50	60	70	80	90	100	110
100	-0.3603	-0.4096	-0.4589	-0.5082	-0.5575	-0.6068	-0.6561	-0.7055	-0.7548	-0.8041	-0.8534
90	-0.3805	-0.3998	-0.4191	-0.4384	-0.4577	-0.4770	-0.4963	-0.5157	-0.5350	-0.5543	-0.5736
80	-0.4007	-0.3900	-0.3793	-0.3686	-0.3579	-0.3472	-0.3365	-0.3259	-0.3152	-0.3045	-0.2938
70	-0.4209	-0.3802	-0.3395	-0.2988	-0.2581	-0.2174	-0.1767	-0.1361	-0.0954	-0.0547	-0.0140
60	-0.4411	-0.3704	-0.2997	-0.2290	-0.1583	-0.0876	-0.0169	0.0537	0.1244	0.1951	0.2658
50	-0.4613	-0.3606	-0.2599	-0.1592	-0.0585	0.0422	0.1429	0.2435	0.3442	0.4449	0.5456
40	-0.4815	-0.3508	-0.2201	-0.0894	0.0413	0.1720	0.3027	0.4333	0.5640	0.6947	0.8254
30	-0.5017	-0.3410	-0.1803	-0.0196	0.1411	0.3018	0.4625	0.6231	0.7838	0.9445	1.1052
20	-0.5219	-0.3312	-0.1405	0.0502	0.2409	0.4316	0.6223	0.8129	1.0036	1.1943	1.3850
10	-0.5421	-0.3214	-0.1007	0.1200	0.3407	0.5614	0.7821	1.0027	1.2234	1.4441	1.6648
0	-0.5623	-0.3116	-0.0609	0.1898	0.4405	0.6912	0.9419	1.1925	1.4432	1.6939	1.9446

Note: Shaded cells indicate combinations of tract income and tract percentage black actually present in the study area. Boldface type indicates coefficients significantly different from zero at $p < 0.05$. Tracts in the area bounded by the box qualify as underserved according to GSE standards.

is much greater in the higher-income, predominantly white tracts where blacks experience higher denial probabilities. For example, the likelihood of having a loan application denied in a tract with a \$70,000 median household income and 0 percent black is 156 percent higher for black than for white applicants.³⁴ Denial odds in a tract with a \$60,000 median income and 100 percent black are 45 percent higher for white than for black applicants—the largest black advantage observed.

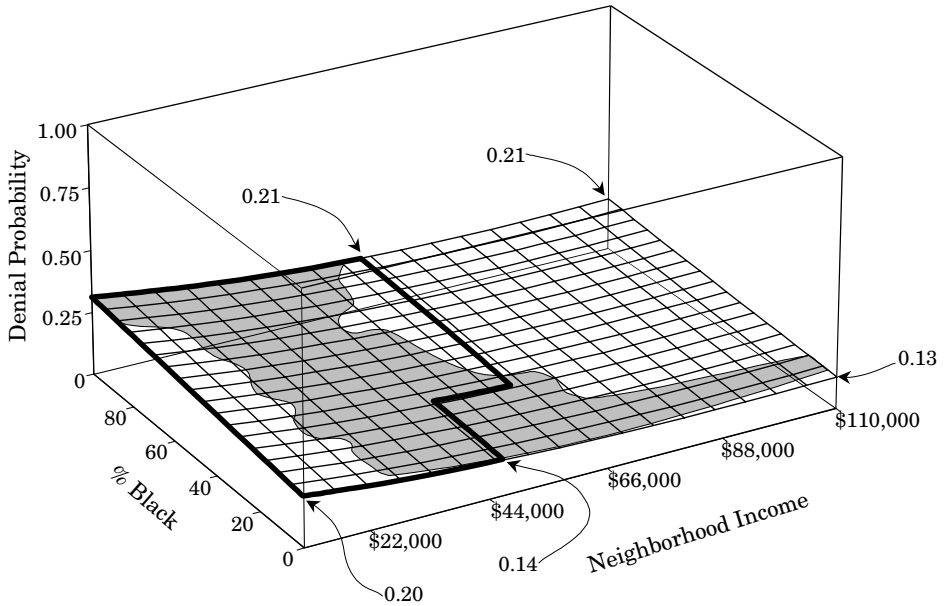
Parameter estimates in logistic regression models are notoriously difficult to interpret substantively. To illustrate the combined impact of neighborhood variations in income and racial composition on loan denial probabilities, we constructed predicted probability plots (Liao 1994) separately for whites and blacks (figures 2 and 3). We constructed these plots using the estimated parameters from model 3 in table 4, supplying median values for continuous independent variables (see table 2) and setting the dummy variable for traditional family equal to unity. These X-Y-Z plots show very different patterns for the two races. For white applicants (figure 2), denial probabilities are highest in the poorest neighborhoods with the greatest percentage black. Denial probabilities decline with increasing neighborhood income levels and with decreasing minority representation, reaching their lowest level in predominantly white neighborhoods with the highest income levels. The pattern for black applicants is more complex (figure 3). A negative relationship between neighborhood income and black denial probabilities is present unambiguously only in predominantly black neighborhoods. The relationship is positive unambiguously in predominantly white neighborhoods and mixed in between. A positive relationship between tract percentage black and black denial probabilities is present only in low-income neighborhoods. Overall, black denial probabilities are somewhat bimodal across the range of tract income and percentage black values present in the study area. They reach their highest value in the highest-income, predominantly white neighborhoods, with a secondary peak in the lowest-income, predominantly black neighborhoods.

