Majority-minority boards of directors and decision making: The effects of homophily on lending decisions

Online Supplemental Appendix

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Appendix A: A model of homophily and lending decisions

Here I build a signaling model to motivate variation in the mortgage lending decisions of credit unions with different racial compositions of their boards. The model is a simple adaptation of a model used by Aigner and Cain (1977) to explain discrimination in employment decisions. The key feature of the model is that lenders do not know an applicant's true level of risk (*q*) due to asymmetric information and instead observe only a noisy signal (*y*) of an applicant's risk based on the loan application data. Assume that lenders use this signal, referred to here as the credit score, to base their decision to grant a loan and that this is a proxy measure of the true underlying risk, *q*. A higher credit score, *y*, and value of *q* indicates lower risk. Lenders know the observed credit score, *y*, is noisy in the sense that it is a linear function of the underlying risk, *q*, and an unobserved error, *u*, where $y = q + u$. The error is assumed to be normally distributed with mean equal to zero and constant variance. Similarly, *q* is assumed to be independent of *u* and have a normal distribution with mean equal to α and constant variance. Lenders observe the credit score, *y*, and use this value to determine the expected value of an applicant's risk, *q*. The expected value of *q* given *y* is therefore represented by the familiar bivariate regression equation of *q* on *y* and a constant:

$$E(q \mid y) = \hat{q} = (1-\gamma)\alpha + \gamma y, \tag{1}$$

where α is the mean of both *q* and *y* and the slope is given by

$$\gamma = \frac{\operatorname{cov}(q, y)}{\operatorname{var}(y)} = \frac{\operatorname{var}(q)}{\operatorname{var}(q) + \operatorname{var}(u)}. \tag{2}$$

The slope parameter is constrained by $0 < \gamma < 1$, where var(*q*) measures the variation of an applicant's underlying risk about the mean and var(*u*) captures the lender's uncertainty in the observed measure of risk, as a signal of the underlying risk.

Let us assume there are two types of applicants {*a*,*b*} and that lenders have learned from past experience that type *b* is on average riskier, i.e. $\alpha_a > \alpha_b$, but the two applicant types have the same variance in underlying risk, i.e. $\text{var}(q_a) = \text{var}(q_b)$, and the strength of the signal does not vary by applicant type, i.e. $\text{var}(u_a) = \text{var}(u_b)$. The later condition implies lenders view the observable risk characteristics of both applicant types as being similarly reliable measures. Lenders use equation (1) to predict an applicant's risk score, where average risk, α, varies by applicant type. For a given credit score (*y*), applicants of type *a* have a higher predicted risk score (i.e., are lower risk) than applicants of type *b* ($\hat{q}_a > \hat{q}_b$), which implies type *b* applicants are more likely to be rejected than type *a* applicants with similar observables (see Figure 1).

We next model the effects of homophily between lenders and applicants, under the assumption homophily affects a lender's belief in their ability to reliably assess an applicant's risk based on the observables. Assume there are two types of lenders {*a*,*b*} and lenders believe they have an ability based on homophily to more reliably assess the risk of applicants of their own type, which is to say the signal contained in the observed credit score, *y*, contains less noise, i.e. less variance, for applicants of the lenders' type. This implies for lenders of type *a* the signal from an observed credit score will be more trusted for type *a* applicants where $\text{var}(u_{aa}) < \text{var}(u_{ab})$ and signals are more trusted for type *b* lenders for type *b* applicants where $\text{var}(u_{bb}) < \text{var}(u_{ba})$. We assume the effects are symmetric such that lender type *a* can assess type *a* applicants as well as lender type *b* can assess type *b* applicants, i.e. $\text{var}(u_{aa}) = \text{var}(u_{bb})$ and lender type *a* can assess type *b* applicants as well as lender type *b* can assess type *a* applicants, i.e. $\text{var}(u_{ab}) = \text{var}(u_{ba})$. The relative difference in asymmetric information between lenders with type *b* applicants is then measured by the difference in type *a* lender's belief in their ability to estimate the risk of type *b* applicants, relative to type *b* lenders, which is given by

$$\mathrm{var}(u_{ab}) - \mathrm{var}(u_{bb}) > 0. \quad (3)$$

The difference in equation 3 reflects the asymmetric information lenders of different types have with respect to assessing the risk of type *b* applicants, as type *b* lenders are better able to assess the risk of type *b* applicants. A similar relation is implied among type *a* lenders and applicants.

