# Illuminating a Dark Side of the American Dream: Assessing the Prevalence and Predictors of Mortgage Fraud across U.S. Counties[1]

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Using novel county-level data, the authors document that nearly 25% of residential mortgage loans originated between 2003 and 2005 in America contained one or more indications of mortgage fraud but also that rates were highly variable across counties. Multivariate regression models reveal that rates of mortgage fraud were higher in areas with greater loan volumes, a larger share of loans originated by independent mortgage companies, elevated rates of preexisting property crime, and higher levels of black-white racial segregation; it was less prevalent where government-sponsored enterprises purchased a larger share of the loans sold in secondary mortgage markets. The findings are most consistent with classic and contemporary anomie theories and perspectives that highlight the geographic targeting of selected housing markets with loan products and tactics that provided fertile ground for mortgage fraud. The authors discuss the implications of these patterns for developing a more comprehensive understanding of contemporary spatial inequalities.

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## INTRODUCTION

Housing patterns have long conjured images of both social progress and social inequality (Wright 1981; Squires 1994; Williams, Nesiba, and McConnell 2005; Hyra and Rugh 2016). For much of the past century, buying a home has been described and promoted as a highly valued dimension of attaining the "American Dream" (Rohe, Van Zandt, and McCarthy 2002). Compelling empirical evidence has accumulated that links home ownership to a variety of positive outcomes for both individuals and communities, including increased social mobility, higher levels of life satisfaction, improved health, increased political participation, and lower crime rates (Gilderbloom and Markham 1995; Rossi and Weber 1996; Rohe and Basolo 1997; Krivo and Peterson 2000). Alongside these favorable outcomes, however, significant individual and community disparities in access to mortgage financing for high-quality housing and in exposure to predatory lending practices have been documented (Squires 2003; Roscigno, Karafin, and Tester 2009; Wyly et al. 2012). These disparities have, in turn, contributed to and reinforced inequalities in a wide variety of other social domains (Massey and Denton 1993; Dietz and Haurin 2003; Rugh and Massey 2010; Rugh, Albright, and Massey 2015; McCabe 2016).

The 2000s housing boom and bust in America serves as another vivid reminder of the significant and varied social consequences that can accrue from major shifts in the housing market. On the heels of strong appeals by Presidents Bill Clinton and George W. Bush about the virtues of expanding access to mortgage credit, overall rates of home ownership increased and longstanding racial gaps in mortgage lending and home ownership were reduced during the late 1990s and early 2000s (Williams et al. 2005; Kochhar, Gonzalez-Barrera, and Dockterman 2009). The housing boom also has been linked to reductions in exposure to concentrated poverty, especially among low-income blacks, for whom the probability of moving from a high-poverty to a low-poverty neighborhood increased considerably during the period (Wagmiller 2011). Additionally, many Americans cashed in on large profits associated with rapidly appreciating equity and speculation in real estate markets, which increased overall wealth (Sowell 2009; Zitrin 2010). However, the foundation of these trends rested on questionable, poorly understood, and loosely regulated financial arrangements (Black 2009; Lounsbury and Hirsch 2010; Smith 2010; Fligstein and Goldstein 2011), and by the mid-to-late 2000s several negative by-products of the housing boom had emerged as significant social problems. Many studies have documented the widespread occurrence of, and inequalities associated with, predatory lending practices (e.g., Bostic et al. 2008; Gupta, Sharma, and Mitchem 2010) and subprime lending (Bond and Williams 2007; Been, Ellen, and Madar 2009; Hyra et al. 2013; Hwang, Hankinson, and Brown 2015) during the housing boom, and others have illuminated the sociological causes and consequences of the foreclosure crisis that followed it (Immergluck and Smith 2006; Rugh and Massey 2010; Hall, Crowder, and Spring 2015; Rugh et al. 2015). In this article we focus on another adverse feature of the housing boom—the widespread proliferation of mortgage loan fraud—that was a critical component of what unfolded but has received relatively little attention within sociology.

Mortgage fraud is the "intentional misstatement, misrepresentation, or omission by an applicant or other interested parties, relied upon by an underwriter or lender to fund, purchase or insure a loan" (Federal Bureau of Investigation [FBI] 2007). Mortgage fraud during the housing boom has been estimated to have cost American taxpayers billions in direct losses (Mortgage Bankers Association 2007; Financial Crimes Enforcement Network [FinCEN] 2008; Reuters 2008; Financial Crisis Inquiry Commission 2011). Additionally, evidence has mounted that mortgage fraud contributed significantly to the foreclosure crisis (Mian and Sufi 2015; Griffin and Maturana 2016) and the Great Recession (Tomaskovic-Devey and Lin 2011; Pontell and Black 2012). Further, by influencing the spatial footprint of foreclosure (Baumer, Arnio, and Wolff 2013), mortgage fraud is linked to several related adverse social consequences, including reductions in neighborhood residential quality, civic participation, racial integration, financial security, and public safety (Baumer, Wolff, and Arnio 2012; Williams, Galster, and Verma 2014; Cui and Walsh 2015; Hall et al. 2015; Rugh et al. 2015).

Though classic and contemporary sociological scholarship has been key to advancing understanding of many forms of fraudulent activity in other eras (e.g., Merton 1938; Sutherland 1940; Cressey 1950; Pontell, Jesilow, and Geis 1982; Calavita and Pontell 1991, 1993; Tillman and Indergaard 1999; Steffensmeier, Schwartz, and Roche 2013), much less attention has been devoted to mortgage fraud during the early 2000s housing boom. The harms caused by the fraudulent misrepresentation of mortgage-backed securities by some lenders and Wall Street investment banks have been documented (Buhl 2011; Kahn 2013), and some scholars have offered insightful analyses of the structural arrangements that stimulated such actions (Friedrichs 2010; Smith 2010; Fligstein and Goldstein 2011; Fligstein and Roehrkasse 2016). There also have been rich ethnographic accounts of selected housing markets that illuminate some of the key conditions that promoted fraudulent actions within them (Nguyen and Pontell 2010, 2011). Yet, while recent research has begun to apply creative techniques to estimate the extent and consequences of fraud in privately securitized loans, including borrower income inflation on loan documents (Ben-David 2011; Jiang, Nelson, and Vytlacil 2014; Mian and Sufi 2015), the concealment of second liens (Piskorski, Seru, and Witkin 2015; Griffin and Maturana 2016), and suspected appraisal inflation and misstatements about occupancy status (Griffin and Maturana 2016), there has been little systematic attention paid to the social structural conditions that may have contributed to the apparent proliferation of mortgage fraud during the housing boom.

Drawing from a novel data set, the present study contributes to the social science literature by documenting the prevalence, nature, and geographic distribution of mortgage fraud during the period and by illuminating the conditions that were most germane to fueling especially high levels of fraud in some communities. Our analysis uncovers substantial county-level differences in mortgage fraud across America during the period, which we see as an especially intriguing sociological puzzle. We glean insights from the theoretical literature on crime, stratification, and community inequality to identify factors that may be relevant to explaining the observed geographic variability in mortgage fraud, and we assess their impact by integrating county-level data on housing market conditions and a variety of other social, economic, and demographic attributes. Conforming to narratives highlighting the potential downside of commission-based origination systems, the analysis shows higher levels of fraud in areas where a larger volume of loans was processed. Net of county differences in loan volumes and many other factors, however, we find that mortgage fraud was most prevalent during the early 2000s housing boom in counties with especially high levels of black-white racial segregation and where independent mortgage companies (IMCs) originated a larger share of loans, which is in line with perspectives that emphasize spatial inequalities associated with the targeting of vulnerable communities with questionable lending practices (e.g., Rugh and Massey 2010; Galster 2012; Wyly et al. 2012). The results also reveal support for selected components of classic and contemporary anomie theories. Most notably, we find that employment/income mortgage fraud was more common in counties in which residents had fewer economic means for purchasing homes, which is consistent with Merton's (1938) anomie theory about the conditions that may stimulate fraudulent actions. Additionally, as anticipated by Cloward and Ohlin's (1960) framework, overall levels of mortgage fraud during the period were greater in areas with higher rates of preexisting property "street" crime, and as implied by Messner and Rosenfeld's (1994, 2012) institutional anomie theory, they were lower in places in which government-sponsored enterprises (GSEs) purchased a larger share of the loans sold in secondary mortgage markets.

Below, we elaborate further on the empirical patterns that emerged in our study; but before doing so, we delineate some important conceptual and measurement issues associated with assessing mortgage fraud during the housing boom and we describe in greater detail the overall prevalence and nature of mortgage fraud revealed by the data used for study. We then outline the theoretical foundations for why rates of mortgage fraud may have varied so substantially across counties during the housing boom and describe the data and methods used to evaluate the relevance of a wide range of relevant factors.

We close the article by describing the findings and discussing their implications for extant theory and future research.

## BACKGROUND

### The General Landscape of Contemporary Mortgage Fraud

As the definition provided above implies, although mortgage fraud often yields adverse consequences for many of the parties associated with the transaction, the primary victim in most instances is the lender.[2] The perpetrators can include borrowers from virtually all walks of life, including run-of-the-mill home buyers, mortgage industry personnel, and organized criminal networks (Fulmer 2010). Most often, mortgage fraud involves complicity from both borrowers and mortgage industry participants (FinCEN 2008), which, as elaborated below, makes it a unique form of illegal conduct that blends elements of traditional offending and white-collar crime. The typical profile of victims and perpetrators involved in mortgage fraud distinguishes it from related outcomes, such as predatory lending practices. The latter encompass a heterogeneous mix of actions (e.g., equity stripping, loan flipping, and excessive cost/fee loans), but in contrast to mortgage fraud, it exclusively involves deceptive practices by mortgage lending and servicing representatives against borrowers (Bostic et al. 2008). Predatory lending practices often serve as an important facilitator to mortgage fraud (Nguyen and Pontell 2011; Fligstein and Roehrkasse 2016), but mortgage fraud also frequently occurs without predatory lending practices, and these two sets of actions are conceptually distinct.

The U.S. government has distinguished between two categories of fraudulent activity in mortgage transactions: fraud for housing (or property) and fraud for profit (FBI 2007). Fraud for housing refers to situations in which a mortgage loan is originated under false pretenses for the apparent purpose of attaining home ownership. It is most frequently accomplished by misstating income, debts, or employment status, which sometimes is accompanied by the submission of fraudulent supporting documents and/or identification. The objective of fraudulent acts in such cases usually is to enable borrowers to secure a mortgage loan for which they might not otherwise qualify or for which the terms are much more favorable (e.g., by stretching the truth about assets and debts), but these acts of fraud also enhance the commissions of

[2] This is the case for fraud that occurs during the application and origination stages of the mortgage transaction process, which form the focus of the present study. As Fligstein and Roehrkasse (2016) document, the nature of postorigination fraud, especially related to the mortgage securitization process, encompasses a distinct set of activities that have potentially adverse consequences for financial firms, borrowers, and individual investors.

mortgage brokers and other industry personnel who often help facilitate it (e.g., by embellishing employment histories, inflating salaries, and fabricating financial documents and identities on behalf of borrowers; Zitrin 2010). The FBI contrasts these cases from fraud for profit schemes, where the primary objective is to commit fraud for purposes of gaining illicit proceeds from the sale of one or more properties. Some of the fraudulent actions just noted (e.g., misstating assets and debts) are used to inflate profits obtained from mortgage transactions (FinCEN 2008). However, more common examples of mortgage fraud for profit include inaccurate statements about occupancy intentions, appraisal inflation, identity theft/misrepresentation, straw purchases, and illegal manipulation of sale prices up (flipping) or down (flopping) (Fulmer 2010; FBI 2011).

In practice it is often difficult to discern the specific motivations (e.g., property or profit) that give rise to mortgage fraud in a given case, or even who served as the primary culprit(s). In fact, a comprehensive analysis of Suspicious Activity Reports (SARs) submitted to the FBI in 2006–7 by participating lenders revealed that there frequently is evidence of both "property" and "profit" motivations in a single instance of mortgage fraud (FinCEN 2008). That same analysis also revealed that, in contrast to common characterizations of mortgage fraud as exclusively a white-collar crime committed by mortgage industry representatives or those on "Wall Street" (Carswell and Bachtel 2007), in the majority of instances the detected fraud involved multiple parties working in tandem, and most often both a borrower and a mortgage broker (FinCEN 2008). Thus, while there is compelling evidence that many lenders and investment banks played an important role (Touryalai 2012; Kahn 2013; Raymond 2013; Fligstein and Roehrkasse 2016) and that mortgage industry representatives often were directly involved (Nguyen and Pontell 2011), a global view of the various forms of conduct involved in mortgage fraud during the housing boom yields a more eclectic portrait, with persons from all walks of life implicated as perpetrators and with significant complicity among industry professionals and loan applicants (see also Griffin and Maturana 2016).

## The Prevalence of Mortgage Fraud during the Early 2000s Housing Boom

How prevalent was mortgage fraud in the United States during the 2000s housing boom? What forms were most prevalent? And where were rates of mortgage fraud highest? Addressing these questions has proven to be highly challenging because America lacks a comprehensive, centralized mortgage fraud data collection system. The U.S. government routinely gathers data on a very large share of mortgage loan transactions conducted in the nation through requirements associated with the Home Mortgage Disclosure Act

(HMDA), but that effort does not include an assessment of the fidelity of the information provided. This void has been filled by a wide variety of data-gathering systems, each with strengths and weaknesses.

The two most commonly referenced sources of data on mortgage fraud are the SARs recorded by the U.S. Department of the Treasury's FinCEN and the Mortgage Fraud Index (MFI) generated from LexisNexis's Mortgage Industry Data Exchange (MIDEX). The FinCEN data provided state-level counts of mortgage fraud cases discovered and reported by federally insured lenders during the housing boom. LexisNexis's MFI represents the ratio of the share of "verified" instances of mortgage fraud reported by MIDEX subscribers that occurred in a given area to the share of mortgage loans originated in an area in the preceding year, as recorded in the HMDA data (Mortgage Asset Research Institute [MARI] 2008, p. 13).[3] LexisNexis publishes MFIs for selected states and metropolitan statistical areas (MSAs), usually limited to the top 10 ranked areas. While the FinCEN and LexisNexis data are valuable sources of information about mortgage fraud, they also possess significant limitations for studying mortgage fraud during the housing boom. Neither source yields easily interpreted absolute estimates of mortgage fraud or offers the capacity to assess geographic variability in a comprehensive manner, especially within states. Additionally, in both sources, cases of fraud allocated to a given year may have occurred several years prior to the date on which they were investigated or reported by lenders, which appears to introduce significant measurement error for annual estimates.[4] Perhaps most important, the estimates derived from these sources are based on participating lender reports of known fraudulent activities. Though MIDEX subscribers appear to have represented a broad spectrum of lenders during the housing boom (MARI 2008), independent mortgage brokerage firms were not required by law to submit SARs. Further, by restricting the definition of mortgage fraud to instances that have been discovered and/or verified by lenders, these sources likely exclude a significant amount of fraud. The reasons are both that verified instances of mortgage fraud may not be readily apparent to lenders without intensive investigation and that there often are financial disincentives (e.g., increased loan loss reserves and potential insurance coverage losses) for lenders to devote substantial resources to engaging in such evaluations.