We constructed maps of predicted denial probabilities using the estimated parameters (table 4, model 3) and observed values of tract racial composition and median income to evaluate the geographical expression of these mortgage market processes. Figure 4 shows the predicted probability of loan denial for black applicants, and figure 5 shows the predicted probability for white applicants, using consistent category boundaries (the categories indicated in the legends are based on the ratio of the denial probability predicted for a tract to the unconditional denial probability in the sample—0.14). Very different geographic patterns emerge. First, note that in all tracts except two, a “typical” black applicant (with median personal income seeking the median loan amount) experiences higher denial probabilities than the unconditional sample-based probabilities—that is, black denial probabilities are almost always higher than the sample average 14 percent of applications denied.³⁵ A “typical” white applicant with the same characteristics as the black applicant, however, will experience less than half the sample average denial probability (i.e., less than 0.07) in substantial portions of the most rapidly growing, most affluent neighborhoods in the Atlanta area. Most of these areas are in the subur-

³⁴ Percentage differences in odds between the categories of a dummy variable used in a logistic regression model are calculated by $(e^{b_i} - 1) \times 100$. The values of the parameter estimate associated with the race dummy variable take on different values depending on the tract variables percentage black and median income (table 5).

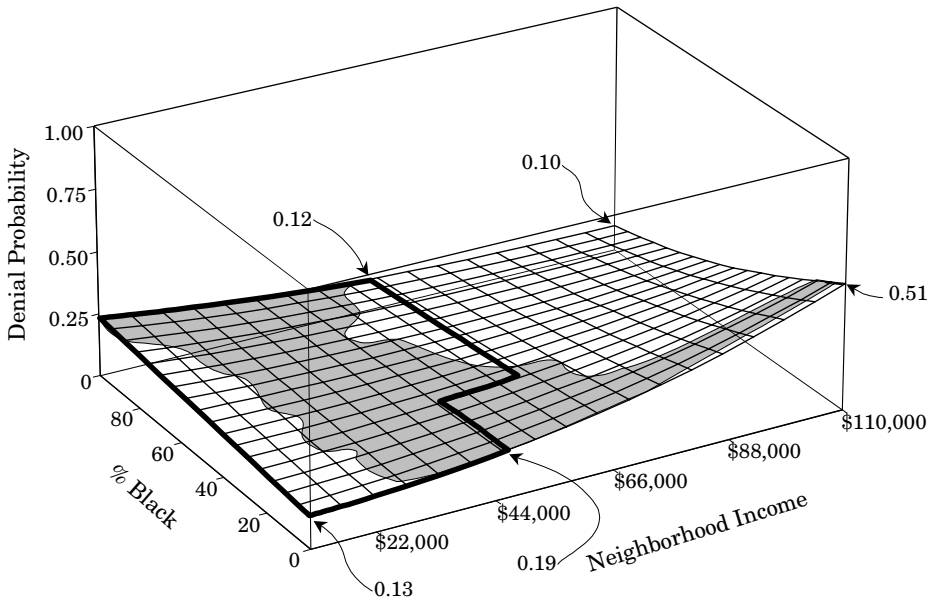
³⁵ This result is even more pronounced if we do not consider the applicants' credit profile. The analogous map constructed from a model that excludes the credit history instrument suggests that black applicants experience considerably higher than average denial probabilities (> 1.5 times as high) in all but a few portions of the study area.