Here I assume there is no difference in the mean level of risk, $\alpha_a = \alpha_b = \alpha$, to allow for comparison with the model later on. Figure 2 illustrates the effect homophily has on introducing heterogeneity into lenders' decision making, as the slope of the prediction equation (see equation 2) is steeper for applicants of the lender's type and the intercept is lower due to the heterogeneous effect on the signal's reliability $(\gamma_{aa} = \gamma_{bb} > \gamma_{ab} = \gamma_{ba})$. Assume lenders simply reject all applicants with scores below α. The figure then suggests two insights into lending. One can see for any credit score greater than α lenders are less likely to deny applicants of their own type, relative to applicants of the other type, and are less likely to deny applicants of their type than are lenders of the other type.

The model used in the article combines features of the two previously discussed models. Minority (non-minority) applicants are represented by type *b* (type *a*), where minority applicants are assumed to be higher risk $\alpha_a > \alpha_b$ (risk decreases with the credit score). This is consistent with the data, as minority applicants, on average, are higher risk. Minorities are shown to be more likely to default on mortgages than white borrowers (Berkovec, 1994) and are more than twice as likely to have a public record of a credit default (Munnell et al., 1996). I also assume that lenders of either type are equally well able to ascertain the risk associated with type *a* (non-minority) applicants, i.e. $\mathrm{var}(u_{aa}) = \mathrm{var}(u_{ba})$. This accounts for the fact that ties of minority individuals tend to be much more racially diverse than those of their white counterparts (McPherson et al., 2001; Korver-Glenn, 2018). Lenders though have different perspectives with respect to their ability to assess the risk of type *b* (minority) applicants. Type *b* lenders (credit unions with majority-minority boards) believe they are more reliably able to assess the risk of type *b* applicants than type *a* lenders (majority-white boards), i.e. $\text{var}(u_{ab}) - \text{var}(u_{bb}) > 0$. I assume lenders reject applications with credit scores less than α_a and the applicant's credit score falls within $\alpha_a < y$. The model then implies (see Figure 3) for this range of credit scores that both type *a* (majority-white board) and type *b* (majority-minority board) lenders are less likely to deny type *a* (non-minority) applicants than type *b* (minority) applicants with the same observed credit quality. Type *b* (minority) applicants though are less likely to be denied by a type *b* (majority-minority board) lender than by a type *a* (majority-white board) lender.

To summarize the model based on figure 3 therefore predicts:

1. Minority applicants are more likely to be rejected than similarly qualified white applicants by lenders with either a majority-minority board or majority-white board.

2. Minority applicants with similar loan characteristics are less likely to be rejected by a lender with a majority-minority board than a majority-white board.

The model also has another implication with respect to the magnitude of the relative difference in asymmetric information between lenders and minority applicants given by $\text{var}(u_{ab}) - \text{var}(u_{bb})$. As the magnitude of this difference increases, the difference in the probability a minority applicant is rejected by a credit union with a majority-white board in relation to a majority-minority also increases in magnitude. This would occur if lender type *a* (majority-white board) became subject to greater asymmetric information with applicants of type *b* (minority applicants), or if lenders of type *b* (majority-minority board) became subject to less asymmetric information with applicants of type *b* (minority applicants).