[3] Verified fraud means that a financial institution has determined that, in light of a thorough investigation, it would not have originated the loan in question because of indications of fraud (MARI 2008).

[4] It is unclear how problematic this temporal mismatch was during the housing boom, but more recent data suggest that for a large majority of cases, there is a relatively long lag (e.g., one to four years) between the occurrence of fraud in mortgage transactions and the discovery and reporting of such fraud by lenders (FinCEN 2013; LexisNexis 2014).

During the early 2000s housing boom, data on the fidelity of information stated on mortgage loan applications also were captured directly by two private providers of proprietary real estate data and analysis: CoreLogic and Interthinx.[5] Many large- and small-volume lenders across the nation used computerized risk assessment systems designed by these companies to screen mortgage loan applications for indicators of possible mortgage fraud. As elaborated below, these automated systems compare the information provided on loan applications with data from a wide variety of other sources to identify possible instances of fraud. Lenders frequently relied on these systems to comply with quality assurance requirements of GSEs (e.g., Fannie Mae and Freddie Mac) and other institutional investors that purchase mortgages in the secondary market, but they also used them to screen loans at the prefunding stage for purposes of making approval decisions and mitigating possible financial losses associated with underwriting a loan that possesses a high level of risk for fraud. The specific sampling protocols that governed lender screening during the housing boom are not well documented, but to maintain status as an approved GSE seller and servicer of residential home mortgages, lenders were required to have an established quality assurance system directed at verifying the fidelity of information stated on loans that included an assessment of a random sample of at least 10% of the loans they originated or serviced (see, e.g., Fannie Mae 2002 and 2006 Selling Guides, http://www.allregs.com/tpl/public/fnma_freesiteconv_tll.aspx). Representatives from CoreLogic and Interthinx with whom we consulted suggested also that many of their clients often used random sampling to identify loans for discretionary screening at the prefunding stage because doing so limited the costs and time associated with quality assurance and increased the chances of identifying loss potential across a wide spectrum of loans.

Like the SAR and MIDEX data, the fraud detection services provided by CoreLogic and Interthinx have been used to estimate levels of fraud for the nation and selected states during the housing boom (e.g., Interthinx 2011; CoreLogic, http://www.corelogic.com/products/loansafe-fraud-manager.aspx). The procedures and specific metrics used to express the prevalence of mortgage fraud differ across the two sources, but the underlying foundation of the estimates they report is the percentage of loans screened by lenders that are identified as being at "high risk" for containing fraudulent information. The measures generated from these systems have several attractive

[5] Complementing these efforts, some scholars recently have developed methods for indirectly estimating selected forms of mortgage fraud, including misstatements of income (Jiang et al. 2014; Mian and Sufi 2015) and illegal home price inflation (Ben-David 2011). Additionally, researchers have begun to work directly with proprietary mortgage loan data and other sources to infer suspected fraud (Piskorski et al. 2015; Griffin and Maturana 2016), but this research has been restricted to originated loans sold in the secondary mortgage market to private securitizers.

features for our study of mortgage fraud during the housing boom. In particular, they are based on assessments of very large samples of loans from lenders across the nation, they are not limited to loans identified and reported as fraudulent by lenders or detected by law enforcement officials, and they can be used to evaluate differences in levels of mortgage fraud across most local areas within American states.

We base our analysis on data captured through the proprietary mortgage risk mitigation system developed by Interthinx, which is now a part of First American Mortgage Solutions (obtaining comparable data from CoreLogic was cost-prohibitive). As we elaborate in appendix A, this system—aptly named FraudGUARD—uses a computerized algorithm developed by fraud detection experts to compare the integrity of data provided on a residential loan application with data from a wide variety of publicly and privately held sources to assess the likelihood that a loan contains fraudulent information. The estimates of mortgage fraud during the housing boom derived from FraudGUARD are based on a comprehensive catchment process that includes an assessment of millions of loans from lenders across the nation at different stages of the funding process, rather than being limited to cases of fraud detected by lenders or reported to law enforcement. Additionally, this system yields estimates of several distinct forms of mortgage fraud for local communities within states based on samples of loans that closely approximate the geographic distribution of loans independently reported in the HMDA data during the period (see app. A for a more detailed discussion of the external validity of the estimates of mortgage fraud generated by this data system).

Using the output from the computerized algorithms applied to lender-screened loans through FraudGUARD, Interthinx identifies four specific types of suspected mortgage fraud (i.e., property valuation, identity, occupancy, and employment/income). As defined by Interthinx (2011, pp. 9–12), property valuation fraud refers to instances in which property values are illegally "manipulated up (flipping) or down (flopping)" to increase the profit margin on a property resale. Identity fraud typically involves the use of fabricated identification documents and/or the use of a straw buyer with valid credentials in order to "hide the identity of the perpetrators and/or to obtain a credit profile that will meet lender guidelines." Occupancy fraud involves a false claim, usually by an investor, regarding the intention to occupy a purchased property, an action that can be instrumental in "obtaining a mortgage with lower down payments and/or interest rates." Finally, "employment/income fraud occurs when an applicant's employment status or income is misrepresented" (by the borrower, broker, and/or loan officer) for purposes of qualifying for a loan that might otherwise be unattainable. FraudGUARD gauges the probability that mortgage loans may include each of these forms of fraud by comparing details provided on applications for a given property with public and private financial, loan, and property transaction data, including information listed on multiple applications by the same borrower and/or applications from others for the same property.

The Interthinx data can be marshaled to compute an estimate of the overall level of mortgage fraud in America during the early 2000s housing boom. As shown in figure 1, on the basis of the parameters applied in FraudGUARD, 24.2% of the loans screened from 2003 through 2005 were deemed to potentially contain one or more indications of mortgage fraud. It is important to emphasize that estimates of absolute levels of fraud are contingent on the thresholds applied to discern the occurrence of fraud. This is especially pertinent for determinations of whether seemingly aberrant deviations on stated income or property valuation represent fraudulent actions rather than legitimate outliers. The specific thresholds used to generate the estimated levels of overall mortgage fraud reported in figure 1 are proprietary, but it is noteworthy that the Interthinx-based estimate approximates the 30.1% estimate of overall mortgage fraud (asset misrepresentation, appraisal inflation, and occupancy fraud) obtained by Griffin and Maturana (2016), which was generated using different procedures. The figure reported by Griffin and Maturana is based on a comparison of data provided on loans included in non-agency-mortgage-backed securities between 2002 and 2007 with independent data on home values and property transactions over the same period, and it uses parameters that are likely very similar to those applied in FraudGUARD.[6] In light of existing research that documents less mortgage fraud in loans purchased by GSEs (Mian and Sufi 2015), coupled with evidence we report below that reveals lower levels of fraud where lenders retained a larger share of loans they originated, it makes sense that the estimate we derive from the data compiled by Interthinx is slightly lower.

Figure 1 also displays estimates for the four separate types of fraud assessed through FraudGUARD during the period. According to the Interthinx data, the most prevalent forms of mortgage fraud risk for loans assessed between 2003 and 2005 were property valuation fraud (14.17%) and identity theft (8.98%). More modest levels were obtained for employment/income fraud (4.27%) and occupancy fraud (4.07%).[7] Like the overall mortgage fraud rate, the estimates for occupancy fraud and property

[6] Perhaps most notably, the 30.1% estimate reported by Griffin and Maturana (2016) is based on the assumption that appraisal values that are 20% or more above an independently derived estimate obtained from an automated valuation model are indicative of fraud. They report higher rates of appraisal inflation, and overall fraud, when using a 5% threshold; but given the substantial increase in home prices during the period in many parts of the country, we suggest that the 20% threshold is a more valid threshold for detecting suspected fraud.

[7] Mortgage loans can contain multiple forms of fraud, so the summation of the four forms of fraud risk displayed in fig. 1 does not equal the estimate shown for total fraud.

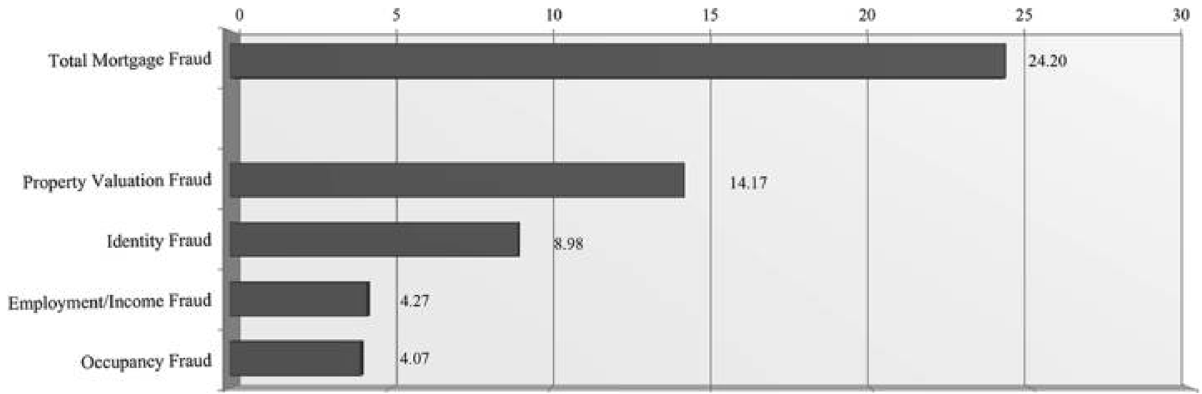


FIG. 1.—The prevalence and distribution of mortgage fraud in the United States, 2003–5. Data are from Interthinx, Inc.

valuation fraud are just slightly lower than estimates reported by Griffin and Maturana (2016) based on different data and methods applied to privately securitized loans. We could not locate comparable estimates of identity fraud or employment/income fraud in mortgage transactions during the housing boom. However, because of the increasing use of "stated" loan products (e.g., no income, no asset and no income, no job, no asset loans) during the period under investigation that did not require documentation (Engel and McCoy 2011), for which fidelity cannot be as readily assessed through a computerized algorithm, the Interthinx figure for employment/income fraud is likely a lower-bound estimate.[8]

The finding that almost one-quarter of residential mortgage loans originated in America between 2003 and 2005 were likely to have contained some form of fraudulent information affirms observations that the housing boom had a notable dark side (Sugrue 2009; Rugh and Massey 2010; Wasik 2012). Some observers have suggested that it was, in retrospect, a predictable outcome in light of prevailing structural arrangements in mortgage markets and their positioning in the broader financial system (Engel and McCoy 2011; Kahn 2013). Many factors have been implicated, but the increased transactional distance between lenders and borrowers, the unreliability of automated underwriting for subprime loans, and the growth in "private-label" securitization of mortgage loans by Wall Street investment banks and other firms have been identified as key culprits (Smith 2010; Engel and McCoy 2011; Fligstein and Goldstein 2011; Wyly et al. 2012; Mian and Sufi 2015). As conveyed in the compelling documentary *The Untouchables*, the pervasive securitization of mortgage loans may have been especially instrumental, as it fueled a "fund 'em" mind-set within mortgage markets with relatively little regard for due diligence in assessing loan risk or the fidelity of information provided on loan applications (Smith 2013).[9] Yet, an apparent pattern that has been less fully appreciated is that, while these structural and institutional conditions permeated the nation during the housing boom, mortgage fraud was much more prominent in some American communities than in others.

[8] Some research suggests that fraudulent statements about income are more prevalent in low-documentation loan products (Jiang et al. 2014). More pertinent to the findings we report below, such loans were fairly ubiquitous during the housing boom (Zibel 2008; Blackburn and Vermilyea 2012), and we are aware of no evidence that their prevalence, or the tendency for them to contain fraud, varied systematically across geographic areas.

[9] As one industry expert who had served as a loan officer trainer during the 1990s and 2000s described, the prevailing mind-set was "Don't worry about whether the documents are valid. Don't worry about whether we can verify income. Don't worry if the appraisal is any good. Just worry about getting the damn loan closed because if you can get that closed, we can get that securitized and then turn around and do another loan. Don't worry about it. There's too much money out there. Just get the loan closed" (Smith 2013).

Figure 2 displays U.S. county-level rates of overall mortgage fraud risk for 2003–5. The estimates shown were generated by dividing the number of loan applications within each county that were scored in FraudGUARD as having a high risk of containing some form of mortgage fraud by the total number of loan applications assessed within each county and multiplying this quotient by 100. The Interthinx database we obtained provided data on loans screened in 3,122 of the 3,141 U.S. counties defined in the 2000 census. To minimize the influence of extreme values associated with the estimation of mortgage fraud rates for relatively small, densely populated areas in which there were few mortgage loan transactions during the period covered in our research, we constructed estimates of mortgage fraud risk only for counties in which there were at least 20 mortgage loans screened through FraudGUARD between 2003 and 2005. This decision rule yielded estimates of mortgage fraud for 2,519 U.S. counties.[10]

The mean rate of overall mortgage fraud risk across the counties shown in figure 2 is 15.4%, but as the map reveals, estimates range substantially—from 0% to 50%—across U.S. counties.[11] Indeed, the observed rate of mortgage fraud risk during the height of the housing boom was well below 5% in many counties, while many others exhibited levels greater than 35%. We constructed parallel measures for each of the four types of mortgage fraud risk discussed above, which, along with the overall index of mortgage fraud, serve as dependent variables in the analysis presented below. Each form of mortgage fraud exhibited substantial variability across counties during the early 2000s. Thus, not only was mortgage fraud a relatively prevalent social problem in America during the period; it also emerged in a highly uneven magnitude across U.S. counties. While some of that variation may reflect important state-level differences in levels of mortgage fraud risk, which also can be discerned from figure 2, what strike us as more intriguing are the substantial differences in mortgage fraud risk observed across counties, within states.

Much of the public discourse about mortgage fraud during the housing boom highlighted national-level patterns and state-level differences, emphasizing in particular weak federal and state regulations of mortgage

[10] We experimented with other minimum loan volume thresholds (e.g., 30, 40, and 50) and observed very similar results. The excluded counties ($n$ = 606, denoted with hatch marks in fig. 2) are predominantly sparsely populated areas in which there are relatively few housing units. On the basis of the 2000 census, these counties contain, on average, about 6,400 residents and 3,000 housing units; the comparable averages among the included counties was approximately 110,000 residents and 45,000 housing units. Given that a large majority of housing units in most areas tend to fall outside the real estate market for various reasons, it is not surprising that there were relatively few mortgage loan applications within these sparsely populated areas.

