Foreclosures In Ohio: Does Lender Type Matter?

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Abstract

Whether mortgages are originated mostly by depository institutions regulated by the Federal agencies or by less-regulated lenders does not seem to affect the foreclosure filing rate in Ohio's counties. What seems to matter is whether the lenders have a physical presence in the market, in which case, foreclosure rates are lower.

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1. Introduction

As mortgage delinquencies and foreclosures grow across the nation and reports of allegedly-abusive lending practices abound in the popular media, the debate over who is responsible for the mess is heating up. National Consumer Law Center's Seniors Initiative notes:[1]

> Deceptive lending practices, including those attributable to home improvement scams, are among the most frequent problems experienced by financially distressed elderly Americans seeking legal assistance. This is particularly true of minority homeowners who lack access to traditional banking services and rely disproportionately on **finance companies and other less regulated lenders**.

Moreover, a study by the Joint Center for Housing Studies of Harvard University finds that higher-priced loans are more likely to originate from less-regulated lenders (i.e., mortgage lenders regulated by HUD) than from regulated-lenders (i.e., mortgage lenders regulated by the FED, OTS, OCC, FDIC or NCUA).[2] In the popular media, Ameriquest, Ameritrust, Franklin Financial and others have become poster boys for the aggressive lending practices in the mortgage market.

This paper examines the relationship between troubled mortgages and the level of regulation faced by the financial institutions lending in the market. Put differently,

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[1] Available at http://www.consumerlaw.org/initiatives/seniors_initiative/helping_elderly.shtml as of December 2007.

[2] The State of the Nation's Housing 2007, available at http://www.jchs.harvard.edu/publications/markets/son2007/index.htm as of December 2007.

does the way lenders are regulated matter for delinquency and foreclosure rates? The answer to the question will be a step toward answering more broad regulatory questions such as whether the problem is really the lack of regulation or whether the problem would go away if all mortgage lenders were regulated and supervised the same way.

Using the lenders' loan application register (LAR) sheets collected under the Home Mortgage Disclosure Act (HMDA) between 1997 and 2004, I identify three types of lenders in each of Ohio's 88 counties and in each year: regulated lenders with a branch in the market (local banks), regulated lenders without a branch (non-local banks) and the less-regulated lenders. I find that the foreclosure rate in a county increases significantly with increasing share of *non-local* banks and less-regulated lenders in originations.[3] Overall, there does not seem to be a statistically significant difference between the less-regulated lenders and their non-local regulated counterparts in terms of their impact on foreclosures.

Whether a lender has a physical presence in a market may matter for multiple reasons. First, local depository institutions may know their neighborhoods better than out-of-town lenders and less-regulated mortgage lenders because they constantly interact with consumers and businesses on both sides of their balance sheets by making loans and taking deposits. The information advantage, if there is one, is likely to show up in higher loan quality. Second, even in the absence of any informational advantage, local lenders may be less likely to foreclose on properties because of their ties to the community. The pressure from community groups, for example, may be a factor that affects a bank's decision to foreclose or to come up with a work-out plan.

There is a rich literature on the factors associated with mortgage delinquencies, and the final outcome post-delinquency (i.e., mortgage is cured, foreclosed, etc.; see the next section). The delinquency is modeled as a put option on the house, owned by the borrower. As suggested by the option pricing theory, the option is most valuable and delinquencies most frequent if, among other things, the house price volatility is high or the market value of the house is less than the money owed. The transition from

[3] I use the term "bank" generically to refer to all insured depositories.

delinquency to foreclosure is less likely if, among other things, the loan-to-value ratio is low or the borrower's time on the job is high.

My approach to the problem is fundamentally different from the existing literature in two ways. First, the previous studies use individual loan data obtained from a single lender or from a pool of securitized mortgages and apply logistic regression to estimate the probability of various outcomes. This type of data does not allow the study of the impact financial market structure has on the loan performance, such as whether delinquencies and foreclosures are a function of lender type, because either there is only one originator or the originator information is absent in the data. To get at these issues I employ a different strategy and examine how the level and the rate of change of delinquencies and foreclosures in a market are related to the lagged-values of each type of lenders' market share. So, in lieu of loan-by-loan analysis that tracks the performance of individual loans, I concentrate on broad market trends.

Second, instead of focusing on loans originated throughout the country by a single lender, I focus on loans originated in a single State---Ohio---by all lenders. Focusing on a single State allows me to divorce the discussion from State-specific factors, such as State regulation of mortgage brokers, judicial vs. non-judicial procedures for foreclosure, efficiency of the State judiciary, etc.

The remainder of the paper is organized as follows. In section 2, I will identify the variables that are relevant to the analysis. Section 3 describes the data sources and the econometric method. Section 4 presents the results. Section 5 concludes.

2. Factors Affecting Mortgage Performance

Home mortgage delinquencies are best analyzed within the context of contingent claims models. Delinquency is a put option on the collateral. As such, the observed frequency of delinquencies should depend on variables that affect the value of a put option; namely, asset price relative to exercise price, volatility, interest rate, expiration date, transaction costs and dividend yield (Kau and Kim, 1994; Kau, Keenan, and Kim, 1994; Quigley and Van Order, 1995; Capozza, Kazarian, and Thomson, 1997, 1998).

Local economic factors such as unemployment and trigger events such as divorce may also force the exercise of the option even when it is not in the money.

Foreclosure is the second part of the two-step default process. Ambrose and Capone (1996) were first to recognize (analytically) that all delinquencies don't end up in foreclosure. After a delinquency, the subsequent process is more of a negotiation between the borrower and the lender than the lender simply using its right to seize the property. The borrower can prepay the loan, the lender may choose to forbear, restructure the loan, agree to a short-sale or foreclose.

The recognition of the existence of various resolution options led to a more detailed analysis of which factors determine the default probability and the final outcome after a delinquency (Ambrose, Buttimer and Capone, 1997; Ambrose and Buttimer, 2000). Ambrose and Capone (1998) found that whether the final outcome will be a foreclosure strongly depends on the reason the mortgage became delinquent in the first place. If the borrower optimally exercised its put option because it was in the money, the mortgage will end up in foreclosure unless there is an event that changes the borrower's valuation of the option (ruthless default). If the borrower was involuntarily pushed into delinquency by a trigger event (divorce, unemployment, etc.), he will try to avoid the foreclosure if he can find an alternative source of funds. So, in predicting the incidence of foreclosures, it is important to account for both types of defaults by controlling for trigger events as well as factors that put the default option in the money.

Equity is one such factor that affects the value of the put option. The importance of the original and current loan-to-value ratio has long been recognized (Von Furstenberg, 1969; Campbell and Dietrich, 1983). Greater levels of equity ownership (the loan amount---the strike price of the put option---falling behind home value) is associated with lower delinquencies and fewer foreclosed properties. A second factor that may be related to the borrower's equity position is the age of the mortgage; as the mortgage is paid off, the equity increases. Kau, Keenan and Kim (1993, 1994) find that foreclosures are more likely with recently originated loans.

Capozza, Kazarian, and Thomson (1998) study the effect of home price and interest rate volatility as well as the dividend (rental) yield on default. Their crucial finding is that the effects are highly nonlinear in the level of equity (loan-to-value---LTV---ratio). For example, at high levels of equity (low LTV), high house-price volatility has a positive impact on default probabilities. At low levels of equity (high LTV), high house-price volatility means that there is value in waiting to see if home prices will fall even further; so, the probability of default drops.

Transaction costs are the costs associated with the exercise of the default option, incurred by the borrower. For example, the damage to the borrower's creditworthiness may affect future employment opportunities and limit access to credit (Phillips and VanderHoff, 2004).

3. Data and Method

The dependent variables of interest in this paper are foreclosures and delinquencies. The number of foreclosure filings in each county, in every year from 1999 to 2006 is reported in the Ohio Supreme Court's Ohio Courts Summary. Note that filings do not represent properties that were eventually foreclosed on; they represent the first legal step in a long process. Some of the troubled mortgages may eventually be cured but the filings are the only reliable foreclosure-related data reported at county level for all counties of Ohio. Furthermore, the fact that the mortgage has not been cured between the beginning of the delinquency and the filing date (at least 90 days) indicates that these mortgages are in worse shape than other loans in the delinquency pool. Although a filing does not always end in actual foreclosure, it is still interesting to examine how the presence of these severely delinquent mortgages varies with the lender mix in the county. The foreclosure rate for county i at time t is F_{it}, defined as the number of filings per owner-occupied housing units.

Obtaining total delinquencies, D_{it}, is more problematic. Past-due mortgages are not publicly reported at county level. Therefore, as a proxy for the market delinquency rate, I will use the average mortgage delinquency rate of the regulated depositories lending in the county, weighted by the share of the county in their originations (see

Appendix A). Given that for many lenders, each Ohio county constitutes only a small fraction (less than 1%) of their total originations, those lenders that originate less than 1% of their loans in the county will get zero weight in the calculation to limit the noise.

Lenders' mortgage delinquency rates are reported in bank and thrift quarterly regulatory reports. Such a proxy comes with an obvious warning flag. The delinquency rate of the regulated institutions may be affected by the competition among them or the presence of less-regulated lenders. In that case, any relationship between the delinquency rate and the type of lender may be due to competition and not necessarily due to the regulatory environment the lender operates in. While I attempt to control for the level of competition in the market, such controls are never perfect and there will undoubtedly be some residual effects.

The identity of the financial institutions lending in the market comes from the HMDA-LAR sheets from 1997 to 2004. I determine whether a lender is regulated or not from its supervisory agency. Lenders supervised by the FED (state member banks and mortgage subsidiaries of financial holding companies), OCC (national banks), OTS (thrifts), FDIC (state non-member banks), and NCUA (credit unions) fall into the regulated-entity category; the remainder is less-regulated. I further divide the regulated lenders into two groups based on whether they have a branch in the county (local) or not (non-local). Branch location is provided in the FDIC's Summary of Deposit files. All information related to the regulated-lender characteristics comes from bank call and thrift reports.

I use two estimation techniques in this study. The first one is a dynamic panel regression, which I describe in the next section. The second technique is a series of cross-sectional regressions I describe in Section 3.2.

The advantage of a dynamic panel over cross-sectional analysis is two-fold. First, the Arellano-Bond first-differenced GMM estimator allows to control for unobserved county-specific effects. Second, the technique accounts for auto-regressive dynamics and allows for explanatory variables that are not strictly exogenous.

The cross sectional regressions have their own advantages. First, they do not suffer from the potential bias in the dynamic panel that arises from the large number of instruments relative to the number of cross sections (more on this in the next section). Second, my dataset contains the 2000 Census levels of some crucial demographic factors. Because I cannot capture the time-variance in these factors, they automatically drop out of the dynamic panel.[4] So, the cross sectional analysis allows a richer control variable set.