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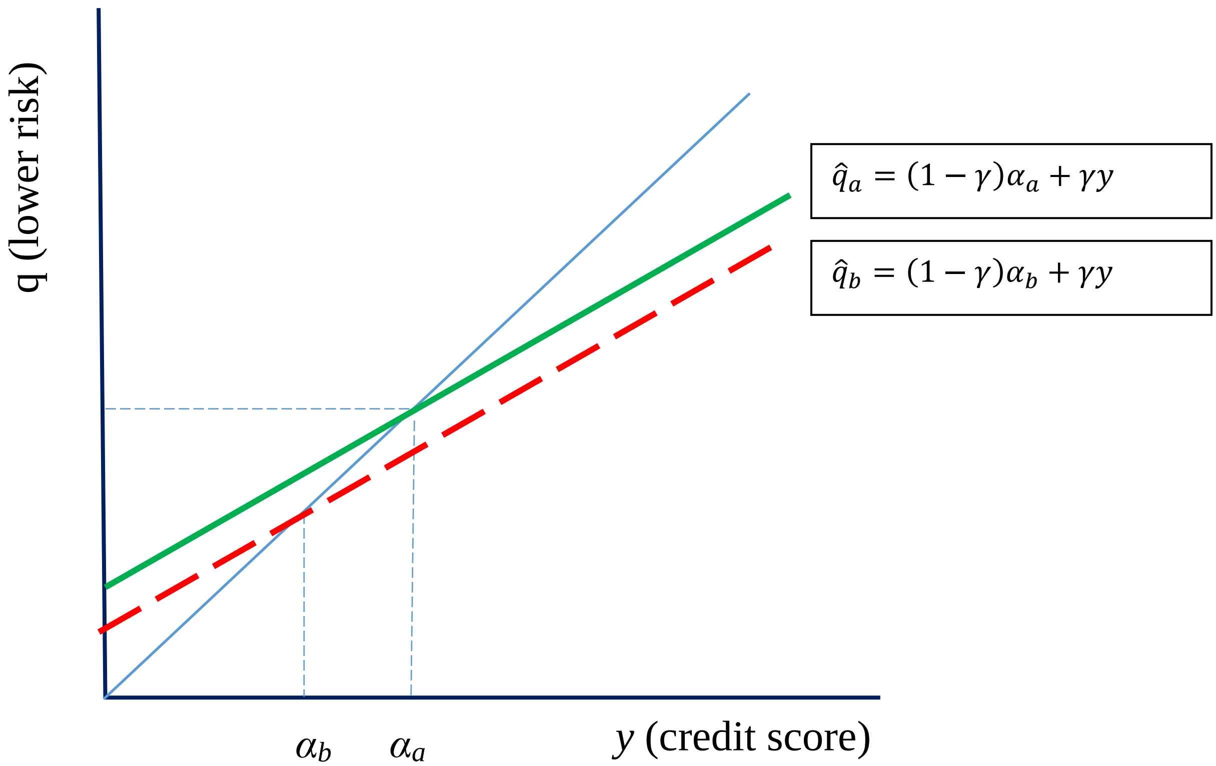

Fig. A1. Perception of Risk with Differences in Average Levels of Risk.
A lenders' perception of an applicant's risk $\{\hat{q}_a, \hat{q}_b\}$ is based on differences in the average level of risk by applicant type $\{a, b\}$. Type *a* applicants are less risky, on average, than type *b*, i.e. $\alpha_a > \alpha_b$ as risk decreases with *q*. Type *a* applicants are therefore perceived to be lower risk than type *b* applicants with th e same credit score, i.e. $\hat{q}_a > \hat{q}_b$ for any value of *y*.