[11] The cross-county mean is lower than the national estimate reported in fig. 1 because the former represents an unweighted mean (i.e., all counties are weighted equally, irrespective of the number of loans considered), which is not the case for the national estimate.

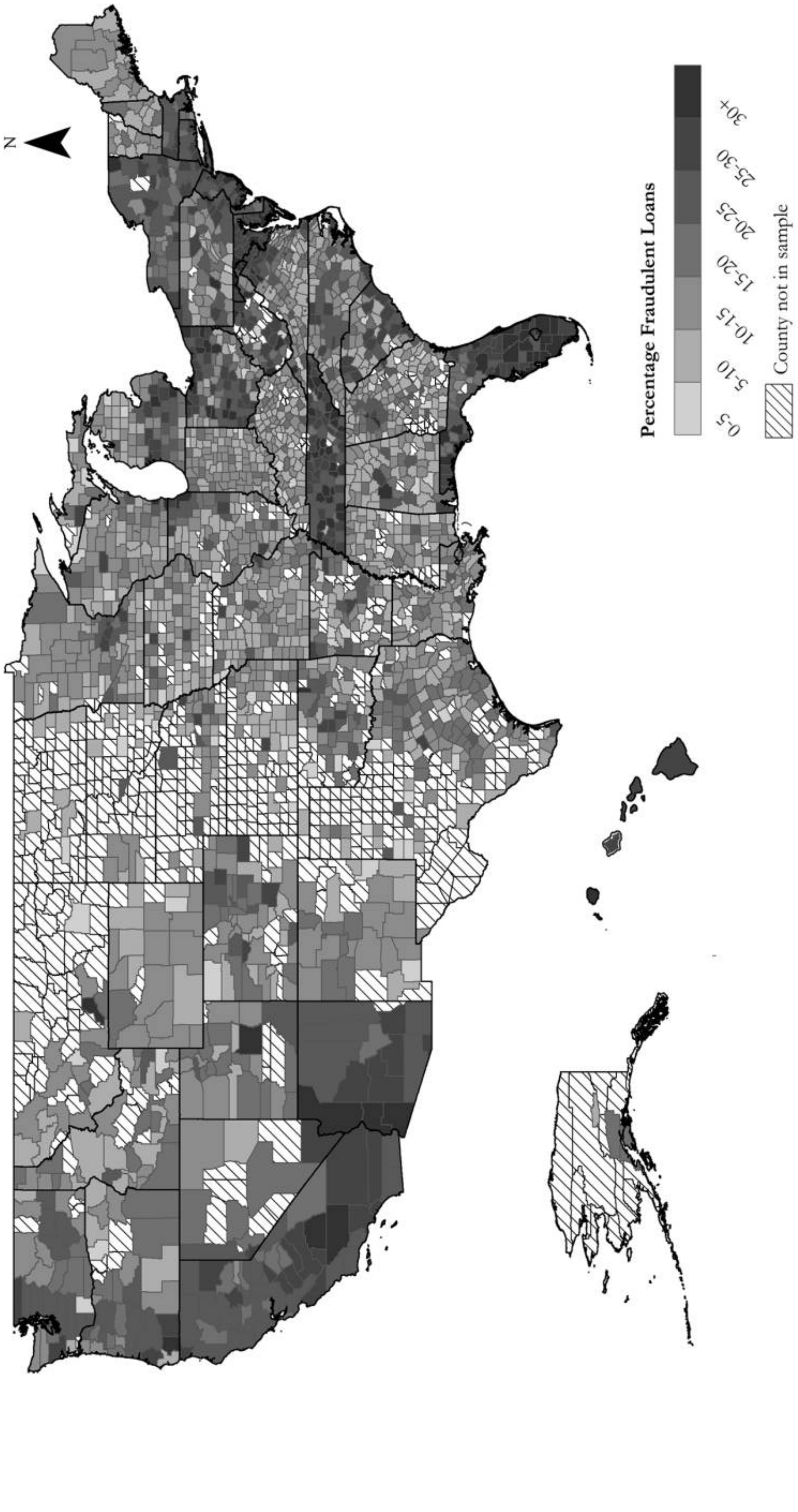


FIG. 2.—Percentage of loans containing one or more indications of mortgage fraud risk, 2003–5 ($N$ = 2,519)

transactions as a major antecedent to high levels of mortgage fraud during this period (e.g., Zitrin 2010). While those broad regulatory features are an important part of the story, they cannot account for the considerable county-level differences in mortgage fraud risk shown in figure 2, for they were invariant within states. This implies that a variety of other factors may have been important for generating county-level differences in levels of mortgage fraud during the housing boom. In the next section of the article, we suggest that the sociological literature provides useful insights about conditions that may have been germane.

## EXPLICATING THE THEORETICAL SOURCES OF COUNTY-LEVEL VARIATION IN MORTGAGE FRAUD

Mortgage fraud shares some fundamental features with more commonly studied forms of "street" crime, leading one industry expert to label it "bank robbery without a gun" (Fulmer 2010, p. 2). Like many other crimes that involve deceit for ill-gotten gains (e.g., stealing, writing a bad check, and selling stolen goods), mortgage fraud typically is perpetrated by individuals motivated by instrumental concerns (Nguyen and Pontell 2010), which as noted above can encompass the attainment of home ownership and/or the pursuit of financial profit. Yet, at the same time, the commission of fraud within a mortgage transaction also is frequently committed, or at least aided and abetted, by real estate and lending professionals (FinCEN 2008; Griffin and Maturana 2016). Thus, it also embodies elements consistent with both classical and contemporary definitions of white-collar crime (Sutherland 1940; Geis 1968; Coleman 2002; Shover and Hochstetler 2006), and especially what some sociologists have referred to as "collective embezzlement" (Calavita, Tillman, and Pontell 1997). Mortgage fraud emerges within the context of an organized business transaction, involves at its heart a violation of trust, and often is perpetrated or facilitated by industry professionals who may be motivated to maximize commissions and bonuses for themselves and/or to yield such benefits for their employers.

In light of the complex mixture of motives and participants in mortgage fraud, what are we to make of the substantial county-level variation in rates of mortgage fraud observed during the early 2000s housing boom? Integrating several strands of social science literature, we delineate a variety of conditions that may have coalesced during the period to generate social contexts in some jurisdictions that promoted fraudulent choices in mortgage transactions and weakened constraints against such actions. Media coverage and qualitative assessments of housing market dynamics during the early 2000s housing boom suggest that rational considerations of costs and benefits rendered mortgage fraud a particularly rewarding choice in some contexts. Extending those arguments, we draw on other sociological literature to highlight two other general perspectives: one that emphasizes how geographic targeting by certain types of lenders of vulnerable populations with high-risk loans may have been prominent in shaping where mortgage fraud was most pervasive and another that outlines how certain social and economic conditions may have stimulated or constrained fraudulent responses in a housing market (and era) many have described as highly anomic. We summarize these three general perspectives, and the empirical predictions we extract from them, in figures 3, 4, and 5 below.

### Low Risks of Detection, Strong Incentives, and Rational Choices to Engage in Mortgage Fraud

The uneven spatial distribution of mortgage fraud in America during the early 2000s housing boom may have reflected to a large degree the underlying geographic distribution of risks and rewards associated with submitting fraudulent loan information. Filling out and processing a loan application encompasses a series of choices by the borrower and several mortgage professionals (e.g., mortgage brokers, appraisers, and underwriters) who participate in the origination process, and the fidelity of information provided may be influenced by rational considerations of the potential penalties and benefits of providing fraudulent information, elements that are part and parcel of rational choice theory. Though the core of rational choice theory is an individual-level cognitive comparison of subjective and objective costs and benefits of a specified act, both alone and in relation to alternatives (Hechter 1994), social scientists have long recognized the potential utility of the framework for enhancing understanding of aggregate-level patterns of various behaviors as well (e.g., Hedström and Swedberg 1996; Hechter and Kanazawa 1997). In the present context, this perspective leads us to anticipate that levels of mortgage fraud may have been more prevalent in areas where the benefits associated with securing mortgage loans were greater, and the anticipated costs associated with mortgage fraud were perceived to be relatively low.

Descriptions of the housing market during the early 2000s highlight an environment laden with incentives that may have led participants to contribute fraudulent information on loan applications (Engel and McCoy 2011; Smith 2013). The overall compensation for many mortgage professionals during the period was driven to a significant degree by commissions and bonuses, an important determinant of which was the value associated with the loans they originated (Patterson and Koller 2011). Given that the potential profits were especially large in markets where home prices and loan values were high, brokers and other lending representatives involved in mortgage transactions during the housing boom may have had greater incentives to engage in fraudulent actions (e.g., embellishing an applicant's income or employment history, inflating the value of a property, and/or fabricating an appraisal) in such areas. This prediction is represented in figure 3 as an anticipated positive effect of average sales prices on mortgage fraud.

Rapid housing price inflation also may have served as a relatively strong fraud incentive for prospective borrowers contemplating the housing market as a means of obtaining cash proceeds from real estate transactions. Markets undergoing price inflation were a particularly ripe landscape for speculators with aims of turning a quick profit through house flipping, and fraudulent means (e.g., misstatements of property valuation and occupancy fraud) were frequently used to facilitate that objective (Fulmer 2010). Additionally, major increases in home prices may have stimulated employment/income fraud where refinance loans were prominent, because this enhanced the amount of cash equity available to borrowers. As summarized in figure 3, these arguments suggest that major increases in home prices may have stimulated mortgage fraud directly and that this may have been especially likely where there was a larger share of loans made for the purchase of non-owner-occupied dwellings (i.e., investor loans) and to facilitate mortgage refinances.

High or rising home prices, alone, may not have served as a strong enticement for borrowers interested in attaining home ownership to engage in fraud or to overlook fraud committed by others on their behalf. Instead, for this group the benefit or "relative utility" of committing certain types of fraud (e.g., employment/income fraud) may have been stronger in contexts in which home prices outpaced financial resources available for housing and in which the primary alternative—the rental market—was more expensive. These predictions are expressed in the figure as moderator relationships, highlighting how the anticipated positive effects of increasing home prices on county mortgage fraud levels may be amplified by conditions of high rental prices and limited economic resources. The former prediction considers the broader set of housing choices available to prospective home buyers and suggests that employment/income mortgage fraud, in particular, may be especially likely to increase in response to rising home prices where rental prices

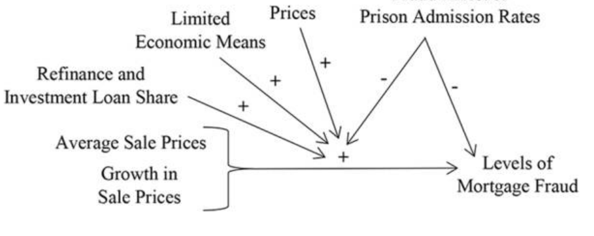


Fig. 3.—Low risks of detection, strong incentives, and rational choices to engage in mortgage fraud.

also were relatively high. The latter prediction highlights the potential importance of reduced housing affordability (i.e., the capacity for the typical borrower to purchase the average priced home) and suggests that rising home prices may have been more likely to yield a calculus—by borrowers and/or brokers—that generated employment/income fraud where economic means were limited.[12]

Discussions of mortgage fraud during the housing boom have emphasized to an even greater degree the role of inadequate regulations, which many suggest yielded an environment in which the perceived risks associated with mortgage fraud were quite low. A potentially important cost consideration for both borrowers and industry professionals who may have contemplated fraud during the housing boom came in the form of the risks associated with formal social control efforts. Although the regulatory environment that governed mortgage transactions during the housing boom varied somewhat across states, all transactions within a given state were subject to the same set of rules, which probably rendered such regulations (e.g., state differences in predatory-lending laws and broker licensing requirements) as relatively unimportant for influencing between-county variation. However, local differences in the application of state laws may have been pertinent. More specifically, as summarized in figure 3, a higher local risk of arrest and imprisonment for fraud and related offenses may have reduced the prevalence of mortgage fraud during the housing boom directly or may have dampened the impact of high or rising home prices, which as noted were likely an important impetus for mortgage fraud during the housing boom.

## Spatial Inequalities, Ethnoracial Context, and High-Risk Lending

The uneven geographic distribution of mortgage fraud during the housing boom also may have reflected conscious choices by mortgage industry representatives to target selected populations and geographic areas (Wyly et al. 2012). Many scholars have noted that an important contributor to the housing boom was an expansion of the typical reach of mortgage credit to consumers who in previous eras may not have qualified for loans, facilitated largely by redistributing (i.e., securitizing) the elevated risk associated with

[12] Such conditions may have stimulated income fraud among borrowers on their own accord, but qualitative assessments of housing markets during the housing boom suggest that mortgage professionals, and especially brokers, often played an important role by encouraging or submitting inflated income data while applying creative loan programs (e.g., no-interest loans, adjustable interest rate loans coupled with a low introductory rate, negative amortization loans) that convinced many borrowers that they could "afford" to buy a house even when their income was not sufficient according to conventional standards (Nguyen and Pontell 2011).

doing so (Dymski 2002; Raynes and Rutledge 2003; Mian and Sufi 2014). Two important avenues through which this expansion was accomplished were the increased use of high-cost subprime loan arrangements and the explicit targeting of geographic areas with historically low rates of home ownership where loan sellers preyed on large numbers of underserved consumers who tended to be financially unsophisticated and have relatively limited mortgage financing options (Peterson 2007; Fisher 2009; Bayer, Ferreira, and Ross 2013). Previous research has shown that these lending practices yielded substantial geographic variation in subprime lending and the types of financial entities providing mortgage services (Williams et al. 2005; Engel and McCoy 2011; Hyra et al. 2013; Hwang et al. 2015; Rugh et al. 2015), and that variability also may help to explain some of the observed differences in levels of mortgage fraud across counties.