Figure 2. Predicted Probabilities of Loan Denial for White Applicants



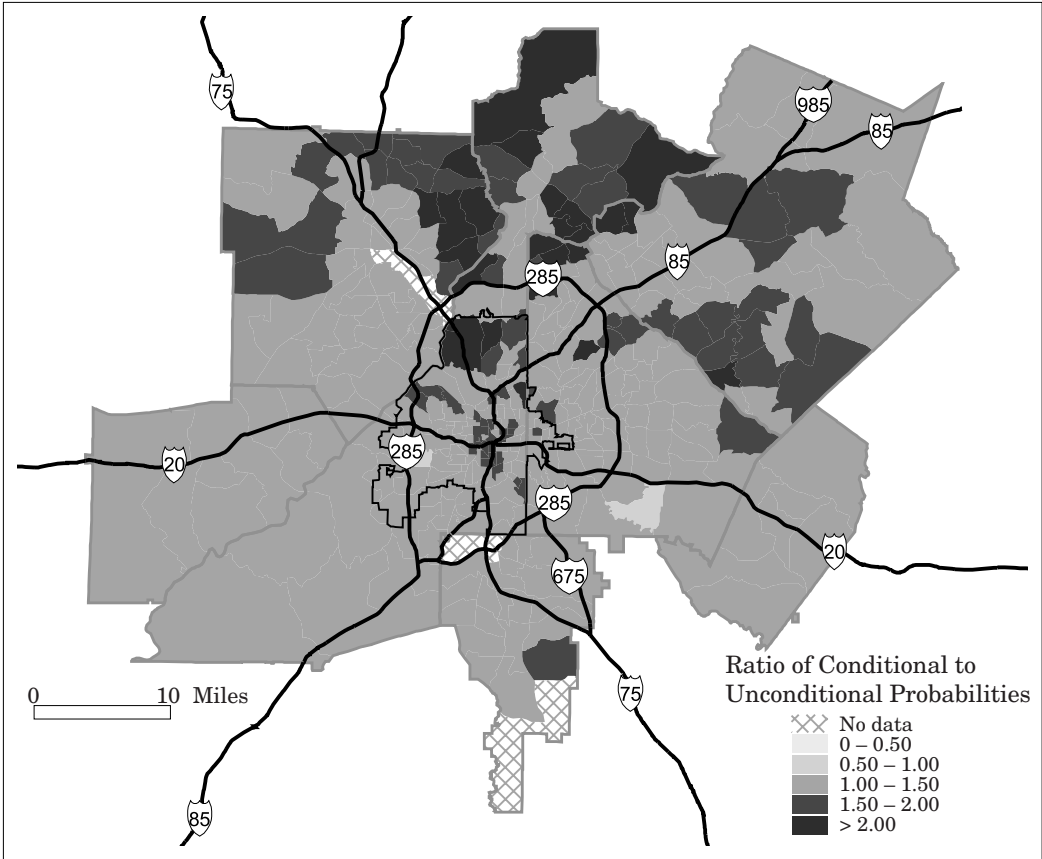
Note: Height of the surface represents the predicted probability of loan denial for an average applicant, calculated from a loan denial probability model that incorporates interactions between applicant’s racial identity and variables describing neighborhood income and neighborhood percentage black (see table 4, model 3). Shaded portions of the diagram represent combinations of tract income and percentage black actually present in the study area. Tracts in the area bounded by the box qualify as underserved according to GSE standards.

Figure 3. Predicted Probabilities of Loan Denial for Black Applicants



Note: Height of the surface represents the predicted probability of loan denial for an average applicant, calculated from a loan denial probability model that incorporates interactions between applicant’s racial identity and variables describing neighborhood income and neighborhood percentage black (see table 4, model 3). Shaded portions of the diagram represent combinations of tract income and percentage black actually present in the study area. Tracts in the area bounded by the box qualify as underserved according to GSE standards.

Figure 4. Geographic Distribution of Predicted Loan Denial Probabilities: Black Applicants