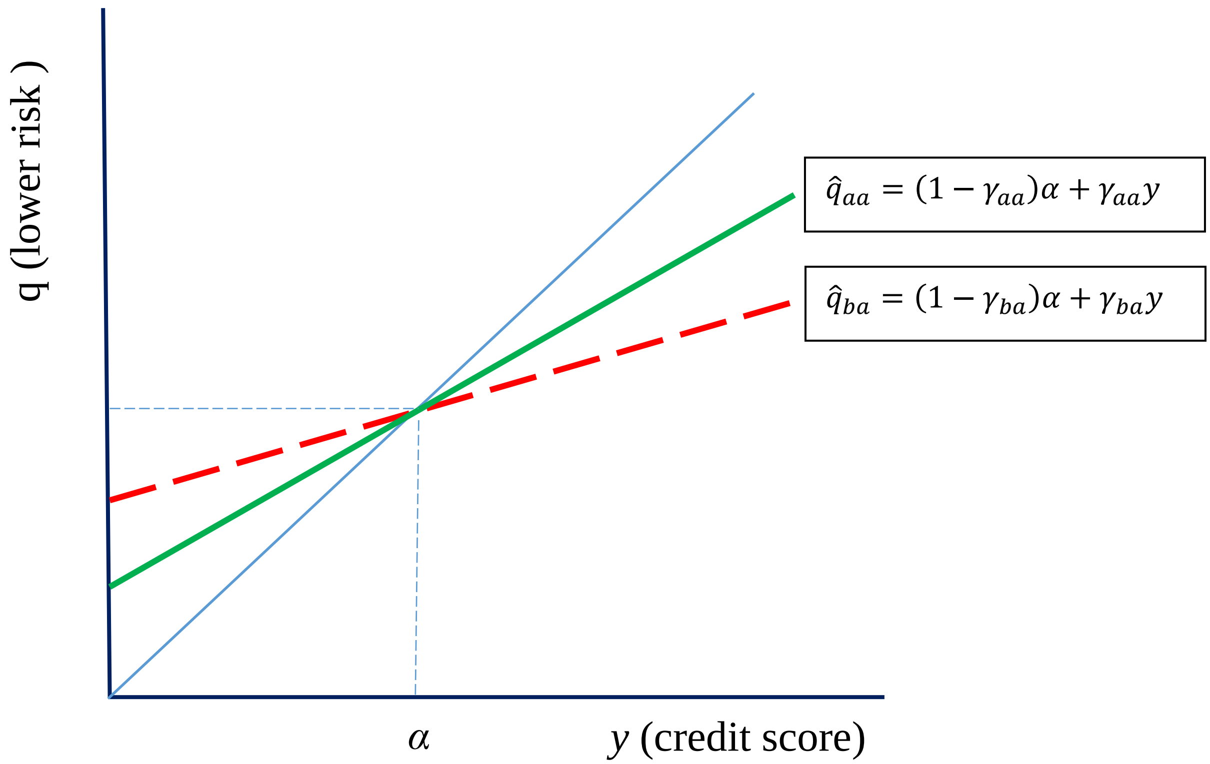

Fig. A2. Perception of Risk with Lender Homophily.
A lender of type *a*'s (*b*) perception of an applicant's $\{\hat{q}_{aa}, \hat{q}_{ab}\ ;\ (\hat{q}_{ba}, \hat{q}_{bb})\}$ risk given their homophily with applicant type *a* (*b*). For lenders of type *a* the signal from an observed credit score will be more informative for type *a* applicants where $\mathrm{var}(u_{aa}) < \mathrm{var}(u_{ab})$ and signals are more informative from type *b* applicants for type *b* lenders where $\mathrm{var}(u_{bb}) < \mathrm{var}(u_{ba})$. The symmetry in the model implies $\hat{q}_{aa} = \hat{q}_{bb}$ and $\hat{q}_{ab} = \hat{q}_{ba}$. For a credit score larger than α, lender *a* is more likely to approve loans to type *a* applicants than type *b*, i.e. $\hat{q}_{aa} > \hat{q}_{ab}$, and type *b* lenders are more likely to approve loans to type *b* applicants than type *a*, i.e. $\hat{q}_{bb} > \hat{q}_{ba}$.