3.1 Dynamic Panel Analysis

I begin the analysis by estimating the system below with the Arellano-Bond first-differenced GMM applied in two-stages:

$$D_{it-1} = f\left(D_{it-2}, LoanD_{it-2}, RegNLD_{it-2}, LRegD_{it-2}, Arm_{it-2}, X_{it-2}\right) + \xi_i + \varepsilon_{it-1} \quad (1a)$$

$$F_{it} = f\left(F_{it-1}, Loan_{it-2}, RegNL_{it-2}, LReg_{it-2}, \widehat{D_{it-1}}, X_{it-1}\right) + \eta_i + \nu_{it} \quad (1b)$$

Note that the predicted values from the first stage are used on the right-hand side of the second stage, as indicated by the $\widehat{D_{it-1}}$ notation in (1b). X_{it} is a vector of time-varying variables that influence the value of the default option. I will describe them later in this section. The total *number* of loans originated by all lenders per owner-occupied housing unit in each county *i* and year *t* is denoted by $Loan_{it}$. To determine a particular type of lender's market share, I add up the number of loans originated by each type of lender irrespective of loan purpose--- the loan may be for a home purchase, refinancing or home improvement--- in each county. The *share* of loans originated by the regulated non-local, and the less-regulated lenders is $RegNL_{it}$, and $LReg_{it}$, respectively. In (1a), the total *dollar amount* of loans originated by all lenders per housing unit is $LoanD_{it}$. The distinction between numbers and dollar amounts is necessary because the delinquency measure, D_{it}, is defined as a *dollar amount* and the foreclosure measure, F_{it},

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[4] Arellano-Bover/Blundell-Bond system-GMM allows the use of time-invariant factors but it requires that there be more cross-sections in the sample than moment conditions. This requirement cannot be satisfied in my small sample of 88 counties with a large number of explanatory variables.

refers to the *number* of foreclosures. The dollar-share of the lenders, $RegNLD_{it}$, and $LRegD_{it}$, is calculated by adding up the dollar amounts instead of numbers.[5]

It is often reported in the press, that frequent, costly refinancings are used to erode homeowners' equity in their houses. To distinguish between home purchase loans and refinancings, I create six new variables: $Purch_{it}$ is the number of home purchase loans originated in county i, year t per owner-occupied housing units. $PRegNL_{it}$, and $PLReg_{it}$ are the shares of regulated non-local lenders and less-regulated lenders, respectively. Similarly, $Refi_{it}$ is the total number of refinancings and $RRegNL_{it}$, and $RLReg_{it}$ are the respective market shares of regulated non-local lenders and less-regulated lenders in the refinancing market. The market shares in dollars are denoted by adding a '*D*' to the end of the variables' names.

Taking the first difference of (1) eliminates the unobserved, individual-specific, time-invariant effects, ξ_i and η_i.

$$\Delta D_{it-1} = f\left(\Delta D_{it-2}, \Delta LoanD_{it-2}, \Delta RegNLD_{it-2}, \Delta LRegD_{it-2}, \Delta Arm_{it-2}, \Delta X_{it-2}\right) + \Delta\varepsilon_{it-1} \qquad (2a)$$

$$\Delta F_{it} = f\left(\Delta F_{it-1}, \Delta Loan_{it-2}, \Delta RegNL_{it-2}, \Delta LReg_{it-2}, \widehat{\Delta D_{it-1}}, \Delta X_{it-1}\right) + \Delta\nu_{it} \qquad (2b)$$

Note that the identification of ΔF_{it} is a critical issue. In the remainder of this section, I will discuss the identification of ΔF_{it} first. Then, I will examine the components of X_{it}. Finally, I will discuss my assumptions about the workings of the mortgage market that lead to this particular model.

Identification

I identify ΔF_{it} using two different techniques. The first one deals with the endogeneity of the lagged foreclosure rate, ΔF_{it-1} in (2b). This technique involves the use of lagged values of the right-hand side variables as instruments, which I treat as pre-determined. In other words,

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[5] Using dollars or numbers has no noticeable impact on the results.

$$\left.\begin{array}{c}\operatorname{cov}\left(\Delta Loan_{it-1-s},\Delta\nu_{it}\right)\\ \operatorname{cov}\left(\Delta RegNL_{it-1-s},\Delta\nu_{it}\right)\\ \operatorname{cov}\left(\Delta LReg_{it-1-s},\Delta\nu_{it}\right)\\ \operatorname{cov}\left(\widehat{\Delta D_{it-s}},\Delta\nu_{it}\right)\\ \operatorname{cov}\left(\Delta \mathrm{X}_{it-s}\right)\end{array}\right\} = 0 \qquad \forall s \geq 1 \tag{3a}$$

$$\left.\begin{array}{c}\operatorname{cov}\left(\Delta Loan_{it-1-s},\Delta\nu_{it}\right)\\ \operatorname{cov}\left(\Delta RegNL_{it-1-s},\Delta\nu_{it}\right)\\ \operatorname{cov}\left(\Delta LReg_{it-1-s},\Delta\nu_{it}\right)\\ \operatorname{cov}\left(\widehat{\Delta D_{it-s}},\Delta\nu_{it}\right)\\ \operatorname{cov}\left(\Delta \mathrm{X}_{it-s}\right)\end{array}\right\} \neq 0 \qquad \forall s \leq 0 \tag{3b}$$

The reasoning behind this assumption is that a rise in foreclosures in the current period may affect the characteristics of the local real estate market---e.g., home values, lending market competition, etc.---in the future (3b). However, the lags will be uncorrelated with $\Delta\nu_{it}$ (3a).

The second identification technique involves the use of an instrument, which is correlated with D_{it-1} but uncorrelated with the error term in the second stage, ν_{it}. My choice for instrument is a variable correlated with the incidence of adjustable-rate mortgages (ARM) in the market, Arm_{it-2}. The rate-reset of ARMs has been associated with high delinquency rates.[6] In a rising interest rate environment, loan payments resetting to a higher level may be associated with higher delinquencies. Alternatively, ARMs can be used as an affordability product that lowers interest costs in the short-run.

[6] It is also true that many loans originated in recent years defaulted before the rate reset.

This latter effect may show up in lower delinquencies as long as home prices are growing and refinancings are available. Either way, once the loan is delinquent, whether it will be prepaid, restructured or foreclosed on does not depend on whether it has an adjustable rate or not; it depends on the borrower's ability to make timely payments in the future. In other words, after the delinquency, a lender would treat an ARM the same way it treats a fixed-rate mortgage.

In terms of data availability, HMDA does not contain information about whether a loan is fixed or adjustable rate. I create a county-level proxy for this variable by calculating the average share of ARMs in the mortgage holdings of the regulated financial institutions, where each institution is weighted by its mortgage market share in the county. This measure makes two important assumptions. First, I assume that the balance-sheet ARMs are representative of the total ARM production of the local depositories (including the securitized loans). The second and somewhat stronger assumption is that the ARM origination rate of regulated entities is highly correlated with the ARM origination rate of the less-regulated lenders. That is, the composition of the depositories' on-balance-sheet mortgage loan portfolios is representative of the market.

In estimating the first stage (2a), I treat ΔArm_{t-2} and the other right-hand side variables as predetermined.

Valuing the Default Option at County Level

In this section, I take each component of the default-option valuation models described earlier, and identify their equivalent for county-level aggregate analysis included in X_{it}.

One of the critical variables in the contingent-claim models I described earlier is the **home values**. Average or median value of homes in each county are not available annually (available only in the Decennial Census). Therefore, I infer the average home value in each county from the Ohio Department of Taxation's property tax records. In 2000, the correlation between the median home value reported by the Census and the average home value I calculate from the tax records in the same year is 75 percent. I conclude, therefore, that tax records provide a reasonable annual proxy to home values.

HMDA began reporting the interest-rate spread of "high-priced" loans over maturity-matched Treasuries in 2004.[7] Therefore, the mortgage **interest rate** in each market going back to late 1990s is another variable that requires a proxy. My proxy is the average funding cost (interest expense over interest-bearing liabilities from bank call reports) of small local banks in the county, *FundCost*. The presumption is that the higher the funding costs are, the higher the lending rates must be. Using the spread data from HMDA, I find a positive correlation between *FundCost* and the mortgage spreads to the tune of 17-21 percent depending on the year. To further examine how closely I can approximate the spreads, I regress the spreads reported in HMDA on *FundCost* and all the right hand side variables in X_{it} in 2004 and 2005. While this estimation is omitted from the paper (available upon request), I find that I can explain more than 50 percent of the volatility in spreads; so there is some, admittedly imperfect control for the level of interest rates in the analysis.

In earlier research that dealt with individual loans, borrowers' creditworthiness (i.e., the **transaction cost** of exercising the default option) has been measured by the applicants' credit score. I work with data aggregated to state level and I don't have the credit score data in the entire analysis period. Instead, I create a variable from HMDA based on lenders' reported rejection rates due to poor credit histories. More specifically, when a lender rejects an application, it has to give at least one and up to three reasons for the rejection (e.g. insufficient cash, high debt, mortgage insurance denied, etc).[8] One of these reasons is the borrower's credit history. I conjecture that the lower the credit scores are in a county, the greater is the likelihood of observing credit-history as a reason for loan denial. So, my credit quality variable, *Denial*, is the share of loans denied due to poor credit history among all loans denied. In fact, in 2003, the only year in which I have access to county median credit scores, the correlation between the median score

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[7] A mortgage is "high-priced" if the interest spread exceeds 3% for first-lien mortgages and 5% for second liens. Only the high-priced loan spreads are reported by HMDA. The calculation of the ***unconditional*** mean spread is explained in detail in Ergungor (2006).

and my denial variable derived from the 2003 HMDA is -40% (lower score is associated with higher rate of rejection due to poor credit history).

An additional transaction cost is the non-pecuniary cost of losing one's home and leaving a familiar neighborhood. The more people are involved in or committed to their neighborhood, the less likely they are to consider mortgage default as an option in response to financial troubles. To capture people's involvement in their community, I use the election turnout, *Turnout*. Ohio Secretary of State publishes the election turnout in each county in even-number years. I estimate a turnout for odd years by averaging the preceding and the subsequent turnout rate. The downside to using *turnout* is that it may not be a clean measure of community involvement as one would like; it is also possible that people will vote in large numbers in economically stressed areas to effectuate some change in their neighborhoods. While I expect a negative coefficient from the community involvement effect, the coefficient may turn positive if the economic effect dominates.