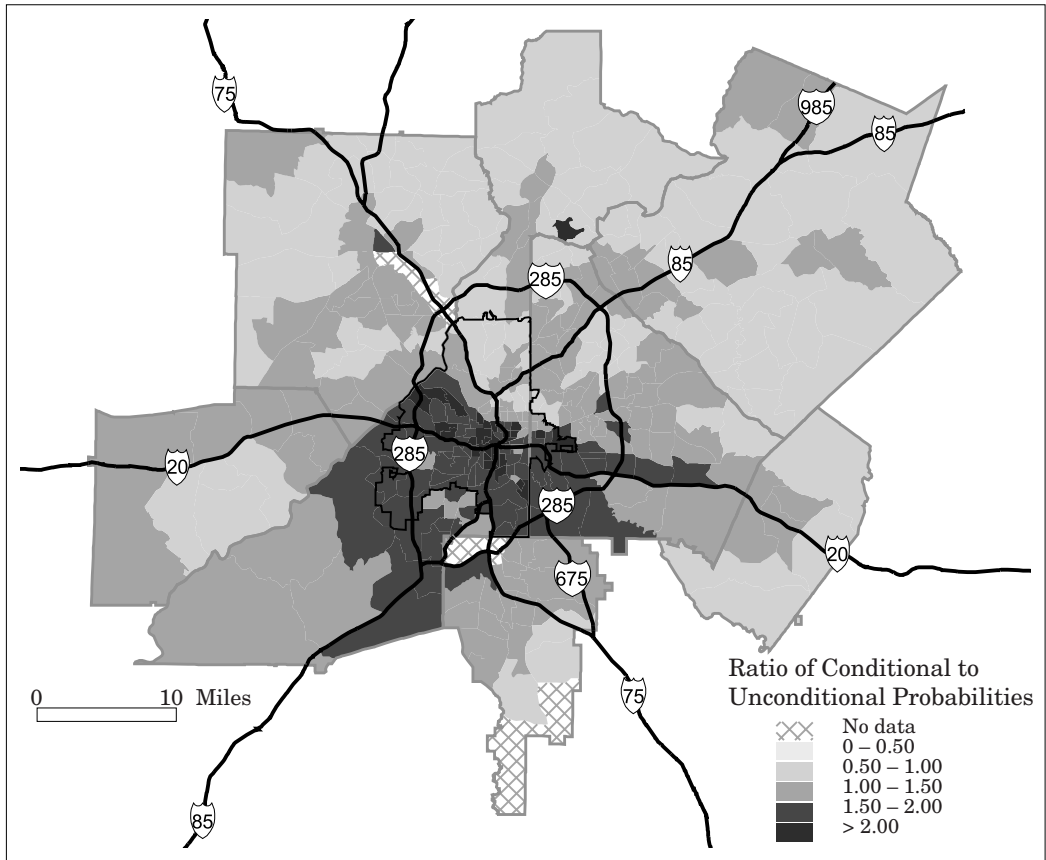


Note: Darkness of the shading indicates the predicted probability of loan denial for an average applicant, calculated from a loan denial probability model that incorporates interactions between applicant’s racial identity and variables describing neighborhood income and neighborhood percentage black (see table 4, model 3).

ban periphery of the area, in northern Fulton County, Gwinnett County, and Cobb County. The areas of white advantage that lie within the perimeter freeway are in higher-income, “trendy” neighborhoods such as Buckhead.

Racial disparities in denial probabilities predicted by the model within neighborhoods are particularly striking. In many of the same neighborhoods where white applicants enjoy relatively low denial probabilities, otherwise identical black applicants face rejection probabilities 1.5 or even 2 times the average for all borrowers in the study area. Two additional maps (figures 6 and 7) directly address racial disparities in loan denial probabilities for each tract in the study area. Figure 6 depicts the ratio of black-to-white predicted denial probabilities. Progressively darker shades identify neighborhoods in which denial probabilities are substantially higher for black than for comparable white applicants. Predicted black denial probabilities are at least twice those for whites in a broad swath of predominantly white suburbs on the north side. Conversely, note that even though predicted denial probabilities are lower for blacks than whites in many neighborhoods—mostly in inner-city, predominantly black low-income areas on the southwest side of the city—the ratio of white-to-black predicted

Figure 5. Geographic Distribution of Predicted Loan Denial Probabilities: White Applicants



Note: Darkness of the shading indicates the predicted probability of loan denial for an average applicant, calculated from a loan denial probability model that incorporates interactions between applicant’s racial identity and variables describing neighborhood income and neighborhood percentage black (see table 4, model 3).