Nguyen and Pontell (2010, p. 595) make a strong case that subprime markets provided a fertile ground for fraudulent activities. They argue that this was the case both because of the poor underwriting standards that tended to prevail in such markets and because the higher fees and interest rates attached to subprime loans served as incentives to get borrowers qualified, even if it often meant "intentionally misstating financial information." Many different types of lenders were eventually attracted to subprime markets (Rugh et al. 2015), but the evidence suggests that IMCs were particularly prominent in distributing nontraditional high-cost loans (Hyra et al. 2013), especially during the early 2000s housing boom (Wyly et al. 2012). Loans originated by IMCs may be more likely than other loans to contain fraud both because of a greater reliance on subprime loan products and because of the unique regulatory position of these types of lenders during the period. Compared to depository banks, IMCs were subject to much less regulatory oversight during the housing boom (Reid and Laderman 2009; Kirk and Hyra 2012).[13] This not only may have permitted more racial discrimination in lending by IMCs (Savage 2011) but also could have yielded higher levels of mortgage fraud where they originated more loans (Smith 2013). As shown in figure 4, we examine whether the geographic distribution of both risky loans (i.e., the percentage of mortgage loans originated by subprime lenders and the prevalence of high-cost loans) and the share of loans originated by IMCs can explain some of the variation in mortgage fraud observed across counties in America during the early 2000s housing boom.

A growing literature also suggests more generally that particular types of geographic areas were targeted during the housing boom by mortgage professionals who used questionable sales tactics that often were accompanied by fraudulent actions, both in the subprime and prime markets and by lend-

[13] Unlike depository banks and thrifts, IMCs are not regulated by the Community Reinvestment Act (Apgar, Bendimerad, and Essene 2007).

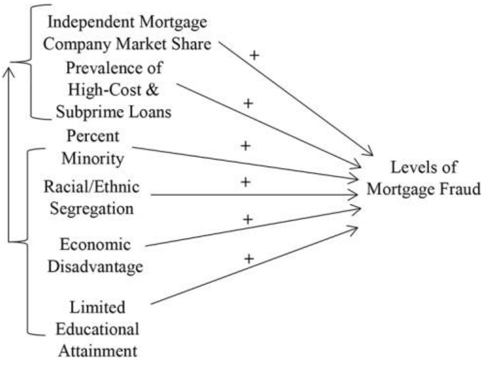


FIG. 4.—Spatial inequalities, ethnoracial context, and high-risk lending

ers of various types, including depository banks and IMCs (Wyly et al. 2012). Rugh and Massey (2010, p. 630) argue that persistently poor, segregated minority communities provided relatively large pools of untapped and financially vulnerable mortgage clients during the housing boom because of a "legacy of redlining and institutional discrimination" that restricted access to mortgage credit in earlier eras. While many lenders had largely steered clear of such communities in the past, during the late 1990s and early 2000s the proliferation of securitized mortgages transformed these areas into vibrant markets of potentially big profits, with relatively little—or at least highly dispersed—risks (Dymski and Veitch 1992; Stuart 2003).

Persuasive evidence has emerged that some lenders, mortgage brokers, appraisers, underwriters, and real estate agents conspired in "reverse redlining" practices to target low-income, low-educated populations in segregated, minority areas with aggressive sales strategies, deception, and predatory lending tactics (Galster 2012; Rugh 2015). These patterns have been persuasively linked to elevated MSA-level foreclosure rates (Rugh and Massey 2010) and identified as the foundation of newly established geographically based racial and ethnic inequalities (Wyly et al. 2012). Importantly, there is evidence that these practices often were accompanied by a significant amount of mortgage fraud. Pendley, Costello, and Kelsch (2007) discovered fraudulent statements about occupancy intentions in approximately two-thirds of the subprime loans they analyzed, many of which were concentrated in low-income areas. Similarly, Fisher (2009, p. 102) reports on several cases in which fraud was prominent in the origination of loans in high-poverty, minority communities where "in many cases, loan officers and mortgage brokers—without borrowers' knowledge—concocted false income and assets and ordered inflated appraisals, all to obtain mortgages generating large profits for themselves." The anecdotal evidence suggests that such practices may have been especially prominent in predominantly black segregated housing markets, but Utt (2008,

p. 16) highlights similar circumstances in areas of concentrated immigration, where mortgage industry representatives targeted "modest-income immigrants with limited financial sophistication and English language skills." Additionally, while much of the literature implicates mortgage industry professionals in fraudulently manipulating real estate transactions for ill-gotten gains in disadvantaged minority areas, where home values were often depressed and consumers less well equipped to detect such actions, there is evidence also that others contributed to fraud in such areas. Galster (2012, p. 232) explains how teams of speculators in Detroit scammed lenders by making a legitimate purchase of a large home in a declining neighborhood and then turning around to "secure a ridiculously inflated appraisal from a coconspirator appraiser" and selling the property at the newly appraised value to a fellow "skipper" who secured a low–down payment loan from an unknowing lender. Neither party to the transaction makes a mortgage payment, yet each walks (i.e., "skips") away with significant proceeds equal to the difference between the two sale prices.

Collectively, these arguments imply that many forms of mortgage fraud may have been more prevalent during the 2000s housing boom in communities with segregated minority populations and those that were characterized by high levels of economic disadvantage and relatively low educational attainment. Such conditions may have been especially germane to generating neighborhood-level differences in mortgage fraud, but we anticipate that they also could have contributed to observed county-level variation in mortgage fraud. As illustrated in figure 4, we evaluate that possibility by integrating data on county-level rates of mortgage fraud risk with indicators of county ethnoracial context (i.e., racial composition, recent immigration, and segregation), economic disadvantage, and limited educational attainment. The literature suggests that these factors may be linked to elevated mortgage fraud because they are associated with higher rates of lending by IMCs and a greater prevalence of high-cost and subprime loans, but that they also may influence rates of mortgage fraud independently from these lending attributes. We consider both possibilities in the present study.

## Geographic Differences in Economic Means, Property Crime Levels, and the Regulation of Secondary Markets

The "anomic" cultural and structural context that defined the early 2000s housing boom contains many of the ingredients Merton (1938, 1968) highlighted as key to producing high rates of "innovative" behavior, including fraud. In his words, "fraud . . . becomes increasingly common when the emphasis on the *culturally induced* success-goal becomes divorced from a coordinated institutional emphasis" (Merton 1938, pp. 675–76). Home ownership had long been a culturally valued symbol in America (e.g., Cullen

2004), but there were renewed efforts through the political airwaves and government policies of the 1990s and early 2000s (e.g., President Bill Clinton's "National Homeownership Strategy: Partners in the American Dream" and President George W. Bush's American Dream Downpayment Act) to promote and expand it. As noted above, growth in subprime lending helped to translate such pleas into increased home ownership rates and decreased racial disparities in the distribution of mortgage credit (Williams et al. 2005), but during this period housing also increasingly became seen as a means by which to build wealth. As Sugrue (2009) puts it, "the dream of home ownership turned hallucinogenic" and "the notion of home-as-haven" became increasingly replaced with perceptions of "home-as-jackpot" and the idea that "anyone could be an investor, anyone could get rich."

Merton's (1938) classic arguments suggest that mortgage fraud may have been a logical response to prevailing cultural and structural conditions that permeated housing markets during the early 2000s, which reveals the overlap of his theory with rational choice perspectives (Hedström and Swedberg 1996). However, both classic and contemporary anomie theories depart from the rational choice framework by identifying social structural conditions that may condition whether fraudulent actions are used to pursue valued goals. This insight offers a potentially useful lens through which to understand county-level variation in levels of mortgage fraud.

Merton (1938) suggested that instrumental responses to high levels of anomie would be less likely to occur in societies in which the supply and distribution of legitimate avenues for pursuing valued success goals were more abundant and widely dispersed throughout the population. While mortgage brokers and other industry professionals who contribute to loan originations may not be affected by such conditions since they often reside outside the jurisdictions in which they do business (Smith 2010), Merton's arguments have relevance for choices made by borrowers in the context of a strong cultural emphasis on attaining home ownership and maximizing monetary profits from real estate investments. Merton's theoretical insights imply that, all else equal, mortgage fraud in the form of income inflation or misstatements about employment status should have been higher in communities in which economic means were more limited. This empirical expectation is summarized in figure 5.

Other anomie theorists suggested additional social structural conditions that may help to account for the observed geographic variation in levels of mortgage fraud during the early 2000s housing boom. We consider two extensions of Merton's theory especially relevant. First, Cloward (1959) aptly argued that even when cultural and structural conditions were well organized for stimulating high rates of illegal behavior, the latter is more likely to occur where illegal opportunities are more readily available. Cloward followed Sutherland's (1939) lead by emphasizing a multidimensional conception of il-

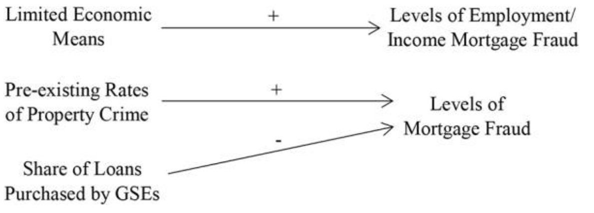


FIG. 5.—Geographic differences in economic means, property crime, and regulation of secondary markets.

legitimate opportunity structures that integrates both access to roles that provide tangible prospects for committing illegal acts and the presence of a normative learning context in which illegal responses to anomic conditions may be encouraged and facilitated. Cloward (1959, p. 169) recognized that the former often are ubiquitous yet unlikely to yield purposeful action in the absence of "conditions encouraging participation in criminal activity." This latter point is further clarified by Cloward and Ohlin (1960), who highlight the critical role for the differential presence of criminal networks and value systems for generating high rates of illegitimate behavior as an adaptation to anomic environments. We lack indicators of the prevailing value systems for U.S. counties during the early 2000s that would permit a direct test of this idea, but as we outline in figure 3, the logic of Cloward and Ohlin's arguments leads us to posit that forms of mortgage fraud that may be aided by the presence of criminal networks, such as identity and property valuation fraud, may have been more prevalent during the 2000s housing boom where levels of property "street crime" had been persistently higher. Areas in which a larger share of the population was engaged in traditional forms of property crime likely offered a more abundant supply of persons who were attracted to mortgage fraud scams when opportunities became plentiful (e.g., Bianco 2008; Fulmer 2010). Additionally, some of the requisite technical skills and ingredients that facilitate major forms of mortgage fraud (e.g., falsifying appraisal documents, acquiring stolen identities, and finding willing straw buyers) are likely to be more easily acquired in places with high rates of traditional property crimes, where criminal infrastructures are better established (FBI 2011).

Second, Messner and Rosenfeld (1994, 2012) suggest in their "institutional anomie theory" that, in addition to legitimate and illegitimate opportunity structures, noneconomic social institutions can play a prominent role in shaping choices people make within anomic environments. Social institutions regulate conduct, they argue, by providing protections from prevailing market forces, transmitting prosocial norms about pursuing culturally valued goals through legitimate means, and serving as important sources of external social control and social support that channel behavior in conventional ways. Though the apparent cultural push in America during the 1990s and early 2000s for extending the reach of home ownership and for using housing as a means of building wealth may have generated widespread pressures to consider illicit actions in mortgage transactions, through the lens of institutional anomie theory, the tendency for such pressures to yield a high prevalence of fraud should have been lessened where the social structure provided greater constraints on mortgage markets. Messner and Rosenfeld (2012) emphasize the importance of several dimensions of the social structure, including the potential regulating role of educational, familial, and political institutions, but the last of these strikes us as particularly germane to mortgage fraud and the conditions that prevailed during the 2000s housing boom. Specifically, drawing insights from Messner and Rosenfeld's argument, we consider whether the government's role in the secondary mortgage market may have functioned to keep levels of mortgage fraud lower in some areas during this period.

Many lenders during this period sold the mortgages they originated in the secondary market to private firms (e.g., Countrywide, Lehman Brothers, Bear Stearns, and Bank of America) or pseudo government agencies, such as the Federal Home Loan Banks, Fannie Mae, and Freddie Mac (Engel and McCoy 2011). In both cases, the sold mortgage loans were typically repackaged in bonds or other investment vehicles and then sold to investors (i.e., securitized). Originators had relatively little incentive to thoroughly validate the data borrowers put on loan applications that, if funded, would be sold in the secondary market to investors. This process of securitization allowed lenders to transfer the risk of default, and according to Simkovic (2013, p. 215), it fueled "a race to the bottom" in underwriting standards. Fligstein and Roehrkasse (2016) document substantial evidence of fraud during the securitization process, but other research also suggests that the large-scale securitization of mortgage loans by privately held firms likely played a pivotal role in facilitating, or at least permitting, widespread fraud within mortgage transactions at the application and origination stages as well (Keys et al. 2010; Financial Crisis Inquiry Commission 2011; Barnett 2013; Mian and Sufi 2015). Thus, we expect rates of mortgage fraud to be higher where a greater proportion of loans were sold in secondary markets and lower where a larger share were held by originating lenders. More pertinent to institutional anomie theory, however, we suggest that the impact of securitization on levels of mortgage fraud during the housing boom was likely contingent on the structure of purchases within secondary markets. Specifically, according to this theoretical framework, mortgage fraud should have been less prevalent in areas in which GSEs purchased a larger share of mortgages, relative to the share of loans sold to private-label securitizers (Blackburn and Vermilyea 2010; see also Bubb and Kaufman 2009; Simkovic 2013). The reason is not that the GSEs imposed particularly tight underwriting standards for the loans they purchased in secondary markets; in fact, like the private purchasers, there is evidence that GSEs accepted many fraudulent loans for which there was little oversight over the fidelity of the data provided (Marshall and Concha 2012). However, GSEs were more selective than private-label securitizers in the types of mortgages they purchased (e.g., focusing on "conforming" loans) during the housing boom (Felton 2008), and since the failure of lenders to follow basic underwriting guidelines designated by GSEs (e.g., to require documentation of borrower information) had the potential to result in the loss of a valued business partner, mortgage fraud rates may have been lower where GSEs purchased a larger percentage of loans in the secondary market (see also Mian and Sufi 2015). This prediction is consistent with the general argument advanced by Messner and Rosenfeld (2012) that political institutional arrangements can suppress illicit conduct that might otherwise emerge in contexts in which private-market forces offer appealing incentives for such behavior.

## DATA AND METHODS

### Sample

Our county-level analysis focuses on assessing the effects of a wide array of housing market conditions and social structural characteristics during the early to mid-2000s on levels of mortgage fraud risk observed between 2003 and 2005. As described above, the Interthinx data used in our study yield estimates of mortgage fraud risk for 2,519 U.S. counties, which reflects the number of counties in which 20 or more loans were evaluated for possible indications of fraudulent activity. We obtained data on housing market dynamics, fraud sanction risk, racial and economic conditions, property crime, and the other factors considered for 2,232 of these counties, which were nested within 47 states. This serves as the sample for the analysis reported below.[14]

### Measures

The dependent variables in our analysis include an indicator of overall mortgage fraud risk, defined as the percentage of loan applications screened

[14] Because we omit by definition counties with very few mortgage transactions, our sample underrepresents sparsely populated rural areas. Thus, compared to the full universe of counties ($N = 3{,}141$), the analysis sample ($n = 2{,}232$) is composed of counties that exhibit a significantly larger mean population size (104,118 vs. 53,898) and higher median incomes ($43,610 vs. $38,590). Nonetheless, two-sample $t$-tests reveal that our analysis sample mirrors the total population of counties in terms of subprime lending rates, racial composition, property crime levels, and home ownership rates (results not shown in tabular form).

through FraudGUARD between 2003 and 2005 that were rated as having a high risk of containing one or more forms of mortgage fraud, and parallel measures for the four specific forms of fraud tracked through this system during the early 2000s housing boom: employment/income fraud, property valuation fraud, identity fraud, and occupancy fraud.