I cannot control for **interest and house price volatility** directly because high-frequency data are not available at county level. However, I can control for the volatility of the underlying local economy, which, I assume, will be correlated with the volatility of interest rates and home prices. My proxy for the volatility in the economy is the standard deviation of the monthly unemployment rates in each year, $\sigma Unempl$. The data source is Ohio Job and Family Services.

In terms of **trigger events**, I control for the divorce rate, *Divorce*, in each county annually from 1997 to 2006 and the unemployment rate, *Unempl*, over the same period. The divorce data comes from Ohio Department of Health. The unemployment rate is reported by the Ohio Job and Family Services.

Other Variables of Interest

While the contingent claims models are an attractive way of thinking about mortgage defaults, they entail some oversimplifications when it comes to thinking about

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[8] The three reasons are *not* ranked in any particular order of importance.

the problem empirically. For example, racial composition of the neighborhood or competition among the lenders may affect the terms of the loan and the lending standards. Admittedly, lax standards, for example, would show up in the data as high LTV ratios or low minimum credit scores. Still, controlling for race and competition separately provides a more colorful picture of the default process.

I measure the **competition** in the mortgage market, *Herf*, with a Herfindahl-Hirschman market-concentration index, calculated using the mortgage-market share of all the institutions lending in each county, irrespective of their regulatory status or branch presence in the market. The data source is HMDA.

The final control variable captures the **incentive effect** of previous loan restructurings on mortgage performance. More specifically, *Lenient*, is the ratio of restructured mortgage loans to the sum of Other Real Estate Owned (OREO) and restructured mortgage loans. As this ratio increases, future borrowers may expect a rescue after delinquency and become more likely to default. Alternatively, leniency may reduce the observed delinquencies in the short-run. The ratio is calculated using the weighted-average of individual regulated-lender ratios where the weight is the share of the county in the lender's total originations (once again, lenders are deleted if the county's share in their mortgage portfolio is less than 1 percent).

Timing of Events

A significant challenge that arises from the way I track defaults and explain them with the lender mix in earlier periods is determining when the effect of a change in the lender mix shows up in the data. The model I estimate in (2) makes two critical assumptions about the timing of events. The first one is that a foreclosure filing occurs in the year following the delinquency. In other words, F_t is a function of D_{t-1}. This is a sensible assumption given that my delinquency measure is as of December 31st and foreclosure proceedings are typically initiated when three or more mortgage payments are overdue. While a borrower with good credit can technically delay the proceedings for more than a year under a forbearance agreement, I expect these types of arrangements to be a relatively small fraction of delinquencies. The second implicit assumption is that the effect of lending by one particular type of financial institution will be observed in the delinquencies in the following year and in foreclosure filings in the year after that. In other words, D_{t-1} is a function of $Loan_{t-2}$, $RegNL_{t-2}$, and $LReg_{t-2}$. Note that HMDA reports the year of origination, but not the exact date. Therefore, $Loan_{t-2}$, $RegNL_{t-2}$, and $LReg_{t-2}$ capture originations throughout the year $t-2$.

D_{t-1}, however, is as of year-end $t-1$. So, I basically assume that the unobservable lag between originations and delinquencies is longer than a year but less than two years. Is this a reasonable assumption? Pennington-Cross (2003) finds that in his sample of mortgages originated between 1995 and 1998, the mean age of those in default (at the time of analysis) was close to 18 months, with a wide standard deviation of approximately 12 months. So, the lag structure seems reasonable.

3.2 Cross-Section Analysis

In this section, I examine how the market share of various types of lenders affect future delinquency and foreclosures by estimating the system below, *separately* in each year t from 1999 to 2006, using GMM to deal with potential heteroscedasticity.

$$D_{it-1} = f\left(LoanD_{it-2}, RegNLD_{it-2}, NRegD_{it-2}, Arm_{it-2}, \mathrm{X}_{it-2}, CS_i \right) + \varepsilon_{it-1} \tag{4a}$$

$$F_{it} = f\left(Loan_{it-2}, RegNL_{it-2}, NReg_{it-2}, D_{it-1}, \mathrm{X}_{it-1}, CS_i \right) + \nu_{it} \tag{4b}$$

X_{it} is the same vector of time-varying variables as in (1) that influence the value of the default option. As before, Arm_{it-2} is the instrument that identifies F_{it}.

Valuing the Default Option at County Level: Data from the 2000 Census

CS_i is a vector of time-*invariant* explanatory variables from the 2000 Census. These are variables that affect the value of the default option, but were excluded from the panel analysis because they are eliminated by first-differencing.

One such variable is the standard measure of equity in a house, the **LTV ratio**. Unfortunately, HMDA does not report the LTV ratios. As I already have a measure of home values, I will pick a proxy for the mortgage debt-load of homeowners and enter the two variables in the analysis separately. Compared to using an LTV ratio, my approach allows "loan" and "value" to have different coefficients in the analysis and is therefore less restrictive. The key is of course to find a proper substitute for the "loan" component. I use the median monthly owner-costs reported in the 2000 Census, which gives me the approximate level of mortgage and property tax payments in the county. Property tax payments are a function of home values which are already controlled for; so, the new variable mainly captures the effect of mortgage payments. Obviously, the mortgage payments are a flow measure while the debt levels that I am interested in are stock measures. Still, keeping interest rates constant (only to the extent described earlier), mortgage payments must be highly correlated with the debt levels. Therefore, I use the natural log of the owner costs as a proxy for the debt level, *Debt00*.

The real-estate equivalent of the dividend yield is the **rental yield**. I use a price-to-rent ratio, *Ptor00*, to capture the rental yield. The components of the ratio are median home prices and gross rents for each county, which come from the 2000 Census.

I also add to the analysis some population characteristics that make **trigger events** more likely. Given the increasing job losses in manufacturing in Ohio, I expect the share of population employed in manufacturing, *Manuf00*, to be positively correlated with the likelihood of trigger events. Similarly, I expect people with low levels of educational attainment to have less stable jobs and therefore a greater chance of triggering a negative event. My measure of educational attainment, *HSchool00*, is the share of the adult population with a high school diploma or less. Finally, in order to determine the vulnerability of households if trigger events occur, I need some measure correlated with net worth. I choose the share of children living in single-parent households, *ChildSP00*, as such a measure. The presumption is that a single adult with children will be more vulnerable to economic shocks for at least two reasons. First, the income flow is likely to be less than that of a two-parent household and second, the parent may lose work hours because he or she is the only caregiver for the children when there is an illness in the family.

Other Variables of Interest

The log-**population** of the county, *Population00*, is intended to capture the availability of a variety of financial services in the county. I expect a more diverse group of lenders to be present in high-population counties because they are economic centers. The economic-center effect must be isolated before I can examine the effect of lender types on loan performance.

I add the **race** factor in the analysis by controlling for the share of African-Americans in the total population, *Black00*. The data source is the 2000 Census.

4. Results

I begin the discussion of the results with an overview of some sample statistics and univariate relationships between the amount of lending, the market share of different types of lenders and the delinquency and foreclosure rates. That discussion is followed by an examination of the results from the dynamic panel analysis. A discussion of the cross-section analysis concludes this section.

4.1 Summary Statistics

The summary statistics of each variable discussed in Section 3 are presented in Table I. While the market share of regulated *local* lenders, *RegL*, is the omitted variable in the analysis, it is included in the summary statistics table. Table I also shows the county names and the years in which the minimum and maximum values of each variable are observed. As reported in the press, Cuyahoga county is the foreclosure leader in the state. It is also the leader in population, the population share of African Americans and the share of children living in single-parent households. Holmes County, the county with the lowest foreclosure rate, is also the county where the share of the regulated *local* lenders is the highest.

Table II shows the simple correlations among the variables of primary interest. Counties where there is a lot of mortgage lending per household are also the counties where the foreclosure *rates* are high. At the first glance, the correlations also confirm the press reports that the increased presence of less-regulated lenders is associated with increased foreclosures. While the presence of non-local regulated lenders is also positively correlated with foreclosures, this correlation is much weaker than the one with the less-regulated institutions.

4.2 Univariate Analysis

Table III presents the results from the univariate analysis. My method consists of dividing the sample into two groups based on the level of $Loan_{t-2}$ in each county relative to the median $Loan_{t-2}$ in the sample. Then, I calculate the mean and median delinquency and foreclosure rates in each half of the sample (Panel A). As a second step, I divide the high- and low-$Loan_{t-2}$ subgroups further into two based on the market share of regulated-non-local lenders relative to the median market share of those lenders in each subgroup. I calculate once again the mean and median delinquency and foreclosure rates in each quartile. Those results are in Panel B. Panel C repeats the analysis for less-regulated lenders.

Table III Panel A shows that in counties where lenders make more loans per housing unit, the delinquency rates of local small lenders are significantly smaller a year down the road but the market-wide foreclosure rates are higher two years into the future. When interpreted together with the correlation results from Table II, the findings of Table III are consistent with an asymmetric information story where local regulated lenders have an informational advantage about local market conditions relative to lenders that engage in credit-scored, arm's-length lending. The source of this soft information (unverifiable by other lenders) could be the local bank's interaction with the community not just through various types of consumer banking services but through commercial relationships as well. Adverse selection would then explain why copious lending in an area is associated with greater market share for uninformed lenders, lower delinquencies for informed local banks and higher foreclosures going forward. Put differently, uninformed lenders may be scraping the bottom of the barrel in an attempt to increase their market share.

The question then becomes why uninformed lenders would follow such a money-losing strategy, oblivious to adverse selection effects. One explanation is that they may be underestimating the importance of soft information in the mortgage market and depending heavily on mortgage brokers who seem to have neglected their due diligence in recent years according to press reports. Alternatively, these lenders may be attracted to the area in an attempt to make a quick buck while the market is rising. Their overconfidence in their ability to identify the peak of the market may lead to such behavior.

Without proper controls, such conclusions are admittedly highly speculative. I cannot identify lenders' business strategies from the available data. Therefore, I turn to the multivariate results in the remainder of this paper.

4.3 Dynamic Panel Analysis

The results in Table IV-Panel A show that increased market share of non-local regulated mortgage lenders and less-regulated lenders at the expense of local lenders has no significant impact on delinquency rates of local lenders. Two crucial variables that drive delinquencies are income growth and the election turnout. Delinquencies are higher where income growth is slow and election turnout is high. The latter is consistent with the reaction-to-economic-stress story.