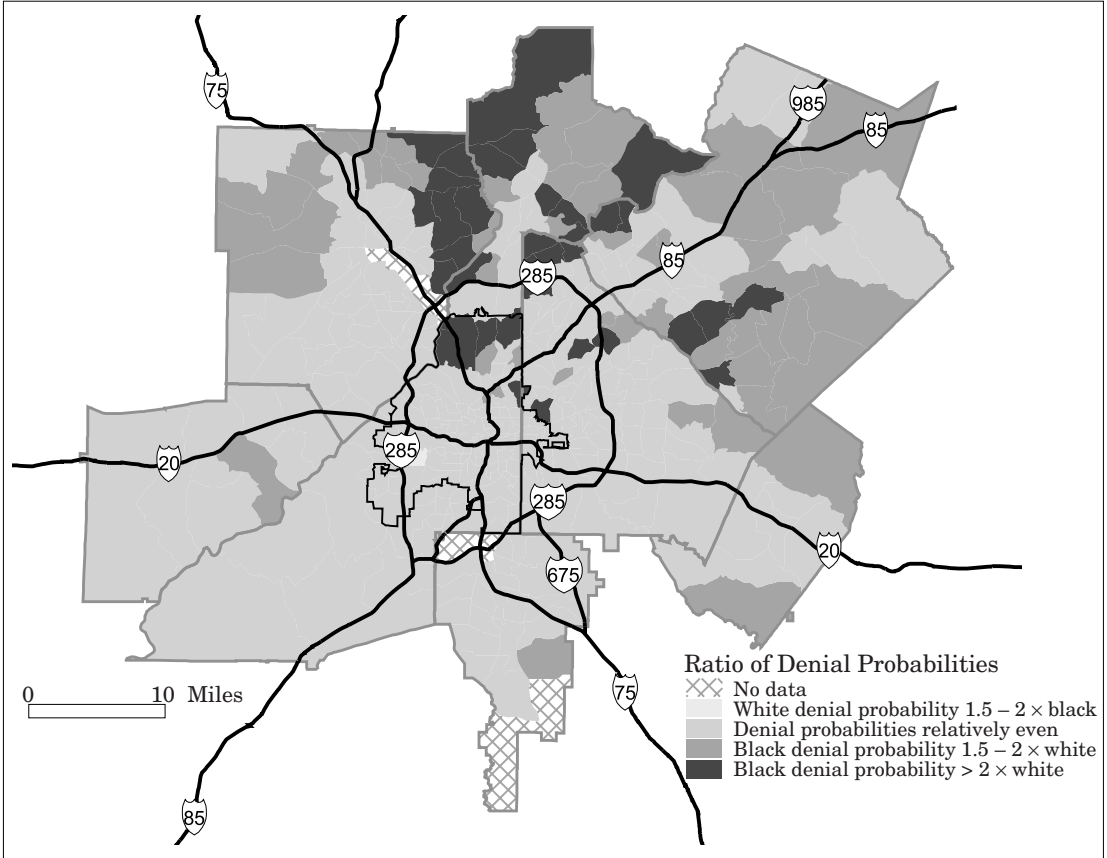
probabilities exceeds 1.5 in only one tract. Figure 7 depicts odds ratios.³⁶ Figure 7 strongly resembles figure 6, confirming that the geographic patterning of racially disparate mortgage lending outcomes is not an artifact of the settings chosen to calculate predicted probabilities.

Discussion

Our empirical analysis demonstrates persistent racial disparities, regardless of the additional statistical controls included. This evidence also clearly suggests that racial geography—the traditional concern of the voluminous literature on redlining—influences mortgage lending decisions, though not in a simplistic manner. The most commonly used statistical test for racial redlining (table 4, model 2) yields a coefficient that is small in magnitude, statistically insignificant, and of the wrong sign. Enhanced models suggest, however, that racial geography conditions the impact of race as an individual-level marker. Moreover, our analysis

³⁶ Odds ratios present a methodological advantage over predicted probabilities because they do not require that the analyst supply values for the independent variables (see Liao 1994).