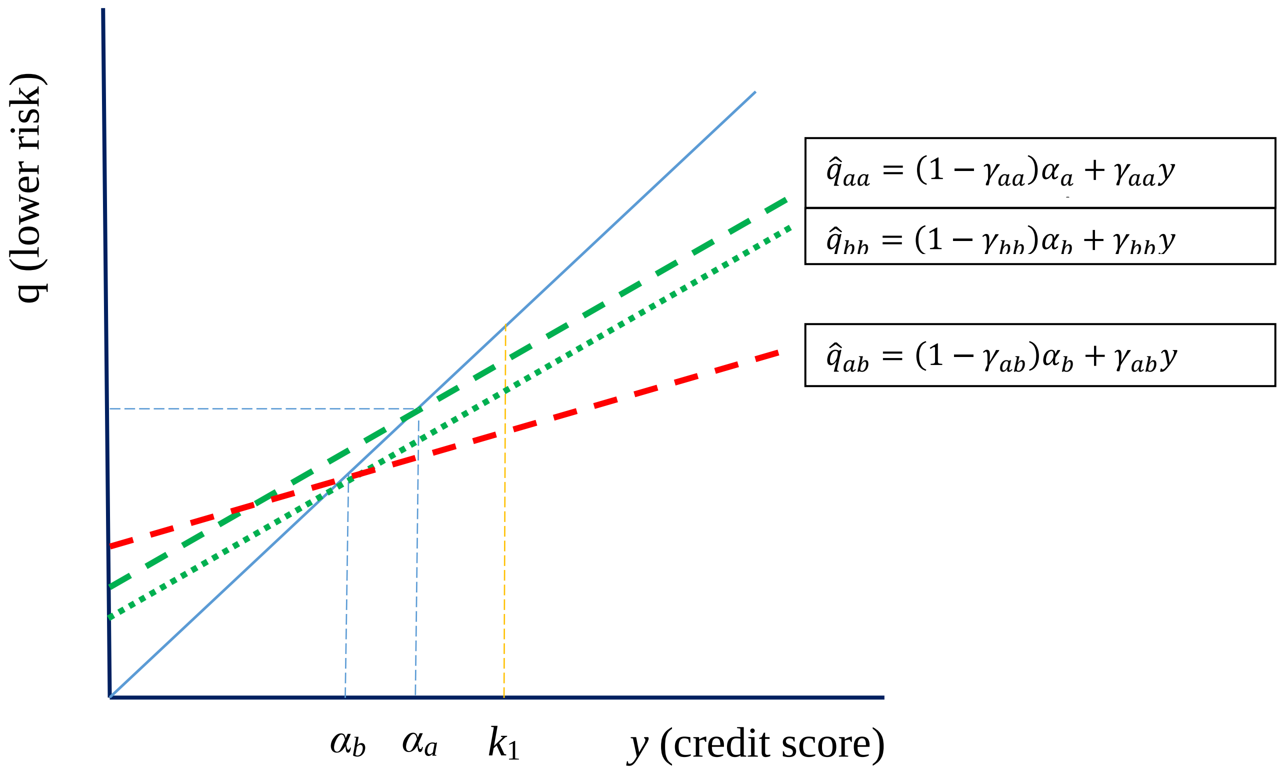

Fig. A3. Perception of Risk with Lender Homophily and Differences in Average Levels of Risk. A lender's perception of risk based on an affinity between type *b* lenders and type *b* applicants and differences in the level of risk by applicant type $\{a, b\}$. Lenders of either type are equally effective at assessing the risk of type *a* applicants, i.e. $\mathrm{var}(u_{aa}) = \mathrm{var}(u_{ba})$, while lenders of type *b* are better able than type *a* lenders to assess type *b* applicants, i.e. $\mathrm{var}(u_{bb}) < \mathrm{var}(u_{ab})$. Type *a* applicants are less risky, on average, than type *b*, i.e. $\alpha_a > \alpha_b$. For credit score, $\alpha_a < y$, we find $\hat{q}_{aa} = \hat{q}_{ba} > \hat{q}_{bb} > \hat{q}_{ab}$. The model implies lenders *a* and *b* are both more likely to approve applicant type *a* than type *b* and lender *b* is more likely to approve applicant type *b* than is lender type *a*.