Table IV-Panel B shows that increased market share of non-local regulated mortgage lenders and less-regulated lenders at the expense of local lenders has a positive impact on foreclosure rates. One standard deviation increase in the total market share of non-local banks (13 percentage points), $RegNL_{-2}$, is associated with a 0.10 percentage points increase in the foreclosure rates. This is approximately equivalent to 8 percent of the mean foreclosure rate in the sample. A similar magnitude increase in the total market share of less-regulated lenders is associated with a similar magnitude increase in the foreclosure rate. Note that the effects are statistically indistinguishable.

The same result holds for mortgages taken for purchasing a house. The impact of lender type in the refinancing market is more muted. In this case, there is no significant relationship between the foreclosure rates and the market share of less-regulated and regulated-non-local lenders.

The panel also reveals a positive correlation, as expected, between the county unemployment rate and foreclosures. So, the health of the local economy is an important driver of foreclosure rates. The only other significant variable is home values. Foreclosure rates tend to be higher in counties where home prices (natural log) were high. One potential explanation is that the lender is more likely to sell the collateral and recover its loan in areas where home prices are high compared to areas where they are depressed. In depressed markets, a work-out may be to everyone's interest.

4.4 Cross-Section Analysis

Table V presents the results from the cross-section analysis that includes all time-invariant explanatory variables. For the sake of brevity, I only present the results that include all mortgages. The results for purchase loans and refinancings are available upon request.

The most striking observation is that in early years (2000-2001), there is a negative relationship between $LReg_{it-2}$ and the delinquency rate, D_{t-1}. This is consistent with the discussion in Section 4.2 that arm's-length lenders may be attracting the riskier end of the borrower pool due to adverse selection (or by choice) and leaving the *local* lenders with safer loans. An interesting question is why the negative relationship disappears in later years. One speculative answer is that the local lenders may have lowered their lending standards in later years to keep up with competition.

$RegNL_{t-2}$ is significant and positive in the foreclosure regressions in six out of eight years. The interesting observation is that its effect becomes economically more significant in later years. One standard deviation increase in $RegNL_{t-2}$ in 2004 is associated with a 0.14 percentage points increase in the foreclosures in 2006 (11 percent of the mean foreclosure rate). This observation may indicate that non-local regulated lenders are less likely to work with borrowers to avoid foreclosure because they have no stake in the community. Alternatively, they may be more realistic about the deteriorating conditions in the housing market and they may be more inclined to foreclose on the property to prevent it from falling into disrepair. Unfortunately, it is not possible to identify lenders' motives in this study.

Six variables enter the regressions with mostly significant results. First, foreclosure rates are higher in counties where there is more lending per household. Second, *Denial* has a positive coefficient in the foreclosure regressions in five out of eight years, which is consistent with the idea that in areas where credit quality is low, lenders are less likely to offer a work-out plan. Third, foreclosure rates tend to be low in counties where the price-to-rent ratio, *Ptor00*, is high (the effect is more muted for delinquencies). This observation suggests that if the price of a house is well above the fundamental value---keeping the price of the house constant---, troubles borrowers can sell their homes and walk away from their debts. Alternatively, the lender may have an incentive to delay the foreclosure since the local market is attractive and the house can be seized and sold in the future if the work-out plan is a failure. Consequently, the lender may be more willing to delay the foreclosure and offer a work-out plan. Fifth, educational attainment, *HSchool00*, is positive indicating that in counties where a larger fraction of the population has a high school diploma or less, foreclosure rates tend to be higher. Finally, the fraction of children living in single parent households, *ChildSP00*, is also positively associated with foreclosures suggesting that low net worth may be a factor behind high foreclosure rates.

The remaining variables are either not consistently significant or they switch signs. Some of the sign switching makes economic sense. For example, in 1999, when the number of homes in foreclosure was relatively small, lenders may have found it easier to foreclose on a property in response to economic shocks (high *Unempl*), which would explain the positive relationship between the unemployment rate and the foreclosure filings. However, the sign switches to negative in 2001. An intuitive explanation is that as the foreclosure stock grows, lenders may begin to react more leniently to economic shocks and refrain from adding to the foreclosure pool. However, if the economy is slow and transaction costs of foreclosures become high (e.g. paying for maintenance and property taxes while the house is sitting on the balance sheet), a work-out may be a better alternative. Sign switching in other variables does not lend itself to a simple explanation. The volatility of unemployment, for example, has a positive impact on delinquencies in 1998, a negative impact in 1999, and a positive impact on 2000. An examination of simple correlation statistics confirms that these relationships exist and are significant in the raw data (not shown). Furthermore, they are not driven by outlier observations. It is highly plausible that my simple cross-sectional model is not fully capturing every aspect of lender and borrower behavior and variations in economic activity.

5. Conclusion

The results suggest that the type of the financial institutions lending in a county is a factor that influences the foreclosure rates. Although the evidence is not consistently strong in every single time period, there are some indications that foreclosures tend to be lower in areas where local regulated-lenders are more active than others.

This observation does not constitute proof that those other lenders have followed predatory practices. As outsiders, they may have overestimated the growth potential of the market or depended upon third parties (brokers) who may have neglected their due diligence in order to generate volume and meet the demand. These are issues that must be addressed in future work.

Table I. Summary Statistics

Variable	Coverage	Mean	Median	Std Dev	Min.	Max.	Min. County Name	Min. Year	Max. County Name	Max. Year
D	1998-2005	0.023	0.020	0.012	0.003	0.129	Paulding	1997	Franklin	2005
F	1999-2006	0.013	0.012	0.006	0.002	0.038	Holmes	2000	Cuyahoga	2006
LoanD	1997-2004	0.111	0.091	0.085	0.006	0.846	Noble	1997	Delaware	2002
Loan	1997-2004	0.121	0.112	0.054	0.017	0.453	Noble	1997	Delaware	2002
RegL	1997-2004	0.363	0.340	0.142	0.000	0.845	Montgomery	2000	Wood	2000
RegNL	1997-2004	0.533	0.537	0.132	0.131	0.941	Montgomery	1998	Wood	1998
LReg	1997-2004	0.115	0.106	0.056	0.011	0.365	Holmes	1997	Champaign	2001
RegLD	1997-2004	0.333	0.303	0.152	0.000	0.855	Noble	1999	Wood	2000
RegNLD	1997-2004	0.555	0.563	0.138	0.123	0.932	Wood	1998	Montgomery	1998
LRegD	1997-2004	0.123	0.112	0.061	0.010	0.396	Holmes	1997	Champaign	2001
PurchD	1997-2004	0.042	0.032	0.037	0.002	0.374	Noble	1997	Delaware	2004
Purch	1997-2004	0.040	0.037	0.021	0.007	0.185	Noble	1997	Delaware	2004
PRegL	1997-2004	0.298	0.275	0.150	0.000	0.791	Pike	1999	Wood	2001
PRegNL	1997-2004	0.579	0.585	0.142	0.130	1.000	Wood	1999	Noble	1997
PLReg	1997-2004	0.130	0.110	0.081	0.000	0.489	Montgomery	1997	Champaign	2001
PRegLD	1997-2004	0.304	0.275	0.159	0.000	0.792	Pike	1999	Wood	2001
PRegNLD	1997-2004	0.574	0.578	0.147	0.133	1.000	Wood	1999	Noble	1997
PLRegD	1997-2004	0.129	0.110	0.082	0.000	0.479	Montgomery	1997	Franklin	1998
RefiD	1997-2004	0.067	0.052	0.0545	0.003	0.533	Noble	1997	Delaware	2002
Refi	1997-2004	0.070	0.061	0.040	0.006	0.280	Noble	1997	Delaware	2002
RRegL	1997-2004	0.360	0.341	0.152	0.000	0.893	Montgomery	2000	Wood	2000
RRegNL	1997-2004	0.535	0.541	0.137	0.093	0.946	Wood	1998	Montgomery	1998
RLReg	1997-2004	0.117	0.107	0.057	0.013	0.359	Wood	1998	Allen	2003
RRegLD	1997-2004	0.338	0.310	0.154	0.000	0.887	Pike	1999	Wood	2001
RRegNLD	1997-2004	0.552	0.565	0.139	0.097	0.929	Wood	1998	Montgomery	1998
RLRegD	1997-2004	0.122	0.113	0.060	0.011	0.371	Wayne	1997	Allen	2003
Arm	1997-2004	0.484	0.473	0.179	0.000	1.000	Marion	1997	Scioto	1997
Unempl	1997-2005	5.692	5.592	1.779	1.858	14.408	Delaware	1999	Marion	1999
σUnempl	1997-2005	0.809	0.665	0.511	0.140	4.691	Franklin	2002	Jefferson	1997
PartRate	1997-2005	0.758	0.768	0.073	0.450	0.975	Vinton	1999	Clark	1998
IncomeGr	1997-2005	1.034	1.033	0.024	0.940	1.133	Noble	1997	Van Wert	1998
Lenient	1997-2005	0.257	0.252	0.158	0.000	0.917	Athens	1998	Noble	1998
Denial	1997-2005	0.354	0.350	0.092	0.121	0.645	Delaware	2002	Vinton	2004
Hvalue	1997-2005	11.146	11.159	0.381	10.060	12.431	Marion	1997	Delaware	2005
Divorce	1997-2005	4.274	4.300	0.948	1.400	8.100	Brown	1998	Franklin	2000
Turnout	1997-2005	0.596	0.598	0.080	0.377	0.818	Clinton	2002	Shelby	2004
Herf	1997-2005	0.067	0.050	0.051	0.017	0.362	Fulton	1999	Delaware	2000
FundCost	1997-2005	0.026	0.026	0.009	0.009	0.047	Hamilton	2003	Gallia	2000

Variable	Coverage	Mean	Median	Std Dev	Min.	Max.	Min. County	Max. County
Black00	2000	0.044	0.023	0.057	0.000	0.299	Meigs	Cuyahoga
Ptor00	2000	194.111	194.131	21.955	151.948	272.038	Harrison	Geauga
ChildSP00	2000	0.362	0.343	0.090	0.107	0.610	Hardin	Cuyahoga
HSchool00	2000	0.660	0.673	0.062	0.448	0.806	Delaware	Hardin
Manuf00	2000	0.250	0.245	0.082	0.073	0.545	Athens	Wood
Population00	2000	10.448	10.330	0.990	8.096	13.429	Vinton	Cuyahoga
Debt00	2000	8.804	8.799	0.108	8.586	9.051	Harrison	Delaware
Rural03	2003	3.765	4.000	2.119	1.000	9.000	Brown	Vinton
Vacant00	2000	0.088	0.077	0.036	0.045	0.242	Geauga	Ottawa

Table II. Simple Correlations

This table shows the simple correlations between the market share of regulated-local lenders, $RegL_{t-2}$, regulated-non-local lenders, $RegNL_{t-2}$, less-regulated lenders, $LReg_{t-2}$, the number of loan originations per household, $Loan_{t-2}$, delinquency rate of local small lenders, D_{t-1}, and the county foreclosure rate, F_t. Panel B repeats the analysis only in counties where $Loan_{t-2}$ is below the sample median. Panel C limits the sample to those counties where $Loan_{t-2}$ is above the sample median. p-values are in parentheses.