Figure 6. Ratio of Black-to-White Loan Denial Probabilities



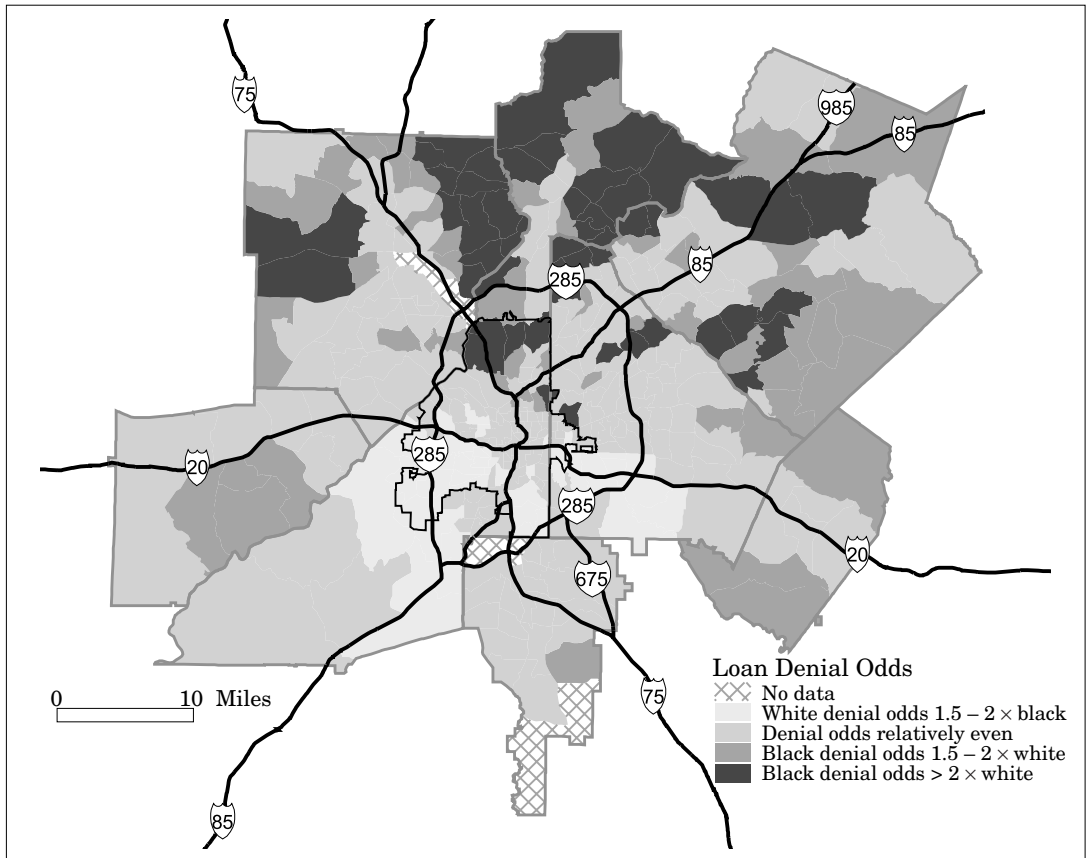
Note: Darkness of the shading indicates the predicted probability of loan denial for an average applicant, calculated from a loan denial probability model that incorporates interactions between applicant’s racial identity and variables describing neighborhood income and neighborhood percentage black (see table 4, model 3).

reveals that in Atlanta, geographic variations in neighborhood income matter as much as variations in neighborhood percentage black in explaining lending decisions.

To interpret the complex interactions between individual and geographical processes and outcomes, we must recall the four sets of factors responsible for contingent lending: preference-based discrimination against all applicants in minority and low-income neighborhoods (Ross and Yinger’s process-based redlining), the inadvertent anchoring of black applicants to traditionally segregated neighborhoods via spatially targeted housing policy and lending programs, preference-based discrimination against black applicants in white neighborhoods, and economically motivated discrimination stemming from fears of neighborhood racial transition.

Our empirical results are consistent with notions of process-based redlining: Predicted denial probabilities rise for black and white applicants in the lowest-income minority neighborhoods. The nature of our data prevents us from determining the underlying reasons for this increase. Indeed, omitted variables may account for some of this finding if we assume that applicants in these neighborhoods are generally poor credit risks in ways that the HMDA data do not capture. Lower denial probabilities for black applicants relative to white applicants may emerge

Figure 7. Loan Denial Odds for Black Applicants Relative to White Applicants



Note: Darkness of the shading indicates the predicted odds of loan denial for an average applicant, calculated from a loan denial probability model that incorporates interactions between applicant’s racial identity and variables describing neighborhood income and neighborhood percentage black (see table 4, model 3).

for several reasons. First, the positive benefits of spatially targeted policies and programs may apply disproportionately to minority applicants. Second, however, as we suggest above, there may be positive self-selection by minority applicants motivated to pursue homeownership through the rigorous requirements of some of the targeted homeownership programs. Either way, any benefits for black applicants are not sufficient to completely eliminate the underlying patterns consistent with redlining arguments.

The results are also somewhat consistent with our suspicion that spatially targeted policies and programs inadvertently anchor minority applicants to traditionally minority neighborhoods. Note that black denial probabilities reach their lowest values in moderate- and middle-income, predominantly minority neighborhoods and in the lowest-income, predominantly white neighborhoods—all of which qualify as underserved according to GSE standards. Moreover, black denial probabilities increase notably in neighborhoods outside GSE spatial targets, and substantially exceed white denial probabilities in nontargeted neighborhoods. We interpret these patterns as evidence of benefits for minority applicants, but benefits that are constrained on one side by evidence of continuing redlining in the poorest minority neighborhoods and on the other side by evidence that benefits do not extend beyond the spatial targets.

Our results are partially consistent with the argument of preference-based discrimination against black applicants seeking properties in predominantly white neighborhoods. There are many predominantly white neighborhoods in which denial probabilities are not appreciably higher for black than for white applicants—there are even some in which white denial probabilities exceed those for black applicants. Nevertheless, as we suggested above, preference-based discrimination against blacks in white neighborhoods may be further conditioned by neighborhood income. Our models are entirely consistent with that notion, as evidenced by the sharp increase in black denial probabilities associated with increases in neighborhood income levels.