Appendix B: Variable Descriptions

Table B1: Description of Variables using HMDA data

Variable	Description
Income	Natural logarithm of applicant income in thousands of dollars.
Loan amount	Natural logarithm of loan amount in thousands of dollars.
Debt to income ratio	Ratio of the loan amount divided by the applicant's income.
Piggyback loan	Indicator variable: 1 if a loan applicant simultaneously applies for a loan to use as part of the down payment in order to avoid purchase of primary mortgage insurance. See Avery et al. (2007) for further details.
Preapproval sought	Indicator variable: 1 if a loan applicant seeks preapproval of their loan application. Preapproval differs from prequalification, as the former involves a formal commitment by the lender. Avery et al. (2007) theorizes preapprovals may use different underwriting policies than loan applications in general.
Female applicant	Indicator variable: 1 if loan applicant is female.
Minority neighborhood	Indicator variable: 1 if census tract where property is located has a minority population of more than 50%.
Minority applicant	Indicator variable: 1 if applicant is either Hispanic or Black based on hierarchical classification (Avery et al., 2007) described in text.
Asian	Indicator variable: 1 if applicant is Asian based on hierarchical classification (Avery et al., 2007) described in text.
Hispanic	Indicator variable: 1 if applicant is Hispanic based on hierarchical classification (Avery et al., 2007) described in text.
Black	Indicator variable: 1 if applicant is Black based on hierarchical classification (Avery et al., 2007) described in text.

Appendix Table B2: Description of Variables using NCUA Call Report Data

Variable	Description
Return on average assets (%)	Net income divided by average assets.
Net worth / Total assets	Net worth divided by total assets.
Interest rate risk / Net worth	Measure of interest rate risk exposure.
Loans / Total assets	Loans divided by total assets.
Members / Potential members	Number of credit union members divided by the number of potential members based on common bond.
Cash and S.T. Investments/ Total assets	Cash and securities divided by total assets.
Size	Natural logarithm of total assets in thousands of dollars.
Credit card loan concentration	Share of loans in credit-cards.
Auto loan concentration	Share of loans in new and used vehicles.
Net long term assets/ Total assets	Share of assets in long term assets
Loans / Deposits	Loans divided by deposits
Majority-Minority Board (MMB)	Indicator variable: 1 if a majority of directors on the board are racial minorities (e.g. Asian, Black, Hispanic, Native American, and Pacific Islander)
Hispanic Board	Indicator variable: 1 if a majority of directors on the board are Hispanic
Minority Membership	Indicator variable: 1 if a majority of credit union members are racial minorities (e.g. Asian, Black, Hispanic, Native American, and Pacific Islander)
Branch in Minority Neighborhood	Indicator variable: 1 if a credit union has a branch or headquarters located in a neighborhood (i.e. census tract) with a minority population of more than 50%.

Appendix Table B3: Description of Additional Variables

Variable	Description
Unemployment Rate (%)	The unemployment rate of the MSA where the credit union is headquartered. County-level data is used if not located within an MSA. Source data: Bureau of Labor Statistics
Bank Deposit Concentration	The Herfindahl-Hirschman Index of bank deposit concentration for the MSA where the credit union is headquartered. County-level data is used if not located within an MSA. Source data: FDIC survey of deposits.
Change in housing price index (%)	The change in housing prices for the MSA where the credit union is headquartered. County-level data is used if not located within an MSA. Source data: FHFA data