We integrate data from several sources to measure county conditions during the early to mid-2000s that may be associated with variation in levels of mortgage fraud. The definitions and sources of the variables considered are provided in table 1. Many of the measures used are commonplace in studies of housing market outcomes and crime, but some warrant elaboration.

First, while state-level lending regulations (Ho and Pennington-Cross 2007; Bostic et al. 2008) and state mortgage broker licensing requirements (e.g., Backley et al. 2006; Pahl 2007) may have represented important risk considerations among those who contemplated mortgage fraud during the housing boom, we account for their impact by incorporating state fixed effects, focusing instead on within-state county differences in the application of formal social control efforts (e.g., arrest and prison admission rates) directed at fraud. We accomplish the latter by including a measure that represents the average annual number of Uniform Crime Report (UCR) arrests in each county for fraud, forgery, and embezzlement from 2000 to 2005 per 10,000 county residents ages 18–64. In a supplementary analysis, we also consider a parallel measure of county-level prison admission rates for these offenses, which is available for a subsample ($n = 1{,}936$) of the counties included in our analysis.[15]

Second, we measure county-level differences in incentives for mortgage fraud with several indicators. We evaluate the expectation that mortgage fraud may have been more enticing where home prices and loan values were higher and undergoing relatively larger increases by including HMDA data on average loan values during the period we observed county mortgage fraud rates (i.e., 2003–5), and the average annual proportional change in median loan values in the housing boom years leading up to that period (i.e., 2000–2003), which we assume to be most pertinent for shaping perceptions that significant profits might be realized from the real estate market. Using other periods of loan value change (e.g., 2000–2005 and 2003–5) yielded results that paralleled those reported below. While actual home sale prices may be more pertinent for those motivated to engage in fraud to obtain housing, such data were not routinely reported for most U.S. counties in the period under observation. However, loan values and home sale prices often

[15] We applied the methods outlined by Baumer, Rosenfeld, and Wolff (2012) for adjusting UCR agency data for the number of months reported and for differential coverage across counties. Prison admission rates were computed from the National Corrections Reporting Program. Using a multiyear average yields more stable estimates, while also minimizing the loss of cases associated with missing data for individual years.

were synonymous during the housing boom because of the prominence of purchase arrangements that required no (or a very low) down payment. Consistent with this claim, in a supplementary analysis (not shown), the HMDA loan value indicators included in our study exhibited very strong interitem correlations ($r > .90$) with county-level data on home prices obtained from Zillow for the 500 largest U.S. counties.

We suggested above that higher home prices may have been especially likely to stimulate mortgage fraud in areas in which rental markets were more expensive and where economic conditions rendered home purchases relatively less affordable. To facilitate an assessment of the former, we include a measure from the 2000 decennial census that reflects the median gross rent for renter-occupied units as a proportion of median household income (i.e., the average price of rental units, relative to average incomes). To evaluate the latter, we conducted a principal components factor analysis of several indicators of county differences in employment and income (i.e., unemployment, wages, median income, poverty rates). That analysis indicated the presence of a single "limited economic means" factor, for which larger values represent higher rates of unemployment and poverty and lower median family income and annual personal wages. Finally, relatively high loan volumes also may have been associated with mortgage fraud because of the commissioned-based compensation structure that governed much of the mortgage industry, so we include an indicator of county differences in mortgage loan rates (i.e., the average annual number of loans originated between 2003 and 2005 per 100 housing units).

Third, we measure the relative presence of subprime high-risk loans with two indicators drawn from the HMDA (see also Bostic et al. 2008), including the proportion of conventional loans originated between 2003 and 2005 by a subprime lender, as identified by Housing and Urban Development, and the proportion of first-lien loans (by any type of lender) originated in 2004 and 2005 defined as "high-cost," or in other words those that exceed the comparable Treasury security by 3% or more (see also Rugh and Massey 2010).[16] For the models of occupancy fraud, we limit the high-cost loan measure to home purchase loans since occupancy fraud requires a home purchase (for the other fraud measures, this indicator references refinance and home improvement loans as well).

Fourth, we use HMDA to construct several other measures of county differences in the nature of lending and mortgage markets that may be relevant for the geographic distribution of mortgage fraud. Consistent with other recent studies of housing outcomes (Kirk and Hyra 2012; Hyra et al. 2013), we computed the prominence of IMCs in local mortgage markets by computing the proportion of owner-occupied first-lien mortgages in 2004 and 2005 that

[16] HMDA did not collect data on rate spread and lien status prior to 2004.

TABLE 1

DEFINITIONS AND SOURCES FOR INDEPENDENT VARIABLES INCLUDED IN COUNTY-LEVEL ANALYSIS OF MORTGAGE FRAUD RISK ($n$ = 2,232)

| Independent Variable | Variable Definition |
|---|---|
| Indicators of risks and incentives: | |
| Fraud arrest rate (logged) | Logged rate of arrest for larceny-theft, forgery and counterfeiting, fraud, embezzlement, and gambling per 10,000 adults 18–64 [mean, 2000–2005]. Sources: Uniform Crime Report (UCR) arrest data and Surveillance, Epidemiology, and End Results (SEER) population data. |
| Average loan values | Median loan value ($10,000s) for conventional loans (mean, 2003–5). Source: Home Mortgage Disclosure Act (HMDA). |
| Change in loan values | Proportion change in annual median loan values for conventional loans, 2000–2003. Source: HMDA. |
| Refinance loan rate | Proportion of conventional loans that were refinances (mean, 2003–5). Source: HMDA. |
| Non-owner-occupied loan rate | Purchase loans for non-owner-occupied units, per 100 (mean, 2003–5). Source: HMDA. |
| Change in non-owner-occupied loan rate | Proportion change in purchase loans for non-owner-occupied units per 100, 2000–2005. Source: HMDA. |
| Rental costs | Gross rent as a proportion of median income, 2000. Source: 2000 decennial census. |
| Indicators of spatial inequality, ethnoracial context, and high-risk lending: | |
| Loans by subprime lenders | Proportion of conventional loans originated by a subprime lender (mean, 2003–5). Source: HMDA. |
| High-cost loans | Proportion of conventional first-lien loans with a rate spread of 3 or more percentage points above the Treasury security of comparable maturity (mean, 2004–5). Source: HMDA. |
| IMC loan share | Proportion of first-lien owner-occupied mortgages originated by independent mortgage companies (IMCs) (mean, 2004–5). Sources: HMDA and the Federal Housing Finance Agency. |
| Percent non-Latino black | Proportion of persons who identify as non-Latino black, 2000. Source: 2000 decennial census. |
| Percent Latino | Proportion of persons who identify as Latino, 2000. Source: 2000 decennial census. |
| Recent immigration | Proportion of foreign-born persons who entered the United States between 1995 and 2000. Source: 2000 decennial census. |
| Black/white dissimilarity | Non-Latino black/white dissimilarity index, 2000. Source: 2000 decennial census. |
| Latino/white dissimilarity | Latino/white dissimilarity index, 2000. Source: 2000 decennial census. |
| Limited educational attainment | Dummy variable identifying counties in which less than 10% of the population ages 25 and older had earned a bachelor's degree or higher in 2000. Source: 2000 decennial census. |

TABLE 1 (*Continued*)

| Independent Variable | Variable Definition |
|---|---|
| Indicators of economic means, property crime levels, and regulation of secondary mortgage markets: | |
| Limited economic means | Four-item principal components factor that combines average unemployment rates, 2003–5 (source: Bureau of Labor Statistics); average median wages, 2003–5 (source: Bureau of Economic Analysis); median family income (source: 2000 decennial census); and the percentage of families below the poverty line (source: 2000 decennial census). |
| Property crime rate | Number of robberies, burglaries, and motor vehicle thefts per 100 persons ages 18–64 (mean, 2000–2002). Sources: UCR and SEER. |
| GSE-purchased loans | Proportion of originated loans sold in secondary market between 2003 and 2004 that were purchased by GSEs. Source: HMDA. |
| Lender-held loans | Proportion of originated loans between 2003 and 2004 retained by lender (i.e., not sold in secondary market). Source: HMDA. |
| Control variables: | |
| Average loan volume | Number of mortgage loans originated per 100 housing units (mean, 2003–5). Source: HMDA. |
| Percent of loans with no income stated | Proportion of loans with no income data provided (mean, 2003–5). Source: HMDA. |
| Home ownership rate | Proportion of housing units that are owner-occupied, 2000. Source: 2000 decennial census. |

they originated.[17] We also include the proportion of conventional loans made for refinances and proxies for the distribution of investor loans (i.e., the proportion of loans for non-owner-occupied units, the average proportion change in loan rates for non-owner-occupied units) and the prevalence of "no-doc loans" (i.e., the proportion of loans with no income stated).[18]

Finally, we draw from HMDA county-level data developed by Ng (2013) to measure the role of GSEs in the secondary mortgage market. Under HMDA, lenders are required to report whether loans they originated were held by them or sold within a given calendar year to another institution; if the latter is true, they also are required to identify the type of institution to which a loan was sold. Using these data elements, we computed county-level estimates of the proportion of loans originated in 2003 and 2004 that were held by the lender (i.e., not sold in the secondary market) and the proportion of loans sold

[17] IMCs were identified using data from Avery, Brevoort, and Canner (2007).

[18] Though income is occasionally omitted on loan applications because of data entry or recording errors, Jiang et al. (2014) show that missing income is especially prominent in low-documentation loans.

in the secondary market that were purchased by a GSE (rather than a private financial firm).

## Analytical Strategy

Prior research has identified several methodological considerations that are germane to drawing valid inferences from county-level crime models. Two issues that often are found to be consequential are the presence of spatial autocorrelation and the prominence of distributions that exhibit substantial skewness and contain many zeros. Studies have documented significant spatial autocorrelation in county-level rates of "street crime," which may arise because of comparable clustering of social and economic attributes that are associated with crime or because of processes of spatial diffusion (e.g., Messner et al. 1999). Failing to account for such spatial autocorrelation can yield biased and inefficient regression estimates (Anselin et al. 2000). Some research suggests that fraudulent behavior might exhibit spatial dependence (e.g., Baker and Faulkner 2003; Patterson and Koller 2011). Consistent with this notion, exploratory analysis of our data yielded evidence of significant positive univariate spatial autocorrelation for each of the specific forms of fraud considered, ranging from low (Moran's $I$ for employment/income fraud $= .04$, $P < .05$) to moderately high (Moran's $I$ for property valuation fraud $= .59$, $P < .05$) levels.[19]

Previous studies also have documented that county crime data often possess distributional properties that can present problems for obtaining valid estimates from traditional regression approaches, especially when based on relatively small denominators as is the case in our research (Osgood 2000). Descriptive statistics presented in table 2 show that each of the measures of fraud considered in our study exhibits significant positive skew. Further, preliminary diagnostic plots of ordinary least squares (OLS) residuals yielded evidence of a statistically significant departure from normality and a heterogeneous error variance for these measures. Finally, with the exception of overall mortgage fraud, the dependent variable measures include a relatively large number of zero values, ranging from about 4% of the cases for identity

[19] These estimates are based on applying a row-standardized five-nearest-neighbor spatial weights matrix. It is important to acknowledge that "spatial holes" arise in our data because we exclude counties with fewer than 20 mortgage loans screened for mortgage fraud (Anselin 2002). This does not appear to introduce significant bias into our analysis, however. We also observed significant spatial autocorrelation of mortgage fraud when analyzing data from samples for which the prevalence of missing counties is much lower, including counties with 10 or more screened loans ($n = 2{,}763$) and five or more screened loans ($n = 2{,}912$). Additionally, parallel results were obtained when using an inverse distance squared spatial matrix, which is less sensitive to missing data from adjacent counties.

TABLE 2
DESCRIPTIVE STATISTICS FOR VARIABLES INCLUDED IN COUNTY-LEVEL ANALYSIS OF MORTGAGE FRAUD RISK ($n$ = 2,232)

| Variable | Mean | SD | Min | Max |
|---|---|---|---|---|
| Dependent variables: | | | | |
| Overall mortgage fraud risk | 15.13 | 7.72 | .00 | 50.00 |
| Employment/income fraud | 3.86 | 2.31 | .00 | 33.33 |
| Property valuation fraud | 4.99 | 7.62 | .00 | 39.09 |
| Identity fraud | 6.73 | 3.11 | .00 | 30.77 |
| Occupancy fraud | 3.20 | 2.21 | .00 | 23.81 |
| Independent variables: | | | | |
| Fraud arrest rate (logged) | .54 | .11 | −.30 | .88 |
| Average loan values ($10,000s) | 7.38 | 3.64 | 2.60 | 45.37 |
| Change in loan values | .11 | .04 | −.05 | .47 |
| Refinance loan rate | .55 | .07 | .26 | .72 |
| Non-owner-occupied loan rate | .60 | .67 | .01 | 9.99 |
| Change in non-owner-occupied loan rate | .26 | .33 | −1.00 | 1.73 |
| Rental costs | .24 | .03 | .14 | .38 |
| Subprime loans | .15 | .05 | .02 | .59 |
| High-cost loans | .22 | .07 | .04 | .53 |
| IMC loan share | .26 | .09 | .05 | .57 |
| Percent non-Latino black | .08 | .13 | .00 | .78 |
| Percent Latino | .06 | .11 | .00 | .98 |
| Recent immigration | .01 | .01 | .00 | .10 |
| Black/white dissimilarity | .37 | .16 | .00 | .86 |
| Latino/white dissimilarity | .23 | .12 | .00 | .70 |
| Limited educational attainment | .13 | .34 | .00 | 1.00 |
| Limited economic means | .00 | 1.00 | −4.36 | 5.33 |
| Property crime rate | 1.55 | .85 | .02 | 4.50 |
| GSE-purchased loans | .35 | .05 | .24 | .59 |
| Lender-held loans | .17 | .03 | .11 | .30 |
| Average loan volume | 10.33 | 6.20 | 1.33 | 56.68 |
| Percent of loans with no income stated | .02 | .01 | .00 | .35 |
| Home ownership rate | .74 | .07 | .31 | .90 |

fraud to 58% of the cases for property valuation fraud, which pose further problems for OLS models (Cameron and Trivedi 2013).