The fourth notion of economic benefits derived from discriminating against black applicants in high-income neighborhoods receives support from our analysis. As suspected, black denial probabilities are highest in high-income, predominantly white neighborhoods. The nature of our data, however, prevents us from being able to distinguish between preference-based discrimination conditioned on the interaction of neighborhood racial composition and neighborhood income, and economically motivated discrimination stimulated by the risk to large loans held in portfolio.

Like every other study that uses public-release HMDA mortgage lending data, our analysis is subject to well-known limitations that preclude conclusive or definitive interpretations regarding discrimination. One of the most publicized forms of potential omitted-variable bias stems from the lack of credit history information. Including a credit history instrument helps to minimize that bias, and every model presented in this article was also replicated without the instrument to explore the robustness of the findings. Overall, the instrument performs as we expected based on published research that includes actual credit history information; its inclusion reduces the magnitude of racial identifiers, but does not eliminate their significance. More important for our analysis, the geographic contingency of the race effect appears with equal magnitude in all models, whether or not we include the credit history instrument.

The limitations of the HMDA data, however, extend beyond the lack of credit history information. As we mention above, there are alternative explanations for the observed geographically varying race–lending relationship demonstrated in our analysis that we are unable to evaluate because of information not available in our data. First, high denial probabilities for black applicants in high-income neighborhoods may be the incidental spatial outcome of differential treatment triggered by the application for a jumbo loan. Second, black applicants seeking expensive properties in high-income, predominantly white neighborhoods may be more asset-deprived than black applicants in any other type of neighborhood and white applicants at the same income level in the same neighborhoods. As we mention above, HMDA evidence, limited though it is, does not support the suggestion that black applicants are denied more frequently because of a lack of cash. Still, we need wealth and purchase price information to directly address that possibility.

Even though we cannot rule out these alternative interpretations because of data limitations, we contend that the interpretation we offer is reasonable. Consider what is logically necessary for our estimates of the interaction terms to be biased upwardly in magnitude. Black applicants for mortgages backed by properties in the highest-income, predominantly white neighborhoods would have to exhibit characteristics systematically associated with higher default risk than would white applicants in the same neighborhoods or black applicants in

other neighborhoods. Moreover, these characteristics would have to be observable to lending institutions. In a sense, high-income blacks seeking to purchase homes in high-income white neighborhoods would have to be a self-selected sample of disproportionately high default risk applicants. We consider that to be unlikely; indeed, we suspect that black applicants in high-income white neighborhoods in many ways may be better credit risks. By the time they meet a loan officer, they already have endured considerable discrimination in the housing search process (recall that Yinger [1995] reports that the probability of encountering discrimination in the search process increases significantly with the intensity of the search) and any pre-market screening that lending institutions may apply.³⁷ Ironically, this explanation is far more appropriate in understanding the results for whites seeking homes in the inner city. Given the geographic logic of racialized housing demand,³⁸ it is relatively rare that whites seek to purchase housing in minority neighborhoods unless they are seeking housing with lower up-front costs because of financial inability to secure similar yet more expensive housing in white neighborhoods. Moreover, although the models attempt to control for credit history problems, which is a reason for denial disproportionately characteristic of black applicants, our analysis does not account for denial codes disproportionately reported for white applicants.

Conclusion

Published more than a decade ago, “The Color of Money” was an influential analysis of racial disparities in mortgage lending in Atlanta. The 1990s brought substantial restructuring of the mortgage lending industry and regulatory changes that resulted in increased lending to minorities and some optimism for declining discrimination. Nevertheless, substantial racial geographic disparities persist in Atlanta, as well as in other cities (Immergluck 1998; Kaplan 1996; Torres et al. 2000; Wyly and Holloway 1999). The purpose of this article is to extend the original “Color of Money” and a recently published replication (Wyly and Holloway 1999) in two ways. First, a multivariate analysis of applicant-level data allowed us to examine racial disparities that persist after accounting for the varied characteristics of prospective borrowers. Second, we explicitly developed and evaluated a hypothesis of geographic contingency in the race–lending relationship. Engaging debates about discrimination in the applied economics literature, we suggest that the processes governing underwriting decisions are geographically contingent for a variety of reasons. Moreover, the outcomes of mortgage lending decisions are geographically contingent.

Our empirical analysis supports the contingency hypothesis: It simply is not possible to understand contemporary racial inequalities in housing finance without analyzing the interaction between applicant race and neighborhood context. The barriers faced by minority loan applicants vary considerably across different parts of the metropolis. “Classical” redlining per-

³⁷ The geography of mortgage demand cannot account for our findings. Almost a third (29.4 percent) of black applications are in predominantly white neighborhoods (> 80 percent white); almost a quarter (22.9 percent) of all black applications are in relatively high-income, predominantly white neighborhoods (top 2 quintiles of neighborhood income—> \$45,600 median income); and more than a tenth (10.5 percent) of all black applicants are in the top-income quintile (> \$56,600 median income), predominantly white neighborhoods.