Panel A. Full Sample

	$Loan_{t-2}$	$RegL_{t-2}$	$RegNL_{t-2}$	$LReg_{t-2}$	D_{t-1}
$RegL_{t-2}$	0.04	1			
$RegNL_{t-2}$	-0.17***	-0.92***	1		
$LReg_{t-2}$	0.30***	-0.44***	0.04	1	
D_{t-1}	-0.15***	-0.03	0.04	-0.02	1
F_t	0.38***	-0.32***	0.17***	0.40***	0.08**

Panel B. $Loan_{t-2}$ Below Sample Median

	$Loan_{t-2}$	$RegL_{t-2}$	$RegNL_{t-2}$	$LReg_{t-2}$	D_{t-1}
$RegL_{t-2}$	0.20***	1			
$RegNL_{t-2}$	-0.31***	-0.93***	1		
$LReg_{t-2}$	0.26***	-0.37***	0.01	1	
D_{t-1}	-0.01	-0.08	0.09*	-0.01	1
F_t	0.51***	-0.23***	0.11**	0.34***	0.14***

Panel C. $Loan_{t-2}$ Above Sample Median

	$Loan_{t-2}$	$RegL_{t-2}$	$RegNL_{t-2}$	$LReg_{t-2}$	D_{t-1}
$RegL_{t-2}$	-0.19***	1			
$RegNL_{t-2}$	0.04	-0.90***	1		
$LReg_{t-2}$	0.36***	-0.53***	0.10*	1	
D_{t-1}	-0.12**	0.07	-0.09	0.00	1
F_t	0.12**	-0.49***	0.36***	0.42***	0.15***

(***), (**), and (*) denote significant at 1%, 5%, and 10% level, respectively.

Table III. Univariate Results

This table presents the means and the medians of the delinquency rates of Ohio's small local lenders and of the foreclosure rates in each of Ohio's 88 counties averaged over the 1999-2006 period. The sample is split into four groups. The first split is across the median of the total number of loans originated by all lenders per housing unit, denoted by $Loan_{t-2}$, two years before the observed foreclosures, F_t, and one year before the observed delinquencies, D_{t-1}. The statistics from the first split are in Panel A. The second split is across the median market share of different types of lenders within each $Loan_{t-2}$ category. In Panel B, the sample is split across the median market share of regulated non-local entities. In Panel C, the split is across the median market share of the less-regulated lenders. The significance of the difference of medians is analyzed with a non-parametric test.

Panel A. The Effect of $Loan_{t-2}$ Levels

		Low $Loan_{t-2}$	High $Loan_{t-2}$	Difference of the Means	Median Two-Sample Test
D_{t-1}	Mean	2.50	2.14	***	
	Median	2.22	1.97		***
F_t	Mean	1.14	1.52	***	
	Median	1.05	1.46		***

(***) denotes significant at 1%.

(continued on the next page)

Panel B. Regulated Non-Local Entities

			Low $RegNL_{t-2}$	High $RegNL_{t-2}$	Difference of the Means	Median Two-Sample Test
Low $Loan_{t-2}$	D_{t-1}	Mean	2.37	2.63	*	
		Median	2.13	2.32		*
	F_t	Mean	1.06	1.23	***	
		Median	0.95	1.17		***
High $Loan_{t-2}$	D_{t-1}	Mean	2.20	2.07		
		Median	2.00	1.95		
	F_t	Mean	1.40	1.63	***	
		Median	1.35	1.59		***

Panel C. Less-Regulated Entities

			Low $LReg_{t-2}$	High $LReg_{t-2}$	Difference of the Means	Median Two-Sample Test
Low $Loan_{t-2}$	D_{t-1}	Mean	2.58	2.41		
		Median	2.24	2.18		
	F_t	Mean	1.09	1.20	**	
		Median	0.94	1.13		***
High $Loan_{t-2}$	D_{t-1}	Mean	2.32	1.95	***	
		Median	2.06	1.91		**
	F_t	Mean	1.44	1.59	**	
		Median	1.33	1.53		**

(***), (**), and (*) denote significant at 1%, 5%, and 10% level, respectively.

Table IV. Dynamic Panel Analysis

This table shows the effect of the lender composition on the foreclosure rate by estimating the following system using the first-differenced Arellano-Bond GMM and robust standard errors.

$$\Delta D_{it-1} = f\left(\Delta D_{it-2}, \Delta LoanD_{it-2}, \Delta RegNLD_{it-2}, \Delta NRegD_{it-2}, \Delta Arm_{it-2}, \Delta \mathrm{X}_{it-2}\right) + \Delta \varepsilon_{it-1}$$
$$\Delta F_{it} = f\left(\Delta F_{it-1}, \Delta Loan_{it-2}, \Delta RegNL_{it-2}, \Delta NReg_{it-2}, \widehat{\Delta D}_{it-1}, \Delta \mathrm{X}_{it-1}\right) + \Delta \nu_{it}$$

where $\Delta Loan_{it-2}$ is the increase in the total number of loans originated by all lenders per housing unit in each county i from year t – 3 to year t – 2. $\Delta RegNL_{it-2}$ and $\Delta LReg_{it-2}$ are the change in the market share of regulated-non-local institutions and less-regulated institutions, respectively. $\widehat{\Delta D}_{it-1}$ is the predicted change in the delinquency rate of residential real estate mortgages held on the balance sheets of local depository institutions. $\Delta \mathrm{X}_{it-1}$ is the change in the factors that affect the value of the default option.

The second column repeats the analysis with purchase mortgages and the third column shows the effect of refinancings.

Pseudo R-square refers to the squared-correlation of the observed dependent variable with its predicted value (Windmeijer, 1995). The first test at the bottom of the table is a test of the hypothesis that the impact of the regulated non-local lenders on foreclosures is statistically equivalent to the impact of the less-regulated lenders. The second test is a test of the null hypothesis that the autocorrelation in the first-differenced errors is zero.

Standard errors are in parentheses.

(Table on the next page)

Panel A. Delinquencies (D_{t-1})

Year	All Loans	Purchase Loans	Refinancings
D_{t-2}	359.63	365.50	372.43
	(140.26) **	(141.47) **	(159.52) **
$LoanD_{t-2}$/$PurchD_{t-2}$/$RefiD_{t-2}$	0.19	-1.34	0.17
	(0.26)	(1.34)	(0.25)
$RegNLD_{t-2}$/$PRegNLD_{t-2}$/$RRegNLD_{t-2}$	2.23	2.45	-0.36
	(15.12)	(10.39)	(16.63)
$LRegD_{t-2}$/$PLRegD_{t-2}$/$RLRegD_{t-2}$	-38.12	-15.49	-27.07
	(31.33)	(18.79)	(36.22)
$Lenient_{t-2}$	2.00	3.56	1.90
	(3.91)	(4.28)	(4.86)
$Unempl_{t-2}$	0.21	0.15	0.06
	(1.04)	(1.04)	(1.02)
$\sigma Unempl_{t-2}$	-1.78	-1.59	-1.79
	(1.45)	(1.68)	(1.33)
$PartRate_{t-2}$	3.77	-1.02	-6.59
	(34.26)	(25.51)	(38.23)
$IncomeGr_{t-2}$	-69.27	-60.00	-66.01
	(30.07) *	(27.91) *	(25.47) *
$FundCost_{t-2}$	-4.03	32.59	30.05
	(151.93)	(168.12)	(171.71)
$Hvalue_{t-2}$	24.11	24.02	15.81
	(41.87)	(67.07)	(45.41)
$Herf_{t-2}$	-25.71	-8.77	-27.90
	(37.12)	(27.33)	(42.85)
$Divorce_{t-2}$	-0.80	-0.94	-1.00
	(1.02)	(1.40)	(1.14)
$Denial_{t-2}$	-12.52	9.31	-18.33
	(23.83)	(25.11)	(23.21)
$Turnout_{t-2}$	55.02	48.87	53.00
	(27.48) **	(39.84)	(24.31) **
Arm_{t-2}	-7.32	-9.38	-6.34
	(9.04)	(9.11)	(10.32)
Yr2001	-1.71	-2.12	-1.23
	(4.02)	(7.20)	(3.39)
Yr2002	-2.04	-0.53	-2.42
	(6.96)	(11.91)	(6.44)
Yr2003	-3.01	-1.01	-3.47
	(7.25)	(12.26)	(8.25)
Yr2004	-2.40	0.66	-0.92
	(8.13)	(12.29)	(10.19)
Yr2005	-9.90	-7.68	-7.20
	(11.74)	(21.02)	(11.89)
Yr2006	-16.04	-12.45	-11.29
	(15.60)	(28.33)	(15.45)
Intercept	-199.33	-206.56	-98.67
	(470.29)	(761.66)	(516.11)
Pseudo R-Square (%)	1	5	2
Test: $RegNL_{t-2} = LRegL_{t-2}$ (p-value)	0.07	0.16	0.26
Test: Zero Autocorrelation in first-diff errors			
First-Order (p-value)	<0.01	<0.01	<0.01
Second-Order (p-value)	0.27	0.28	0.25

(***), (**), and (*) denote significant at 1%, 5%, and 10% level, respectively.