In light of the aforementioned features of our data, we analyze county-level variation in mortgage fraud risk using a count regression modeling strategy that parallels approaches used in other aggregate crime studies (e.g., Osgood and Chambers 2000; Messner, Baller, and Zevenbergen 2005; Lyons 2007). We considered a variety of different count model specifications, but multiple tests (i.e., Pearson's dispersion statistics, $z$-score test, Lagrange multiplier test, and Poisson goodness of fit test) pointed to significant overdispersion in our measures, and appropriate fit statistics (i.e., Akaike information criterion and Bayesian information criterion) affirmed that a negative binomial specification yielded a superior fit to the data. Because we are interested in evaluating county variation in rates of mortgage fraud, we include the number of loans evaluated for mortgage fraud in each county as an exposure variable in the negative binomial models presented below.

To account for the county-level spatial autocorrelation in rates of mortgage fraud noted above, we include spatially lagged measures of mortgage fraud in the models.[20] Further, we include dummy variables for states, with one omitted as a reference group, and report standard errors that are clustered on states. The former strategy controls for unmeasured between-state differences that may influence mortgage fraud, focusing our analysis on within-state county variation (see also King, Messner, and Baller 2009), while the latter approach minimizes potential bias in the estimation of standard errors when observations are not independent within clusters (Cameron and Trivedi 2013).

## RESULTS

Table 3 displays the estimated coefficients that illuminate the effects of each of the variables considered (results for the state dummy variables are omitted from both tables to conserve space). We illustrate the magnitude of some of the relationships observed in the analysis by calculating average adjusted predictions for mortgage fraud rates assuming different values (e.g., very high = 95th percentile, average = 50th percentile, and very low = 5th percentile) of selected independent variables and observed values for all other covariates (see Williams 2012). We refer to such computations in the text where relevant. We emphasize three general patterns that are germane to the theoretical arguments summarized above.[21]

[20] Preliminary estimation of various spatial regression models indicated that a spatial lag model provided the best fit to the data. Because the underlying statistical theory and analytical tools for directly modeling spatial autocorrelation in nonlinear models remain in early stages of development (see Lambert, Brown, and Florax 2010), we adopt a modified form of the two-stage least squares approach explicated by Land and Deane (1992) to minimize the potential bias that can arise from including an endogenous spatial lag term. This approach entailed computing spatially lagged measures of mortgage fraud from the predicted values obtained in the negative binomial regression models and then reestimating the models with the spatial lags included (see also Baller, Zevenbergen, and Messner 2009).

[21] Multicollinearity is not a serious threat to the inferences drawn from the analysis. As the correlation matrix presented in app. table B1 reveal none of the interitem bivariate correlations observed among the independent variables exceeds .70. Further, the mean variance inflation factor (VIF) for the model specification reported in table 3 was below four. Without the state dummy variables, this value dropped below two. Only four indicators exhibited individual VIFs above three, including the limited economic means scale (4.02), the share of loans originated by subprime lenders (3.69), average loan volume (3.51), and average loan values (3.48). We observe nearly identical standard errors for each of these variables when the others are omitted.

First, though much of the dialogue about fraud in mortgage markets during the early 2000s U.S. housing boom emphasized absolute considerations of incentives and costs, our results suggest that they were not major determinants of the geographic distribution of mortgage fraud during the period. Table 3 shows that, contrary to expectations, mortgage fraud was not significantly more prevalent in counties that experienced greater increases in loan values during the early 2000s, net of other factors. The results also provide no support for the idea that rates of mortgage fraud were significantly lower in areas with heightened local risks associated with fraudulent behavior, at least as measured by arrest rates for related offenses (we observed similar results in models that substituted an indicator of prison admission rates for fraud, forgery, and embezzlement for the arrest rate measure).[22] Paralleling our discussion of predictions implied by a rational choice perspective on county mortgage fraud patterns, we extended the analysis presented in table 3 to evaluate whether the association between changes in loan values and mortgage fraud was moderated by arrest (or prison admission) rates or by the prevalence of loans made to investors or for purposes of refinancing. As summarized in appendix C, we found no evidence to support that prediction.[23]

For the most part we also observe that, after controlling for other factors, mortgage fraud risk was very similar across counties that differed considerably in the average value of loans originated between 2003 and 2005. The sole exception is that employment/income fraud risk was more prevalent in counties in which loan values were higher (table 3, model 2, $b = .02$, $P < .05$). All else equal, the results imply that employment/income fraud was about 15% higher in counties with very high average loan values (i.e., the 95th percentile) than in counties with very low average loan values (i.e., the 5th percentile). This pattern could reflect a tendency among borrowers in higher-priced areas to embellish income or employment data on loan applications to enhance the chances of qualifying for a loan that might otherwise have been out of reach, but it also could reflect mortgage professionals misrepresenting such information on behalf of borrowers because getting their clients qualified for larger loans yielded greater commissions (Black 2009; Nguyen and Pontell 2010). We cannot adjudicate fully between these interpretations, but as described earlier, if the former explanation were valid, we

[22] Using a one-tailed ($P < .05$) directional test, the results suggest that employment/income fraud was lower in counties with higher arrest rates for fraud and related offenses (table 3, model 2, $b = -.14$). However, the corresponding average marginal effect indicates a trivial relationship.

[23] Appendix table C1 summarizes the hypothesized multiplicative relationships specified in fig. 3. To simplify the presentation, only estimates for the hypothesized focal and moderator variables are displayed in the tables. The product terms included were computed after mean-centering the component variables.

TABLE 3
NEGATIVE BINOMIAL REGRESSION MODELS OF MORTGAGE FRAUD RISK ($n$ = 2,232)

| | Overall Mortgage Fraud (1) | Employment/ Income Fraud (2) | Property Valuation Fraud (3) | Identity Fraud (4) | Occupancy Fraud (5) |
|---|---|---|---|---|---|
| Fraud arrest rate (logged) | .11 | −.14 | .52 | .14 | −.14 |
| | (.01) | (.09) | (.47) | (.11) | (.13) |
| Average loan values ($1,000s) | .00 | .02* | −.06 | .00 | .01 |
| | (.01) | (.01) | (.03) | (.00) | (.01) |
| Change in loan values | .13 | −.07 | −.54 | .25 | −.52 |
| | (.25) | (.22) | (1.88) | (.24) | (.35) |
| Refinance loan rate | −.09 | −.22 | 1.02 | .02 | −.41 |
| | (.32) | (.27) | (1.60) | (.23) | (.38) |
| Non-owner-occupied loan rate | .01 | .04* | .05 | .01 | .00 |
| | (.01) | (.01) | (.10) | (.01) | (.02) |
| Change in non-owner-occupied loan rate | .01 | .00 | −.06 | .03 | .01 |
| | (.04) | (.04) | (.18) | (.04) | (.05) |
| Rental costs | −.05 | .31 | −1.83 | .00 | .12 |
| | (.51) | (.49) | (2.77) | (.47) | (.66) |
| Loans by subprime lenders | .38 | .09 | .34 | .11 | .26 |
| | (.42) | (.23) | (2.34) | (.22) | (.39) |
| High-cost loans | −.20 | −.34 | −1.23 | .03 | .01* |
| | (.34) | (.30) | (2.03) | (.26) | (.00) |
| IMC share of loans | .40* | .40* | .65 | .51* | .17 |
| | (.20) | (.19) | (1.05) | (.26) | (.28) |
| Percent non-Latino black | −.19 | −.17 | −.82 | −.07 | .34 |
| | (.20) | (.10) | (.94) | (.09) | (.22) |
| Percent Latino | −.07 | .01 | −.67 | .14* | −.17 |
| | (.11) | (.09) | (.53) | (.06) | (.13) |
| Recent immigration | −.56 | −.25 | −5.54 | 1.41* | 2.24* |
| | (1.00) | (1.02) | (4.93) | (.71) | (.94) |
| Black/white dissimilarity | .31* | .03 | 1.86* | .07 | .17* |
| | (.06) | (.06) | (.43) | (.05) | (.07) |
| Latino/white dissimilarity | .06 | −.01 | .14 | .14 | −.10 |
| | (.10) | (.08) | (.57) | (.07) | (.13) |
| Limited educational attainment | −.04 | −.03 | .11 | −.04 | −.04 |
| | (.05) | (.04) | (.26) | (.04) | (.05) |
| Limited economic means | .00 | .03* | −.14 | −.02 | .04 |
| | (.02) | (.01) | (.12) | (.02) | (.03) |
| Property crime rate | .04* | .01 | .22* | .00 | .02 |
| | (.01) | (.01) | (.11) | (.01) | (.01) |
| GSE-purchased loans | −.68* | .16 | −9.48* | −.18 | .13 |
| | (.28) | (.20) | (1.82) | (.27) | (.32) |
| Lender-held loans | −.65* | −1.06* | 2.37 | −.01 | −.88 |
| | (.32) | (.41) | (1.85) | (.29) | (.63) |
| Average loan volume | .01* | −.01* | .10* | .00 | .00 |
| | (.00) | (.00) | (.02) | (.00) | (.00) |
| Percent of loans with no income stated | 1.16* | .59 | 5.40 | .30 | 1.12 |
| | (.57) | (.84) | (4.01) | (.70) | (.83) |
| Home ownership rate | −.83* | .03 | −5.80* | −.19 | −.02 |
| | (.29) | (.19) | (1.26) | (.18) | (.27) |

TABLE 3 (*Continued*)

| | Overall Mortgage Fraud (1) | Employment/ Income Fraud (2) | Property Valuation Fraud (3) | Identity Fraud (4) | Occupancy Fraud (5) |
|---|---|---|---|---|---|
| Spatial lag | .05* | .00 | .11* | .03* | .06* |
| | (.01) | (.01) | (.03) | (.01) | (.01) |
| Intercept | −1.79* | −3.16* | −0.73 | −3.05* | −3.64* |
| | (.27) | (.24) | (1.80) | (.20) | (.29) |
| Adjusted deviance $R^2$ | .54 | .16 | .56 | .30 | .21 |

NOTE.—Dummy variables for states are included in all models but not shown in the table. SEs (clustered on state) are in parentheses.
* $P < .05$, two-tailed tests.

would expect the relationship between loan values and employment/income fraud to be significantly stronger in counties in which economic means were lower and rental prices were higher. When we reestimated model 2 after adding the product terms relevant to evaluating those possibilities, we did not find convincing supportive evidence (see app. C). The estimated relationship between loan values and employment/income fraud was quite similar across counties that varied considerably on levels of unemployment, wages, and median family income.[24] We also find no support for the idea that more expensive rental markets stimulated higher levels of mortgage fraud, either directly (table 3) or by amplifying pressures to engage in fraud where home prices were high or rising more substantially (app. C). It may be that such patterns are limited primarily to loans made to first-time home buyers, a possibility we cannot evaluate with the Interthinx data because their measures of fraud cannot be disaggregated in the data we obtained.

One possible reason that housing prices were not more strongly associated with mortgage fraud during the housing boom is that the overall compensation for many mortgage professionals during the period was driven not merely by the average dollar value of the loans but also by the sheer volume of loans originated. There were strong incentives to close as many loans as possible, and fraud was one means by which this could be accomplished. As Engel and McCoy (2011, pp. 28–30) put it, “From lenders’ perspective, the mortgage machine needed constant feeding in order to generate constant fees. Volume was what mattered. . . . The quest for ever higher revenues went hand in hand with fraud.” Consistent with this assertion, our analysis reveals that property valuation fraud, identity fraud, and overall mortgage fraud were significantly more prevalent during the housing boom in coun-

[24] The interaction term for average loan values and limited economic means is statistically significant in the employment/income fraud model. However, the magnitude of the implied moderated relationship is very small, and further analyses showed that this finding was driven by relatively few counties with very high values on both variables.

ties with higher average loan origination volume (table 3, models 1, 3, and 4). The magnitude of this association was especially strong for property valuation fraud, for which the estimated coefficient (model 3, $b = .10$, $P < .05$) implies rates that were more than four times greater in counties with very high loan rates (i.e., the 95th percentile) than in counties with average loan rates (i.e., the 50th percentile).

A second theme we highlight is that several of the estimated relationships are consistent with predictions derived from classic and contemporary anomie theories. In line with Merton's (1938) arguments, we find evidence of significantly higher rates of employment/income mortgage fraud risk in counties in which legitimate economic means are especially limited (model 2, $b = .03$, $P < .05$), a result that parallels findings from Mian and Sufi's (2015) analysis of income inflation across U.S. zip code areas.[25] The other forms of fraud are not significantly related to county economic conditions, which is interesting given that employment/income fraud is the form that most often involves complicity from borrowers, who may be motivated to provide (or overlook and sign off on) invalid information about income, employment status, or assets for purposes of realizing a cherished component of the American dream—home ownership. As suggested by Merton (1938), such pressures are likely to be less prominent where the means to attain this valued goal are more plentiful, which may explain why rates of employment/income fraud in mortgage transactions are somewhat lower—about 11%—in affluent counties (e.g., a score at the 5th percentile on the limited economic means scale) than in economically depressed counties (e.g., a score at the 95th percentile on the limited economic means scale).[26]

Although we included the share of loans made to investors (i.e., the non-owner-occupied loan rate) primarily as a control variable, its significant positive association with employment/income fraud (model 2, $b = .04$, $P < .05$), but not other forms, also accords with Merton's arguments. Further inspection of this relationship suggests that it was limited to counties that experi-

[25] Mian and Sufi (2015) identify income inflation on mortgage loans during the housing boom by comparing the growth in income reported on home purchase mortgage applications and the growth in average Internal Revenue Service (IRS)–reported income during the same period. Measuring income inflation as the degree to which the former outpaced the latter, their findings indicate that during the housing boom, income inflation was significantly higher in U.S. zip codes with higher levels of poverty and unemployment and lower levels of median household income.