³⁸ In contrast to the geography of black mortgage demand, 43.5 percent of white applicants are located in predominantly white neighborhoods in the top quintile of neighborhood income. Barely 1 percent (1.2 percent) of white applicants seek properties in predominantly black (> 80 percent black) neighborhoods.

sists in the poorest minority neighborhoods, and targeted policies provide spatially limited opportunities for minorities in other LMI neighborhoods. African Americans face the most severe barriers to mortgage credit in predominantly white, high-income neighborhoods.

These findings shed new light on long-standing debates that have been plagued by mixed empirical evidence. Although “a substantial body of objective and credible statistical evidence strongly indicates that discrimination persists” (Turner and Skidmore 1999a, 2), its manifestation is by no means universal. Motivations for differential treatment, and business practices implicated in disparate impact discrimination are geographically contingent; and studies that fail to test for contingency will yield mixed or contradictory results on redlining and discrimination. Let us be absolutely clear: “Contingency” does not imply that mortgage discrimination is incidental, scattered, or purely local. On the basis of the mass of evidence, discrimination remains a fundamental national facet of the enduring “American dilemma” of racism (Boger and Wegner 1996; Myrdal 1944) and thus requires a coordinated federal commitment that extends the record achieved in the Fair Lending Initiative launched in early 1993 (see Vartanian et al. 1995). Public policy, along with community activism and restructuring of the housing finance sector, has helped to reduce discrimination and broaden access to mortgage credit in the 1990s. This progress has been spatially and institutionally uneven, however, and thus coexists with deeply entrenched processes of discrimination in a complex urban landscape of housing opportunities and barriers.

Geographically contingent lending discrimination requires policy interventions and research agendas attuned to the racial political economy of contemporary metropolitan America. Continued federal vigilance against discrimination is essential to ensure that the long-standing national policy commitment to homeownership provides genuine opportunities for wealth building and upward mobility in a society in which race itself is being redefined and contested—even as historically entrenched lines of inequality persist. But variations within metropolitan areas are also critical. Our analysis of Atlanta supports three specific policy recommendations. First, it is necessary to strengthen efforts to open credit markets in the lowest-income minority neighborhoods, where barriers are considerable for both white and black applicants. Diligent enforcement of the Community Reinvestment Act and other antiredlining measures should be balanced with safeguards against gentrification. Second, fair housing enforcement should focus on the possibility that lending practices exclude qualified minorities from the highest-income white neighborhoods. The individual and societal benefits of rising minority incomes are likely to hinge on the success of challenges to the racial exclusion of affluent vanilla suburbs. Third, fair lending audit tests should incorporate theories of contingency and examine differential lender treatment of minorities across the full range of household incomes across a full range of neighborhood contexts.

We conclude with the scholar’s familiar call for further research. The recommendation we make is not made lightly. The literature has been enriched by several excellent reviews that attempt to forge a consensus on issues of lending discrimination (e.g., LaCour-Little 1999; Ladd 1998; Turner and Skidmore 1999b; Yinger 1995). Even so, feedback we received on our geographic contingency arguments offers diametrically opposed interpretations, thus revealing a deep vein of controversy. Some analysts take the persistence of discrimination as given and see the notion of contingency as a threat to federal antidiscrimination policy; others recite economic theory and the many data limitations to dismiss any claim of discrimination (contingent or otherwise) as biased and unscientific. Reconciling these viewpoints requires that we move beyond the current slate of easily dismissed HMDA-based studies and studies

reliant on limited proprietary data from individual lenders. We sorely need an enhanced and expanded replication of the Boston Fed study across multiple metropolitan areas, including those with a sizable minority middle class attempting to gain access to the benefits of high-value suburban neighborhoods. This endeavor will yield valuable insights for policy and contribute to industry efforts to reach new underserved markets. This replication will also inform deliberations about expanding information in the public-release HMDA files and strengthen the emerging body of research on the subprime market and predatory lending—particularly in the home improvement and refinance sectors.

Ultimately, the societal consequences of the long-standing U.S. commitment to homeownership depend critically on efforts to eliminate racial discrimination in housing finance. Although the past decade has brought laudable progress, improvements remain limited and spatially uneven. Understanding the geographically contingent nature of lending is an important and necessary step toward providing a relevant theoretical framework for research and implementing effective policy that achieves further gains in sustainable, equitable homeownership.

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