Panel B. Foreclosures (F_t)

Year	All Loans	Purchase Loans	Refinancings
F_{t-1}	266.86	341.35	344.92
	(113.04) **	(111.62) ***	(107.26) ***
$Loan_{t-2}/Purch_{t-2}/Refi_{t-2}$	7.41	-56.88	10.55
	(7.31)	(59.60)	(8.05)
$RegNL_{t-2}/PRegNL_{t-2}/RRegNL_{t-2}$	8.04	6.53	4.91
	(3.75) **	(3.48) *	(3.71)
$LReg_{t-2}/PLReg_{t-2}/RLReg_{t-2}$	13.17	10.29	2.20
	(9.22)	(3.49) ***	(8.24)
$\widehat{\Delta D}_{it-1}$	-68.86	-66.89	-71.28
	(50.29)	(46.75)	(46.62)
$Lenient_{t-2}$	1.86	1.87	1.80
	(1.33)	(1.60)	(1.48)
$Unempl_{t-1}$	0.54	0.34	0.60
	(0.24) **	(0.25)	(0.26) **
$\sigma Unempl_{t-1}$	0.46	0.07	0.74
	(0.54)	(0.62)	(0.52)
$PartRate_{t-1}$	-2.24	-8.14	1.25
	(5.82)	(6.54)	(5.66)
$IncomeGr_{t-1}$	-0.95	-0.32	-3.18
	(6.99)	(6.80)	(6.39)
FundCost	-66.34	-72.09	-43.90
	(57.47)	(53.64)	(56.24)
$Hvalue_{t-1}$	25.86	33.62	27.31
	(15.32) *	(16.82) **	(16.39) *
$Herf_{t-1}$	-2.34	-2.79	-4.03
	(6.64)	(6.03)	(6.92)
$Divorce_{t-1}$	-0.29	-0.32	-0.37
	(0.22)	(0.25)	(0.24)
$Denial_{t-1}$	-4.59	-2.17	-6.14
	(7.99)	(8.42)	(6.55)
$Turnout_{t-1}$	5.12	5.66	2.78
	(3.95)	(5.16)	(4.15)
Yr2001	0.71	0.12	0.78
	(0.89)	(0.91)	(0.80)
Yr2002	2.06	0.80	1.88
	(1.28)	(1.37)	(1.33)
Yr2003	-0.40	-1.65	-0.85
	(1.87)	(2.21)	(1.80)
Yr2004	-3.09	-4.77	-3.01
	(2.94)	(3.38)	(2.88)
Yr2005	-4.62	-6.96	-4.42
	(3.87)	(4.44)	(3.79)
Intercept	-282.28	-360.86	-295.39
	(171.02)	(186.13) *	(183.65)
Pseudo R-Square (%)	26	22	25
Test: $RegNL_{t-2} = LRegL_{t-2}$ (p-value)	0.62	0.27	0.79
Test: Zero Autocorrelation in first-diff errors			
First-Order (p-value)	<0.01	<0.01	<0.01
Second-Order (p-value)	0.12	0.44	0.36

(***), (**), and (*) denote significant at 1%, 5%, and 10% level, respectively.

Table V. Cross-Section Analysis

This table shows the effect of the lender composition on the delinquency rate of residential real estate mortgages held on the balance sheets of local depository institutions, D_{it-1}, and the foreclosure rate in the county, F_{it}, by estimating the following model using GMM in each year from 1999 to 2006.

$$D_{it-1} = f\left(LoanD_{it-2}, RegNLD_{it-2}, NRegD_{it-2}, Arm_{it-2}, \mathrm{X}_{it-2}, CS_i\right) + \varepsilon_{it-1}$$

$$F_{it} = f\left(Loan_{it-2}, RegNL_{it-2}, NReg_{it-2}, D_{it-1}, \mathrm{X}_{it-1}, CS_i\right) + \nu_{it}$$

where $Loan_{it-2}$ is the total number of loans originated by all lenders per housing unit in each county i, two years before the foreclosure rate is observed, denoted by $t - 2$. $RegNL_{it-2}$ and $LReg_{it-2}$ are the market share of regulated-non-local institutions and less-regulated institutions, respectively, at time $t - 2$. X_{it-1} and CS_i are vectors of time-varying and invariant factors, respectively, that may affect the value of the default option.

Pseudo R-square refers to the squared-correlation of the observed dependent variable with its predicted value (Windmeijer, 1995). The test at the bottom of the table is a test of the hypothesis that the impact of the regulated non-local lenders on foreclosures is statistically equivalent to the impact of the less-regulated lenders.

Note that in the delinquency regressions, the delinquency variable used, $D_{''t-1''}$, is from the year $(t - 1)$ preceding the year in the column title, t.

Standard errors are in parentheses.

(Table on the next page)

	D_{t-1}				F_t			
Year (t)	1999	2000	2001	2002	1999	2000	2001	2002
Intercept	-341.36	-374.44	5.62	464.02	-27.70	-41.25	-50.80	12.48
	(170.50) **	(113.40) ***	(144.20)	(145.50) ***	(41.20)	(41.10)	(30.00) *	(44.20)
$LoanD_{t-2}$	1.79	-0.16	0.20	-0.19				
	(0.80) **	(0.31)	(0.56)	(0.60)				
$RegNLD_{t-2}$	3.82	13.73	18.82	-7.87				
	(7.79)	(7.81) *	(13.30)	(11.70)				
$LRegD_{t-2}$	-32.56	-20.70	-62.68	-53.90				
	(22.30)	(23.50)	(27.90) **	(18.20) ***				
$Loan_{t-2}$					36.38	23.29	67.93	131.78
					(14.70) **	(5.55) ***	(9.77) ***	(18.30) ***
$RegNL_{t-2}$					1.02	7.37	6.60	1.60
					(1.79)	(1.66) ***	(1.56) ***	(2.65)
$LReg_{t-2}$					3.95	16.05	-7.03	19.33
					(6.77)	(5.45) ***	(5.89)	(6.00) ***
Arm_{t-2}	-1.56	-10.97	-9.73	6.68				
	(4.65)	(3.15) ***	(5.61) *	(5.00)				
D_{t-1}					-17.90	-65.39	-1.92	49.18
					(47.60)	(26.20)	(30.50)	(41.20)
$Unempl_{t-2}$	2.12	0.65	0.42	0.94				
	(0.84) **	(0.78)	(0.91)	(2.05)				
$\sigma Unempl_{t-2}$	2.51	-1.43	3.13	2.29				
	(1.28) *	(0.84) *	(1.21) **	(2.06)				
$Hvalue_{t-2}$	0.39	8.29	-7.79	-16.07				
	(11.50)	(7.38)	(13.60)	(10.80)				
$Herf_{t-2}$	-5.08	14.81	-1.97	-161.06				
	(16.30)	(15.40)	(26.30)	(44.50) ***				
$Divorce_{t-2}$	-0.35	0.95	0.77	1.71				
	(0.81)	(0.98)	(1.06)	(1.51)				

(***), (**), and (*) denote significant at 1%, 5%, and 10% level, respectively.

(continued on the next page)

	D_{t-1}				F_t			
Year (t)	1999	2000	2001	2002	1999	2000	2001	2002
$Turnout_{t-2}$	18.09	71.28	73.72	11.03				
	(33.00)	(22.80) ***	(33.10) **	(32.60)				
$Denial_{t-2}$	58.95	1.31	76.05	-4.83				
	(26.30) **	(18.90)	(29.30) **	(25.20)				
$PartRate_{t-2}$	25.91	7.07	33.17	38.33				
	(20.10)	(13.30)	(18.90) *	(27.30)				
$IncomeGr_{t-2}$	11.51	48.01	-108.32	23.80				
	(33.60)	(43.10)	(39.20) ***	(64.00)				
$FundCost_{t-1}$	253.39	190.02	381.59	239.53				
	(135.50) *	(122.10)	(209.10) *	(266.60)				
$Unempl_{t-1}$					0.30	0.26	-1.90	-0.80
					(0.18) *	(0.20)	(0.40) ***	(0.59)
$\sigma Unempl_{t-1}$					-0.30	0.30	1.14	1.97
					(0.22)	(0.25)	(0.56) **	(1.13) *
$Hvalue_{t-1}$					2.66	-0.30	3.02	6.86
					(1.99)	(2.27)	(2.42)	(2.57) ***
$Herf_{t-1}$					-3.32	-5.89	-0.22	2.50
					(3.91)	(5.48)	(9.57)	(5.97)
$Divorce_{t-1}$					-0.31	-0.05	0.02	-0.52
					(0.24)	(0.28)	(0.33)	(0.28) *
$Turnout_{t-1}$					-14.22	-2.85	8.01	-21.37
					(8.46)	(8.38)	(4.97)	(7.95) ***
$Denial_{t-1}$					9.66	-8.86	15.90	32.16
					(4.37) *	(5.37)	(4.62) ***	(5.38) ***
$PartRate_{t-1}$					8.26	5.01	1.63	5.61
					(3.83) **	(3.66)	(7.49)	(7.18)
$IncomeGr_{t-1}$					-9.35	-1.16	31.62	-50.49
					(12.90) **	(11.70)	(17.30) *	(19.70) **
$FundCost_{t-1}$					-14.03	27.64	-18.53	-7.81
					(35.50)	(41.10)	(36.20)	(57.30)

(***), (**), and (*) denote significant at 1%, 5%, and 10% level, respectively.

(continued on the next page)

Year (t)	D_{t-1} 1999	2000	2001	2002	F_t 1999	2000	2001	2002
$Lenient_{t-2}$	-1.86	16.47	7.08	-16.90	0.89	-0.19	-0.22	3.16
	(7.03)	(4.23) ***	(7.45)	(8.17) **	(1.78)	(0.91)	(1.44)	(1.97)
HSchool00	58.14	4.58	1.12	-55.99	12.42	17.57	14.00	12.37
	(24.90) **	(15.90)	(23.90)	(26.30) **	(6.70) *	(5.23) ***	(5.24) ***	(7.05) *
Manuf00	18.78	-46.41	54.00	-4.70	-8.66	0.80	-6.84	6.18
	(26.90)	(16.90) ***	(34.90)	(35.20)	(5.65)	(4.63)	(6.81)	(9.88)
ChildSP00	-34.34	21.86	-10.12	0.71	2.40	17.89	18.24	3.88
	(38.00)	(29.60)	(28.00)	(46.00)	(6.88)	(7.17) **	(8.51) **	(10.60)
Population00	4.04	-1.23	4.46	-6.74	-0.60	-0.28	1.45	1.03
	(2.60)	(1.91)	(3.18)	(2.37) ***	(0.68)	(0.62)	(0.54) ***	(0.63)
Ptor00	-0.19	-0.23	-0.11	0.07	-0.04	-0.03	-0.06	-0.05
	(0.07) **	(0.05) ***	(0.07)	(0.08)	(0.02) **	(0.02)	(0.02) ***	(0.02) **
Debt00	3233.84	3473.98	885.60	-3069.82	251.25	537.20	-556.21	-783.39
	(2292.20)	(1257.70) ***	(2534.00)	(2527.90)	(397.80)	(533.80)	(409.00)	(581.90)
Vacant00	0.76	-9.77	72.64	-44.77	-2.76	1.61	19.20	19.32
	(22.60)	(17.90)	(24.10) ***	(20.30) **	(3.83)	(5.29)	(5.67) ***	(8.80) **
Rural03	0.75	1.74	-1.47	-1.54	-0.04	0.04	0.25	0.29
	(0.90)	(0.57) ***	(0.76) *	(0.84) *	(0.21)	(0.23)	(0.19)	(0.28)
Black00	-1.72	-0.92	-12.00	61.39	28.91	30.37	12.76	37.42
	(40.80)	(29.90)	(33.00)	(46.20)	(28.08)	(17.88) *	(29.08)	(19.84) *
Pseudo R-Square (%)	33	44	31	29	52	69	80	79
Test: $RegNL_{t-2} = LRegL_{t-2}$ (p-value)	0.10	0.15	0.02	0.02	0.70	0.15	0.03	0.01

(***), (**), and (*) denote significant at 1%, 5%, and 10% level, respectively.