[26] It is also possible that the Interthinx data systematically underestimate rates of employment/income fraud risk in higher-income areas. This could be the case if low- or no-documentation loans, for which employment/income fraud is more difficult to detect, were more prevalent in such areas during the housing boom. Though we include in our models a proxy for the prevalence of no-doc loans to account for this possibility, we cannot fully rule out this alternative interpretation without a more direct and comprehensive measure.

enced larger recent increases in housing prices, which suggests that the lure of capitalizing on the housing boom for enhancing wealth in rapidly appreciating markets may have led some investors, or the mortgage personnel working with them, to stretch the truth about income or assets.[27]

We also find evidence consistent with classic and contemporary extensions of Merton's anomie framework. As anticipated on the basis of Cloward's (1959) insights about the distribution of illegitimate opportunity structures (see also Cloward and Ohlin 1960), we find that net of a wide variety of other factors, rates of both overall mortgage fraud (model 1, $b = .04$, $P < .05$) and property valuation fraud (model 3, $b = .22$, $P < .05$) were significantly higher in counties in which preexisting rates of property crime were greater. The latter represents a relatively strong relationship, with estimated rates of property valuation fraud about twice as large in counties with very high property crime rates than in counties with very low property crime rates. This overlap between property street crime and property valuation fraud is surprising in light of widespread discourse about mortgage fraud during the housing boom as primarily a white-collar crime, but it accords with existing qualitative descriptions of property crime. Both field ethnographies of offenders actively engaged in traditional forms of property street crime (e.g., Wright and Decker 1994, 1997) and narrative analysis of property evaluation fraud schemes, such as appraisal falsification, illegal flipping, cash back schemes (FinCEN 2008), highlight important roles for deceit, collusion, forgery, and kickbacks, often with a high level of co-offending.

Messner and Rosenfeld's (1994) institutional anomie theory also obtains some support in the data. Overall, the results indicate that mortgage fraud was significantly more prevalent in counties where a larger percentage of originated loans were sold by lenders in the secondary market and thus lower where lenders retained more of the loans they funded (model 1, $b = -.65$, $P < .05$). In particular, employment/income fraud was significantly lower in counties where lenders held a larger share of loans, suggesting that the fidelity of data about jobs and income may have received greater scrutiny by lenders when they continued to assume risk rather than redistributing it through securitization. More pertinent to Messner and Rosenfeld's arguments about the role of political institutions in regulating behavior in

[27] In supplementary analyses, we added the product of the non-owner-occupied loan rate and changes in loan values to model 2 and observed a statistically significant interaction effect ($b = .0003$, $P < .05$, one-tailed test). The implied adjusted predictions from this model indicated that in counties where loan prices had been relatively flat (e.g., the 5th percentile on the loan change variable), employment/income fraud was quite similar irrespective of lending rates to investors. In contrast, in areas where prices had been increasing substantially (the 95th percentile on the loan change variable), this form of fraud was about 10% higher in counties where loans to investors were relatively common than in counties where such loans were uncommon.

anomic environments, we find that overall levels of mortgage fraud were significantly lower where GSEs purchased a larger share of loans sold in the secondary market, relative to the share purchased by private firms (model 1, $b = -.68$, $P < .05$). Looking to the results for specific forms of fraud reveals that this institutional arrangement regulated mortgage fraud primarily by limiting property valuation fraud (model 3, $b = -9.48$, $P < .05$), and the magnitude of this relationship was nontrivial. Though private firms purchased the majority of loans sold in the secondary market during this period in nearly all of the counties included in the sample, which can be inferred from the descriptive statistics presented in table 2, these regression results imply that rates of property valuation fraud were about 80% lower in counties where GSEs were most active in purchasing loans in the secondary market (95th percentile) than in counties where they were least active (i.e., the 5th percentile).

The third general theme that emerges from our analysis highlights the relevance of spatial inequalities in lending practices and geographic differences in racial and ethnic context. Consistent with expectations, table 3 shows that, net of many other factors, overall rates of mortgage fraud risk were significantly higher in counties where IMCs originated a larger share of loans (model 1, $b = .40$, $P < .05$). Similar patterns were observed for employment/income fraud and identity fraud, suggesting that the type of lender involved was important, yielding levels of fraud about 15%–17% higher where IMCs originated a very large share of loans compared to areas where such lenders originated very few loans. In contrast, the analysis reveals little support for the idea that levels of mortgage fraud during the housing boom were substantially higher in counties where subprime lending was more prevalent. We do observe a statistically significant coefficient for the indicator of high-cost loans in the model for occupancy fraud (model 5), but the implied magnitude of this relationship is modest, and the more pervasive pattern in our data is that county-level differences in levels of mortgage fraud are not strongly associated with variation in subprime, high-cost lending.[28] While somewhat surprising in light of the many adverse features associated with subprime lending, these patterns reinforce a general point made by many observers of lending during the housing boom: fraud was a prominent fixture in both subprime and prime markets (e.g., FinCEN 2008; Fulmer 2010; Smith 2013).

[28] Bostic et al. (2008) make a persuasive case to simultaneously consider the two measures we include to fully capture community differences in subprime lending during the period under review. Nonetheless, since they exhibit a relatively strong bivariate association (Pearson's $r = .67$) in our sample, we also estimated supplementary models with the two items combined into a single subprime lending factor and another set of models in which one or the other was omitted. The conclusions we draw about the role of subprime lending are substantively identical across these alternative specifications.

With a few exceptions, table 3 reveals that counties with a larger proportion of racial and ethnic minorities did not exhibit significantly higher levels of mortgage fraud during the period. One exception is identity fraud, which was significantly higher in counties with a larger proportion of Latinos and recent immigrants (model 4). Model 5 shows that occupancy fraud also was significantly higher in counties with a larger share of immigrants. The patterns observed in areas of recent immigration conform to reports of selected mortgage fraud scams in which recent immigrants were targeted during the 2000s housing boom (Del Rio 2010), but the implied differences across counties that vary substantially on levels of immigrant concentration are modest.[29]

In contrast to the findings for racial and ethnic composition, the influence of racial residential segregation on levels of mortgage fraud appears to be both statistically and substantively significant. Several forms of fraud were significantly more prevalent in counties with higher levels of residential segregation between non-Latino blacks and whites, including overall mortgage fraud, property valuation fraud, and occupancy fraud.[30] Indeed, a comparison of the adjusted marginal effects associated with changes (from the 5th to the 95th percentile) in each of the covariates considered reveals that black-white segregation exhibits one of the strongest relationships observed for these outcomes. The average predicted rates implied by the results in table 3 suggest that rates of overall mortgage fraud were about 20% higher, rates of property valuation fraud were more than 150% higher, and rates of occupancy fraud were about 10% higher in counties where non-Latino blacks were highly segregated from whites (i.e., a black-white dissimilarity index score of .66, the 95th percentile), compared to counties with very low levels of segregation (i.e., a black-white dissimilarity index score of .13, the 5th percentile).

Overall, black-white racial segregation emerges as an important dimension of where mortgage fraud was most prevalent during the housing boom, and the results suggest that what was most distinctive in such communities was an elevated rate of property valuation fraud. Importantly, while much of the literature on racial inequalities in housing outcomes emphasizes the prominence of nonbank lenders and greater prevalence of high-risk loan products in racially segregated areas, our findings reveal statistically and

[29] The results imply rates of identity fraud that are 6% higher, and rates of occupancy fraud about 8% higher, in counties with very high levels of immigration during the 1990s than counties that experienced very little immigration during the period.

[30] We tested for interactions between the indicators of ethnoracial composition and residential segregation. These supplementary analyses (not shown) suggest that the relationship between black-white segregation and rates of overall mortgage fraud was amplified slightly in areas in which non-Latino blacks composed a larger share of the population, but the magnitude of these moderated relationships was relatively small.

substantively important differences in levels of fraud that are independent of geographic differences in subprime high-cost lending and the share of loans originated by IMCs.

## SUMMARY AND CONCLUSIONS

We focused in this article on mortgage fraud, a relatively neglected but key ingredient of the early 2000s housing boom that served as a major stimulus of the housing crisis and, by implication, many of the negative social consequences that ensued. Our study extends the reach of sociological research on community-level patterns of illicit conduct, which has previously focused almost exclusively on "street crime." Further, it contributes an important piece to the emerging portrait of the sociological implications of the housing boom by evaluating the prevalence, nature, and geographic distribution of mortgage fraud during the period.

Drawing from a unique data set, our descriptive analysis revealed that nearly 25% of residential mortgage loans originated between 2003 and 2005 in America contained one or more indications of suspected fraud. We also showed that levels of mortgage fraud risk during this period were highly variable across U.S. counties. Many counties exhibited relatively low levels of mortgage fraud risk, with a small handful having no detected instances of such activity. In contrast, mortgage fraud risk was quite high in other counties, reaching 50% in some areas. An important goal of our study was to explore conditions that may have given rise to this significant geographic variation. Though our data cannot pinpoint the specific perpetrators in given cases or what might have driven them to engage in fraud, the observed aggregate variation in levels of mortgage fraud risk yields interesting insights about the prevalence of illegal behavior within mortgage transactions and the conditions associated with it.

Much of the discourse on mortgage fraud during the housing boom emphasized rational considerations of lucrative incentives and limited risks, which led us to anticipate that the highest rates of fraud would be found where the potential profits were especially high and the chances of detection and punishment were particularly low. We found limited support for these expectations. Mortgage fraud was not systematically more prevalent in counties in which housing loans were larger or increasing more rapidly, nor was it less common where the risk of arrest and imprisonment for fraud was greater. These findings should not be read to suggest that mortgage fraud during the housing boom lacked a rational choice component. Indeed, our analysis revealed higher rates of several forms of mortgage fraud in counties with especially high loan volume, which has been identified as a key means by which mortgage industry personnel enhanced profits during the housing boom (e.g., Engel and McCoy 2011). We cannot discern with our data whether perceptions of benefits and costs differed in counties with very high loan volumes, but we suggest that it is plausible that such market conditions made it more difficult to engage in quality control (Smith 2013), which may have lessened the perceived costs associated with using false identification or straw buyers, artificially inflating property values, or fabricating appraisals. Additionally, the capacity to close a large volume of loans may have lured some mortgage brokers and loan officers to engage in or facilitate these forms of fraud to enhance their commissions.

Insights from other sociological perspectives proved more useful for enhancing understanding of the significant county-level geographic variability in mortgage fraud risk that existed during the housing boom. Through the lens of anomie theory, it is not surprising that the strong cultural emphasis on expanding the reach of home ownership and enhancing wealth through real estate during the period, coupled with a relatively weak normative and legal environment, yielded relatively high levels of fraudulent behavior (Merton 1938). The anomie frameworks we reviewed suggested that this would be the case especially under conditions of limited economic means (Merton 1938), heightened availability of illegitimate means (Cloward 1959; Cloward and Ohlin 1960), and looser constraints in the secondary mortgage market (Messner and Rosenfeld 1994). Several of the empirical patterns that emerged in our study are consistent with these expectations. Employment/income misrepresentation, the form of mortgage fraud risk most commonly committed by persons whose primary interest lies in attaining the American dream of home ownership, was significantly more prevalent in counties in which the population possessed fewer legitimate economic resources. Our results also revealed that mortgage fraud risk was more prevalent in counties with higher preexisting rates of property crime, which is consistent with Cloward's (1959) arguments about the importance of the distribution of illegitimate opportunity structures for shaping the crime potential of an anomic cultural environment. Further, the findings show that where government-sponsored efforts in secondary mortgage markets were more substantial (e.g., a higher prevalence of secondary market loan purchases by GSEs rather than private financial entities), mortgage fraud risk levels were significantly lower. This squares with Messner and Rosenfeld's (1994, 2012) claim that political institutional arrangements can reduce illegitimate conduct under anomic conditions.

The findings also add to a growing body of evidence about the adverse consequences of spatial inequalities in lending and housing outcomes. Spatial inequalities in lending were influential to shaping the geographic distribution of mortgage fraud in America during the housing boom, but geographic variation in the lenders who were marketing and originating loans appears to have been more important than the types of loan products that they were distributing. County differences in the share of loans originated by IMCs contributed to county differences in mortgage fraud, net of a wide array of factors, including the prevalence of subprime and high-cost loans. The extent of racial segregation appears to have been even more influential in the resulting geographic distribution of mortgage fraud. Controlling for the nature of lending, types of lenders, and many other structural conditions and housing market features (including state fixed effects), black-white racial segregation exerted a substantively important association with overall mortgage fraud and both property valuation and occupancy fraud. These patterns are consistent with qualitative assessments that mortgage personnel and speculators capitalized on housing market conditions in areas with relatively large and segregated black populations to bolster profits, especially by fabricating occupancy intentions for speculators and illegally manipulating property values (Fisher 2009; Galster 2012). Elaborating on the latter, the available evidence suggests that property valuation fraud was facilitated in such areas not only by mortgage participants looking to make money through fraudulent appraisals but also by a mortgage origination system characterized by substantial geographic and transactional distance between lenders and the borrowers and homes being funded (Smith 2010), and an environment in which loan underwriters had relatively little incentive to be highly attentive to quality control because they rarely retained the loans they originated (Engel and McCoy 2011).

Our results parallel other findings that point to the importance of racial segregation in structuring contemporary housing outcomes (e.g., Massey and Denton 1993; Rugh and Massey 2010; Wyly et al. 2012; Fischer and Lowe 2015; Hall et al. 2015; Rugh et al. 2015), but they also add a significant element to that narrative by showing that fraud was a critical dimension of what transpired in racially segregated housing markets during the housing boom. When integrated with literature on the spatial patterning of subprime lending (Hyra et al. 2013; Hwang et al. 2015) and research that has documented the consequences of high levels of mortgage fraud (Pendley et al. 2007; Mian and Sufi 2015), our results provide further insights about the especially high levels of foreclosures observed during the housing bust in areas with high levels of racial segregation (Rugh and Massey 2010). The collective narrative that emerges is that during the early 2000s, mortgage brokers and other loan sellers not only targeted such areas with predatory lending practices and subprime loan products that had a high risk of default but also were often complicit in committing or facilitating mortgage fraud in the loans originated in those areas, which subsequently translated into high levels of foreclosure (Baumer et al. 2013). Thus, while mortgage fraud helped to fuel a housing boom that expanded the reach of home ownership and yielded significant financial returns to many, it also had profound adverse social consequences. It was an important driver of the foreclosure crisis, which in turn implicates it as playing at least an indirect role in several related adverse social trends that have emerged during the last decade, including reductions in voter turnout (Estrada-Correa and Johnson 2012), withered trust in housing markets (Ross and Squires 2011), heightened demographic disparities in economic circumstances (Baker 2014; Squires 2014; Rugh et al. 2015), declines in mental health (Houle 2014), higher levels of crime (Hipp and Chamberlain 2015), and a reversal of recent strides made toward residential racial integration (Hall et al. 2015).

Given the substantial financial and social costs associated with fraud within mortgage transactions, additional research on the factors that influence it would be valuable. Our analysis uncovered some identifiable community attributes (e.g., high levels of preexisting property crime, a relatively large and segregated black population) that were significantly associated with elevated mortgage fraud risk and that may therefore serve as useful cues regarding the types of places in which to concentrate prevention efforts. Perhaps of even greater utility, our analysis points to the importance of a set of malleable conditions, some of which were shown to raise levels of mortgage fraud risk (i.e., the share of loans originated by IMCs) and others that appear to significantly reduce it (e.g., the purchase of loans in secondary markets by GSEs), that point to tangible policy changes that could minimize mortgage fraud and its collateral consequences. However, our study was limited to a cross-sectional analysis of county-level data, which is not ideal for extracting or evaluating definitive policy prescriptions. As the data infrastructure for studying mortgage fraud expands and becomes more fully developed, it would be useful to build on our analysis with approaches better suited for doing so.