Table V (cont'd.)

	D_{t-1}				F_t			
Year (t)	2003	2004	2005	2006	2003	2004	2005	2006
Intercept	78.61	27.29	-19.69	-261.94	-78.15	-96.50	-133.77	-157.49
	(173.60)	(117.80)	(152.90)	(231.10)	(50.80)	(35.40) ***	(49.40) ***	(44.70) ***
$LoanD_{t-2}$	0.04	0.21	0.21	-0.71				
	(0.35)	(0.19)	(0.26)	(0.58)				
$RegNLD_{t-2}$	3.80	-10.51	7.14	33.95				
	(10.00)	(9.17)	(9.36)	(18.10) *				
$LRegD_{t-2}$	-5.64	-6.35	1.38	-10.59				
	(16.30)	(17.10)	(16.90)	(44.00)				
$Loan_{t-2}$					47.58	29.59	44.56	108.56
					(13.50) ***	(10.70) ***	(9.79) ***	(20.20) ***
$RegNL_{t-2}$					9.12	10.98	10.74	10.65
					(2.81) ***	(2.66) ***	(4.26) **	(3.61) ***
$LReg_{t-2}$					12.23	10.91	4.10	-4.56
					(6.52) *	(5.73) *	(6.12)	(7.35)
Arm_{t-2}	-4.55	-3.09	6.79	-12.39				
	(5.94)	(4.27)	(5.18)	(12.50)				
D_{t-1}					-41.39	44.81	-197.68	23.24
					(108.30)	(53.40)	(81.30) **	(22.70)
$Unempl_{t-2}$	2.37	3.20	0.16	-3.09				
	(2.84)	(1.47) **	(1.76)	(2.70)				
$\sigma Unempl_{t-2}$	4.51	-0.88	0.31	-1.60				
	(5.86)	(2.47)	(3.64)	(3.64)				
$Hvalue_{t-2}$	-5.35	16.42	-15.31	20.56				
	(12.40)	(11.00)	(9.20) *	(19.10)				
$Herf_{t-2}$	-49.98	15.33	13.41	106.18				
	(39.30)	(31.10)	(23.30)	(124.80)				
$Divorce_{t-2}$	2.03	0.77	-1.96	-4.03				
	(1.76)	(1.34)	(1.38)	(2.35) *				

(***), (**), and (*) denote significant at 1%, 5%, and 10% level, respectively.

(continued on the next page)

	D_{t-1}				F_t			
Year (t)	2003	2004	2005	2006	2003	2004	2005	2006
$Turnout_{t-2}$	-27.31	5.59	40.68	25.71				
	(43.20)	(20.80)	(28.90)	(44.50)				
$Denial_{t-2}$	41.77	31.25	-31.83	-148.11				
	(49.70)	(20.60)	(20.60)	(46.20) ***				
$PartRate_{t-2}$	52.86	37.47	-0.58	-65.30				
	(31.30) *	(24.00)	(37.40)	(51.80)				
$IncomeGr_{t-2}$	125.02	180.86	78.22	-28.01				
	(55.90) **	(37.00) ***	(51.60)	(76.50)				
$FundCost_{t-1}$	80.37	-872.32	-69.57	1695.78				
	(231.80)	(193.20) ***	(296.60)	(646.80) **				
$Unempl_{t-1}$					-0.67	-0.68	-0.21	-0.23
					(0.69)	(0.40) *	(0.44)	(0.36)
$\sigma Unempl_{t-1}$					0.43	-2.43	-2.28	-0.17
					(1.36)	(0.80) ***	(0.91) **	(0.65)
$Hvalue_{t-1}$					3.30	7.17	1.42	4.98
					(4.13)	(2.93) **	(3.97)	(2.83) *
$Herf_{t-1}$					-6.30	6.56	-26.30	-12.37
					(17.90)	(9.28)	(21.00)	(14.40)
$Divorce_{t-1}$					1.59	1.85	-0.24	0.19
					(0.55) ***	(0.46) ***	(0.44)	(0.42)
$Turnout_{t-1}$					-2.74	-10.01	-7.84	-1.70
					(9.86)	(9.37)	(9.10)	(9.11)
$Denial_{t-1}$					26.20	8.78	-8.95	41.75
					(10.30) **	(8.36)	(9.41)	(9.75) ***
$PartRate_{t-1}$					9.42	-8.24	8.63	5.53
					(8.18)	(8.30)	(12.20)	(6.27)
$IncomeGr_{t-1}$					-3.96	-22.08	9.12	-22.45
					(15.30)	(17.80)	(17.30)	(38.70)
$FundCost_{t-1}$					38.15	79.54	109.12	-123.29
					(101.30)	(115.70)	(130.40)	(96.60)

(***), (**), and (*) denote significant at 1%, 5%, and 10% level, respectively.

(continued on the next page)

	D_{t-1}				F_t			
Year (t)	2003	2004	2005	2006	2003	2004	2005	2006
$Lenient_{t-2}$	17.93	2.81	-7.27	11.09	-1.47	1.87	1.61	1.45
	(9.04) *	(5.61)	(7.53)	(10.20)	(2.16)	(1.71)	(2.79)	(1.64)
HSchool00	-49.52	-4.42	48.27	119.91	18.99	36.71	51.14	31.33
	(34.10)	(20.50)	(30.60)	(47.80) **	(9.93) *	(6.31) ***	(9.75) ***	(8.51) ***
Manuf00	147.48	2.00	-56.60	-17.68	27.78	17.90	-7.55	15.08
	(44.30) ***	(24.30)	(34.10) *	(58.70)	(15.00) *	(10.10) *	(13.30)	(7.33) **
ChildSP00	-39.16	-70.39	5.27	61.11	3.48	12.01	30.03	27.34
	(58.80)	(40.40) *	(50.40)	(80.10)	(18.50)	(10.70)	(12.00) **	(11.50) **
Population00	-5.67	-0.55	4.75	-1.17	0.63	1.73	3.02	2.67
	(3.12) *	(2.46)	(3.15)	(4.57)	(1.12)	(0.74) **	(1.17) **	(0.83) ***
Ptor00	-0.07	-0.06	-0.08	-0.36	-0.05	-0.05	-0.07	-0.04
	(0.09)	(0.07)	(0.07)	(0.13) ***	(0.03) *	(0.02) **	(0.03) **	(0.03)
Debt00	-1141.13	-5346.76	798.91	2242.89	202.01	94.88	833.78	736.79
	(2699.10)	(2380.70) **	(2848.20)	(3087.40)	(711.70)	(581.60)	(826.90)	(527.40)
Vacant00	-47.67	26.64	21.24	60.36	15.79	8.89	24.63	14.98
	(31.30)	(23.80)	(22.30)	(47.40)	(11.20)	(7.95)	(9.85) **	(6.24) **
Rural03	-2.07	-0.98	0.62	1.03	-0.30	-0.08	0.46	0.21
	(1.02) **	(0.71)	(0.85)	(1.51)	(0.30)	(0.26)	(0.38)	(0.26)
Black00	89.51	42.17	-53.04	11.71	51.59	42.19	18.91	36.47
	(55.30)	(46.30)	(37.40)	(57.30)	(32.70)	(39.86)	(11.30) *	(40.60)
Pseudo R-Square (%)	29	32	30	29	68	71	68	83
Test: $RegNL_{t-2} = LRegL_{t-2}$ (p-value)	0.56	0.83	0.77	0.29	0.61	0.99	0.40	0.10

(***), (**), and (*) denote significant at 1%, 5%, and 10% level, respectively.

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Appendix A

Calculating the mortgage delinquency rates of depository lenders

The calculation involves determining the delinquency rate of each depository lender (commercial banks and thrifts) in the county and add their delinquency rate to a weighted-average formula where the weight is the share of the county in the lender's total mortgage originations. Denoting the share of county i in lender j's portfolio by s_{ij}, the delinquency rate in county i, D_i, is

$$D_i = \frac{\sum_{\forall j} s_{ij} D_j}{\sum_{\forall j} s_{ij}}$$

where D_j is the share of past-due and non-accruing loans on lender j's balance sheet. The delinquency rate of lenders comes from bank and thrift regulatory reports. The share of the county in each lender's total origination portfolio comes from HMDA. Table A.1 shows the distribution of portfolio shares of each county.

Notice that there is significant variation among the counties in terms of the size of their presence on a particular lender's balance sheet. While Crawford County does not hold a significant position on any lender's balance sheet, Hamilton County has a prominent position (more than 60 percent of a lender's total originations) on the balance sheets of approximately 10 institutions.

Table A.1. The distribution of the portfolio shares (percent)

County	Mean	Min	p1	p5	p10	Median	p90	p95	p99	Max
Adams	0.7299	0.0000	0.0001	0.0003	0.0007	0.0108	1.0890	2.6110	14.5500	22.6530
Ashtabula	5.1612	0.0001	0.0004	0.0011	0.0021	0.0281	3.5980	42.8970	98.7880	100.0000
Allen	1.0578	0.0001	0.0003	0.0010	0.0018	0.0236	2.3840	6.8850	17.8360	20.7210
Ashland	2.1342	0.0001	0.0003	0.0014	0.0032	0.0409	1.4260	5.0640	90.2840	99.6340
Athens	0.8264	0.0001	0.0002	0.0006	0.0010	0.0116	0.4250	7.0590	15.4770	47.6680
Auglaize	2.6829	0.0002	0.0003	0.0007	0.0013	0.0157	5.3580	11.3370	57.7710	100.0000
Belmont	5.3945	0.0000	0.0002	0.0007	0.0012	0.0163	19.1760	41.7520	79.6320	92.3110
Brown	3.2094	0.0002	0.0005	0.0013	0.0024	0.0359	4.9280	21.2460	70.5760	87.7100
Butler	3.6207	0.0002	0.0019	0.0079	0.0171	0.1998	10.8460	17.2820	48.5630	100.0000
Carroll	1.5955	0.0001	0.0002	0.0008	0.0013	0.0168	0.8020	8.2360	39.7870	70.1150
Clermont	1.8438	0.0002	0.0004	0.0009	0.0015	0.0195	1.1040	4.4710	68.3410	78.6970
Champaign	2.7940	0.0002	0.0006	0.0023	0.0042	0.0466	1.3610	7.0490	72.9050	93.3310
Clinton	4.1322	0.0003	0.0016	0.0067	0.0133	0.1383	9.1140	15.4540	83.9660	100.0000
Clark	0.6281	0.0001	0.0006	0.0012	0.0025	0.0263	0.9520	2.8920	15.0370	25.7250
Columbiana	4.3671	0.0000	0.0003	0.0015	0.0027	0.0330	3.4230	27.3980	91.0080	100.0000
Crawford	0.1115	0.0000	0.0001	0.0005	0.0010	0.0103	0.3420	0.6000	1.2600	3.8490
Coshocton	5.7199	0.0001	0.0002	0.0007	0.0011	0.0185	11.1430	47.2880	98.6130	100.0000
Cuyahoga	3.7011	0.0006	0.0029	0.0109	0.0262	0.2277	7.6290	22.5700	64.9080	100.0000
Darke	1.0537	0.0001	0.0003	0.0009	0.0015	0.0210	1.5420	3.7730	19.6850	74.0810
Defiance	2.0572	0.0000	0.0002	0.0005	0.0010	0.0116	1.3890	12.0250	52.5390	59.0760
Delaware	2.5048	0.0005	0.0020	0.0071	0.0144	0.1313	3.4860	8.6480	72.2730	100.0000
Erie	0.8645	0.0001	0.0003	0.0017	0.0030	0.0391	1.2270	2.7880	20.5290	76.7410
Fairfield	3.4311	0.0004	0.0011	0.0039	0.0074	0.0754	4.9340	18.8090	79.9650	99.5500
Franklin	0.6337	0.0001	0.0002	0.0005	0.0009	0.0102	0.4650	1.1100	22.4010	27.1370
Fulton	3.6728	0.0006	0.0033	0.0138	0.0338	0.3168	7.0390	18.3080	69.1880	100.0000
Fayette	2.9555	0.0001	0.0003	0.0008	0.0015	0.0183	5.4170	33.4800	44.8930	70.3890
Gallia	1.2378	0.0000	0.0002	0.0004	0.0006	0.0078	1.1850	3.7400	36.0590	41.5330
Geauga	2.3418	0.0000	0.0013	0.0031	0.0065	0.0578	3.0180	12.2490	51.1480	100.0000
Greene	0.8733	0.0002	0.0012	0.0041	0.0075	0.0684	1.6460	4.0040	15.9930	57.4230
Guernsey	0.6920	0.0001	0.0001	0.0004	0.0008	0.0125	0.8670	2.1550	14.5350	49.4510

County	Mean	Min	p1	p5	p10	Median	p90	p95	p99	Max
Hamilton	9.4424	0.0001	0.0028	0.0126	0.0265	0.3457	43.2070	68.2430	85.5840	100.0000
Henry	1.0100	0.0002	0.0006	0.0012	0.0024	0.0252	0.9810	6.1600	25.5220	55.1570
Highland	0.3451	0.0001	0.0002	0.0007	0.0012	0.0120	0.6120	2.2360	5.8250	8.6010
Harrison	0.7300	0.0001	0.0001	0.0003	0.0005	0.0123	1.1480	4.5930	15.6230	19.2610
Holmes	0.7438	0.0001	0.0001	0.0004	0.0008	0.0117	1.7460	5.7250	11.3430	13.5330
Hancock	0.8439	0.0001	0.0002	0.0007	0.0013	0.0176	1.2920	3.3140	25.7950	40.1650
Hocking	0.5454	0.0001	0.0002	0.0006	0.0012	0.0194	1.3190	3.0600	10.8870	19.6030
Hardin	0.9639	0.0001	0.0002	0.0004	0.0007	0.0106	1.4760	6.5570	18.1870	20.6750
Huron	0.7259	0.0001	0.0003	0.0010	0.0020	0.0277	1.0840	3.0780	18.0070	24.2680
Jackson	0.9901	0.0001	0.0002	0.0005	0.0009	0.0079	0.2710	2.4730	32.0060	38.2950
Jefferson	2.8371	0.0000	0.0002	0.0006	0.0012	0.0195	5.3430	15.4010	57.3460	74.8420
Knox	1.2697	0.0001	0.0005	0.0014	0.0026	0.0259	1.5740	3.1080	54.4260	74.2220
Lake	1.5854	0.0001	0.0013	0.0050	0.0086	0.0836	2.7800	7.1010	35.5150	74.3920
Licking	5.7419	0.0001	0.0003	0.0007	0.0013	0.0356	10.2740	46.3530	93.2960	98.2980
Logan	2.6591	0.0002	0.0009	0.0036	0.0077	0.0672	2.9360	9.4260	76.7740	94.4230
Lorain	0.7141	0.0000	0.0003	0.0009	0.0016	0.0233	1.1810	4.7800	12.7450	31.7920
Lucas	3.9559	0.0005	0.0016	0.0053	0.0100	0.0899	3.3250	20.7210	91.1320	100.0000
Lawrence	2.8783	0.0002	0.0015	0.0051	0.0089	0.0908	3.0170	16.6620	58.2560	90.7730
Madison	1.5806	0.0001	0.0005	0.0015	0.0026	0.0347	1.1020	5.8420	65.6560	96.9780
Mercer	2.9132	0.0001	0.0010	0.0029	0.0048	0.0494	3.6490	16.0460	69.5970	80.3060
Medina	0.8904	0.0002	0.0005	0.0013	0.0021	0.0238	0.8110	2.9230	26.3720	32.3610
Morgan	3.2876	0.0003	0.0018	0.0059	0.0098	0.0917	5.8380	15.7230	79.9410	100.0000
Mahoning	0.3692	0.0001	0.0001	0.0004	0.0006	0.0067	0.7980	2.0870	6.5980	7.1620
Meigs	1.8863	0.0002	0.0003	0.0007	0.0013	0.0111	1.3400	6.5000	64.2800	68.8700
Miami	4.7363	0.0002	0.0006	0.0019	0.0036	0.0368	2.3800	41.2690	91.8390	100.0000
Montgomery	1.4095	0.0000	0.0001	0.0001	0.0003	0.0092	2.3050	6.6350	32.3890	49.8610
Monroe	3.0561	0.0003	0.0021	0.0082	0.0167	0.1475	3.5500	13.9690	73.7720	100.0000
Marion	2.7891	0.0000	0.0001	0.0003	0.0004	0.0064	0.9660	4.1700	76.3870	87.5960
Muskingum	1.3280	0.0001	0.0003	0.0014	0.0020	0.0261	2.0800	8.3650	27.0280	31.9780
Morrow	0.7851	0.0003	0.0003	0.0010	0.0021	0.0235	0.9030	3.1820	16.4340	84.9570
Noble	0.6331	0.0000	0.0001	0.0002	0.0004	0.0074	1.0950	3.2000	6.3600	33.1310

County	Mean	Min	p1	p5	p10	Median	p90	p95	p99	Max
Ottawa	1.2668	0.0001	0.0005	0.0016	0.0025	0.0298	1.0570	4.0390	31.0050	85.2310
Paulding	0.7905	0.0000	0.0001	0.0003	0.0006	0.0076	1.4550	6.7130	12.0570	23.2610
Perry	1.8057	0.0001	0.0001	0.0006	0.0011	0.0208	1.5200	3.4280	70.5440	79.8530
Pickaway	2.2274	0.0001	0.0005	0.0013	0.0025	0.0351	1.7430	4.1150	85.8760	100.0000
Pike	0.6033	0.0000	0.0001	0.0003	0.0006	0.0073	0.2620	1.2960	20.0850	21.3670
Portage	2.6357	0.0003	0.0013	0.0034	0.0065	0.0800	4.4370	7.7980	87.3010	94.7980
Preble	1.3682	0.0000	0.0003	0.0010	0.0021	0.0297	1.1250	3.7070	37.0230	59.6500
Putnam	1.9092	0.0001	0.0001	0.0004	0.0008	0.0090	2.1920	6.1620	50.9390	53.4210
Richland	4.2121	0.0001	0.0004	0.0017	0.0031	0.0319	2.9790	22.1550	90.6070	100.0000
Ross	0.6619	0.0001	0.0003	0.0009	0.0019	0.0204	1.1890	2.5590	15.7120	26.7090
Sandusky	1.1006	0.0000	0.0003	0.0011	0.0020	0.0201	1.1080	4.0100	34.6250	69.8330
Scioto	1.1480	0.0002	0.0003	0.0005	0.0011	0.0175	1.1780	5.6580	29.7850	61.8470
Seneca	1.9371	0.0001	0.0002	0.0007	0.0014	0.0208	1.9100	5.3620	63.2430	86.3210
Shelby	1.7277	0.0001	0.0003	0.0009	0.0019	0.0191	1.4380	4.3290	36.1980	77.0970
Stark	3.1947	0.0003	0.0010	0.0034	0.0091	0.1076	4.2960	12.2360	84.5210	100.0000
Summit	3.9063	0.0005	0.0027	0.0087	0.0157	0.1540	7.6610	17.8790	81.1470	96.2140
Trumbull	3.1484	0.0001	0.0006	0.0024	0.0041	0.0449	3.0610	19.0340	72.5120	95.1160
Tuscarawas	0.7842	0.0000	0.0003	0.0012	0.0020	0.0269	0.8800	2.1410	18.9180	27.3390
Union	0.8177	0.0001	0.0006	0.0020	0.0032	0.0356	1.4370	3.5270	11.8920	67.6790
Van Wert	0.7854	0.0000	0.0001	0.0004	0.0008	0.0112	0.7150	1.6900	24.0840	30.6690
Vinton	0.2410	0.0000	0.0001	0.0002	0.0003	0.0049	0.4540	0.8480	5.1680	7.6370
Warren	3.6961	0.0002	0.0026	0.0086	0.0185	0.1892	7.7230	15.5130	70.7470	100.0000
Williams	8.5355	0.0001	0.0002	0.0006	0.0014	0.0233	26.4310	66.7050	98.9940	100.0000
Wyandot	3.0886	0.0003	0.0005	0.0018	0.0032	0.0374	1.7780	6.2370	78.9760	90.1720
Wood	1.7730	0.0001	0.0002	0.0004	0.0007	0.0093	3.3200	12.5220	38.6250	45.3460
Washington	3.1998	0.0002	0.0008	0.0026	0.0049	0.0421	3.4890	16.0410	94.1470	100.0000
Wayne	1.3450	0.0001	0.0001	0.0004	0.0007	0.0104	0.9920	2.2650	72.0510	77.3830