Future studies should integrate longitudinal community-level data to further specify the role of housing market conditions and social, economic, and demographic features. Unfortunately, the mortgage fraud data used for our study were not available prior to the period we investigated (Interthinx began collecting such data in 2003), which precluded a panel analysis during the housing boom. Nonetheless, more recent data from Interthinx and other sources (CoreLogic) are available that could support longitudinal analysis of mortgage fraud trends since the height of the housing boom. Pursuing such analyses would permit an assessment whether the relatively recent introduction of preventive measures, such as Operation Stolen Dreams, new guidelines that govern the home appraisal process (e.g., the Home Value Code of Conduct [HVCC] and the Dodd-Frank Act), or revised data standards imposed by GSEs have reduced fraud within mortgage transactions.[31]

[31] In response to the housing crisis, the federal government and many states passed legislation and stepped up enforcement efforts during the late 2000s that may have relevance to levels of and changes in mortgage fraud. Operation Stolen Dreams is one such effort, launched in 2010; this coordinated national and local effort has yielded several

Another useful direction for future research on mortgage fraud would be to expand on recent loan-level assessments of mortgage fraud in the private secondary market (e.g., Piskorski, Seru, and Vig 2010; Jiang et al. 2014; Mian and Sufi 2015; Griffin and Maturana 2016) to explore in greater depth the influence of borrower, lender, and community factors on mortgage fraud within a multilevel context. Though we could not gain access to such data for the housing boom, doing so for more recent periods may be feasible. Such research would be particularly revealing if it encompassed a wider range of loans (e.g., those held and serviced directly by lenders and loans sold to GSEs) from a diverse set of communities across America and if it were designed to separate loans by the status of buyers (e.g., first-time home buyers vs. others), the purpose of the requested financing (e.g., home purchase vs. refinance), and the level of documentation involved (i.e., full vs. no/low-documentation loans). Finally, to gain more comprehensive insights into the perpetrators of mortgage fraud and the factors that influenced their behavior, it is critical to build on pioneering efforts directed at gathering data on each of the key participants in mortgage transactions (Nguyen and Pontell 2010). Pursuing this broader research agenda would significantly expand knowledge about mortgage fraud and help to enhance understanding of several contemporary social problems that appear to be part of its collateral damage.

## APPENDIX A

### Measuring Mortgage Fraud with FraudGUARD

Interthinx's FraudGUARD compares the integrity of the information provided on residential loan applications to information housed within several other databases, including a wide variety of public records systems, purchased property sale records, and internal data on previously screened loan applications to identify inaccuracies and misstatements (Interthinx, http://www.verisk.com/product-pages/fraudguard-fraud-detection-for-mortgage-lenders-and-investors.html). On the basis of these data integrity checks, a proprietary algorithm is applied to generate a fidelity score ranging from zero to 1,000 for each of the evaluated loans indicating the likelihood that it

convictions for mortgage fraud (FBI 2010), but it is unclear whether it has reduced aggregate rates of mortgage fraud. Similarly, the 2009 HVCC guidelines required lenders to use a third party to select an appraiser and prohibited them from having direct communications with them during the property valuation process, while the 2010 Dodd-Frank Act imposed additional appraiser independence requirements and outlined penalties for violations. More recently, Fannie Mae and Freddie Mac have implemented a Uniform Mortgage Data Program that governs the documentation of appraisals and other data elements on mortgages they purchase. Research evaluating the efficacy of these reforms would be valuable.

contains fraudulent information. Guided by industry standards, Interthinx deems a loan to possess a high risk of mortgage fraud if it receives a score of 400 or below and it contains at least one preselected high-risk indicator of fraud, such as ambiguities about the borrower's identity, property valuation or intended occupancy, or reported income. The identification of a loan as high-risk does not necessarily mean that the loan contains fraudulent information, but that designation is informed by detailed comparisons with other data and extensive knowledge about the markers of fraudulent mortgage transactions.

More than 3 million residential mortgage loans were screened through Interthinx's FraudGUARD system by a large number of national, regional, and local lenders across the nation between 2003 and 2005, the period on which our analysis is focused. Interthinx's data-sharing policy would not permit us to access loan-level data on mortgage fraud (we instead were granted access to aggregated county-level data on the total number of loans evaluated during the period and the number of loans scored as high-risk for mortgage fraud), which would have enabled us to explore in detail the degree to which the loans that make up our county-level measure are representative of all loan applications submitted during the period. However, a comparison of the county-level data obtained from Interthinx with independently gathered county-level data from the HMDA suggests a high degree of geographic representativeness. The overall distribution of the number of loans screened through FraudGUARD per county between 2003 and 2005 mirrors almost perfectly the reported number of loan applications documented in HMDA during the period (Pearson's $r = .97$). Additionally, the county-level share of loan applications screened through FraudGUARD (i.e., the number of loans screened through FraudGUARD divided by the number of loan applications reported in the HMDA) is not strongly related to levels of mortgage fraud or the county-level distribution of loan applicants, loan types, and other county conditions considered in our study. We evaluated bivariate Pearson's correlations between the county share of loans used to generate our mortgage fraud measure and a wide array of other county attributes, including mortgage fraud rates; social, demographic, and economic conditions (e.g., racial composition, residential segregation, home ownership rates, and unemployment rates); and the quantity and quality of loans originated during the period, as measured through HMDA (e.g., the share of loan applications submitted by persons of different races and ethnicities and the share of loan applications from low-income persons, loan volume, loan values, loan type, and the prevalence of subprime loans). With one exception, these measures exhibited relatively weak correlations ($r < .25$) with the share of loans processed through FraudGUARD (the exception was loan volume, which was moderately correlated with the share of loans screened with a Pearson's $r = .45$).

The aforementioned geographic comparisons increase confidence that the county differences in mortgage fraud described in our study are not driven by geographic differences in the distribution of loans screened through FraudGUARD. Like other sources of community-level crime data (e.g., the UCR and the National Incident-Based Reporting System), however, it is difficult to assess more formally the validity of the estimates obtained from Interthinx. Several indirect pieces of evidence suggest that the estimates derived from Interthinx possess acceptable validity. For example, the prevalence of property valuation fraud and occupancy fraud reported in our study approximates that reported in studies that adopt different methods (Griffin and Maturana 2016). Additionally, the limited state-level comparisons that exist suggest a high degree of correspondence to other widely referenced sources (FBI 2011) and Mian and Sufi (2015) report a strong association across zip code areas between the overall mortgage fraud index computed by Interthinx and an indirect estimate of income inflation they compute by integrating data on borrower income and IRS income levels. Finally, communities with high rates of mortgage fraud, as estimated by Interthinx, also tend to have much higher subsequent levels of default and foreclosure (Baumer et al. 2013; Mian and Sufi 2015), which is consistent with loan-level evidence on the link between fraud and foreclosure (Pendley et al. 2007). Nonetheless, definitive conclusions about levels and predictors of county differences in mortgage fraud should await additional research that replicates the analysis presented in our study with fraud data from alternative sources.

## APPENDIX B

### TABLE B1
Bivariate Correlation Matrix for Explanatory Variables ($n = 2{,}232$)

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) | (19) | (20) | (21) | (22) | (23) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Fraud arrest rate (logged) | 1 | | | | | | | | | | | | | | | | | | | | | | |
| 2. Average loan values | −.16* | 1 | | | | | | | | | | | | | | | | | | | | | |
| 3. Change in loan values | .03 | .12* | 1 | | | | | | | | | | | | | | | | | | | | |
| 4. Refinance loan rate | −.10* | .26* | .01 | 1 | | | | | | | | | | | | | | | | | | | |
| 5. Non-owner-occupied loan rate | −.02 | .46* | .00 | −.13* | 1 | | | | | | | | | | | | | | | | | | |
| 6. Change in non-owner-occupied loan rate | −.03 | −.06* | −.10* | −.01 | −.03 | 1 | | | | | | | | | | | | | | | | | |
| 7. Rental costs | −.01 | .26* | .08* | −.11* | .25* | −.06* | 1 | | | | | | | | | | | | | | | | |
| 8. Subprime loans | −.02 | .04 | −.00 | .02 | −.12* | −.01 | .04* | 1 | | | | | | | | | | | | | | | |
| 9. High-cost loans | .12* | −.45* | .04 | −.27* | −.33* | .03 | −.07* | .67* | 1 | | | | | | | | | | | | | | |
| 10. IMC share of loans | −.07* | .32* | .04* | −.07* | .22* | .01 | .17* | .58* | .30* | 1 | | | | | | | | | | | | | |
| 11. Percent non-Latino black | .20* | −.10* | .19* | −.13* | −.03 | −.06* | .15* | .20* | .35* | .08* | 1 | | | | | | | | | | | | |
| 12. Percent Latino | −.14* | .17* | .01 | −.23* | .09* | −.00 | .15* | .35* | .20* | .35* | −.10* | 1 | | | | | | | | | | | |
| 13. Recent immigration | −.07* | .44* | −.02 | −.11* | .23* | −.04 | .20* | .17* | −.09* | .29* | .03 | .55* | 1 | | | | | | | | | | |
| 14. Black/white dissimilarity | −.03 | .03 | .01 | −.06* | −.04 | −.08* | .13* | .07* | .02 | .04 | −.05* | .04 | .12* | 1 | | | | | | | | | |
| 15. Latino/white dissimilarity | .06* | .15* | .03 | −.08* | .04 | −.06* | .09* | .09* | −.03 | .13* | .14* | .09* | .38* | .43* | 1 | | | | | | | | |
| 16. Limited educational attainment | .10* | −.24* | −.04 | .05* | −.17* | .07* | −.03 | .06* | .28* | −.10* | .07* | −.11* | −.17* | −.09* | −.19* | 1 | | | | | | | |
| 17. Limited economic means | .16* | −.58* | .04 | −.16* | −.21* | .04 | .11* | .14* | .56* | .09* | .25* | .11* | −.27* | −.12* | −.26* | .40* | 1 | | | | | | |
| 18. Property crime rate | .17* | .01 | .07* | −.20* | .14* | −.09* | .26* | .30* | .26* | .22* | .43* | .18* | .22* | .19* | .21* | .00 | .20* | 1 | | | | | |
| 19. GSE-purchased loans | .05* | −.31* | .01 | .16* | −.22* | .10* | −.19* | −.18* | .09* | −.32* | .00 | −.22* | −.23* | −.13* | −.17* | .28* | .34* | −.16* | 1 | | | | |
| 20. Lender-held loans | .09* | −.33* | −.01 | −.06* | −.23* | −.00 | −.05* | −.08* | .18* | −.28* | .04 | −.14* | −.21* | −.06* | −.12* | .21* | .30* | −.09* | .32* | 1 | | | |
| 21. Average loan volume | −.14* | .64* | −.02 | .10* | .47* | −.04 | .15* | .02* | −.44* | .30* | −.13* | .08* | .28* | .06* | .16* | −.26* | −.68* | −.00 | −.42* | −.35* | 1 | | |
| 22. Percent of loans with no income stated | −.06* | .48* | .12* | .03 | .45* | −.04* | .24* | −.04* | −.30* | .25* | −.07* | .14* | .23* | .03 | .11* | −.18* | −.28* | .03 | −.24* | −.24* | .38* | 1 | |
| 23. Home ownership rate | −.01 | −.26* | −.05* | .18* | −.17* | .02 | −.41* | −.14* | .06* | −.14* | −.18* | −.27* | −.52* | −.21* | −.34* | .22* | .12* | −.35* | .22* | .13* | −.08* | −.14* | 1 |

* $P \leq .05$, two-tailed tests.

## APPENDIX C

TABLE C1
Multiplicative Negative Binomial Regression Models of Mortgage Fraud Risk ($n$ = 2,232)

| | Overall Mortgage Fraud (1) | Employment/ Income Fraud (2) | Property Valuation Fraud (3) | Identity Fraud (4) | Occupancy Fraud (5) |
|---|---|---|---|---|---|
| Fraud arrest rate (logged) | .10 | −.16 | .58 | .14 | −.16 |
| | (.10) | (.09) | (.49) | (.12) | (.13) |
| Average loan values | −.01 | .02 | −.02 | .00 | .01* |
| | (.01) | (.01) | (.05) | (.01) | (.00) |
| Change in loan values | .11 | −.24 | −.65 | .27 | −.61 |
| | (.25) | (.24) | (1.95) | (.25) | (.37) |
| Refinance loan rate | −.10 | −.23 | .64 | .02 | −.43 |
| | (.32) | (.28) | (1.62) | (.23) | (.38) |
| Non-owner-occupied loan rate | .01 | .04* | .02 | .01 | .00 |
| | (.01) | (.01) | (.10) | (.01) | (.02) |
| Rental costs | −.10 | .50 | −1.59 | −.08 | .28 |
| | (.51) | (.50) | (2.87) | (.52) | (.66) |
| Limited economic means | .00 | .02 | −.16 | −.02 | .04 |
| | (.02) | (.01) | (.12) | (.02) | (.03) |
| Average loan values × limited economic means | .00 | .00* | .02 | .00 | .00 |
| | (.00) | (.00) | (.01) | (.00) | (.00) |
| Average loan values × rental costs | .12 | −.07 | .17 | .04 | −.13 |
| | (.13) | (.06) | (.49) | (.10) | (.09) |
| Average loan values × fraud arrest rate (logged) | .02 | .00 | −.08 | .00 | .04 |
| | (.03) | (.02) | (.14) | (.02) | (.03) |
| Change in loan values × refinance loan rate | −2.82 | .42 | −14.81 | 2.69 | −3.68 |
| | (2.86) | (2.87) | (29.84) | (3.17) | (3.20) |
| Change in loan values × non-owner-occupied loan rate | −.02 | .25 | −1.47 | .04 | −.05 |
| | (.12) | (.16) | (1.14) | (.11) | (.17) |
| Intercept | −1.76* | −3.26* | −1.09 | −2.99* | −3.71* |
| | (.26) | (.24) | (1.73) | (.22) | (.30) |
| Adjusted deviance $R^2$ | .54 | .16 | .56 | .30 | .21 |

Note.—All other county variables considered and dummy variables for states also are included in all models, but estimated parameters for these variables are not shown in the table. SEs (clustered on state) are in parentheses.

* $P < .05$, two-tailed tests.

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