Can Human Capital Explain Income-based Disparities in Financial Services?

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Abstract

Research shows that access to high-quality financial services varies with local income and wealth. We study how financial firms' internal labor allocation decisions contribute to these disparities. Using a near-comprehensive panel of over 350,000 U.S. mortgage loan officers, we document large and persistent differences in productivity and performance. We find that firms' hiring and promotion policies disproportionately assign workers with less experience or poor track records to branches serving low-income customers. Further, the consequences of poor performance differ by location: low sales, bad loans, and misconduct are more tolerated in low-income branches, exacerbating income-based disparities in financial services.

Keywords: Financial Services, Labor Market, Human Capital, Loan Officer, Mortgage, Housing

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I. Introduction

It is well recognized that access to quality financial services varies with potential customers' wealth. Banks have fewer branches in low-income ZIP codes (Goodstein and Rhine, 2017; Célerier and Matray, 2019) and appear to offer inferior service in these areas (Begley and Purnanandam, 2021), which are often served by payday lenders and other suppliers of high-cost credit (Morse, 2011). Less consensus has emerged on the various causes for these disparities, making it difficult to design targeted policy. For example, if financial firms offer similar services across areas, but face weak demand from low-income neighborhoods, targeting economic growth may be appropriate. However, any number of supply-side considerations such as costs, competition, regulation, or even taste-based discrimination may lead firms to provide differential service across areas based on income levels. In these cases, policy should address firms' incentives, as in the Community Reinvestment Act of 1977 (CRA).[1]

In this paper, we use the labor market for mortgage loan officers to study how human capital affects the supply of financial services. A critical advantage of our setting is that multiple loan officers typically work at a single branch. Although areas may be characterized by differences in demand, regulation, or other factors, we can measure each officer's productivity *relative* to his or her peers, hence generating person-specific estimates of productivity orthogonal to regional heterogeneity. Tracking the career paths of loan officers through time then allows us to infer whether firms allocate better or worse employees to traditionally under-served areas.

We build a national panel of mortgage loan officers using data from the Nationwide Mortgage Licensing System (NMLS), which identifies where, when, and by whom each

[1] Recent work by Begley and Purnanandam (2021) finds that CRA incentives to expand credit in low-income areas had a complex effect, with quantities increasing, but the quality of financial services decreasing.

of the over 350,000 loan officers were employed.[2] We then link loan officers directly to the mortgages they originate using data from CoreLogic, and to data on subsequent foreclosures from Zillow. Our assembled data set constitutes a near-comprehensive panel of U.S. mortgage loan officers' career paths and performance from 2014 to 2019.

As a first step, we confirm prior research indicating that the quality of financial services is strongly correlated with local income levels. We track three measures of service: 1) financial misconduct, 2) loans that enter foreclosure within a year of origination (i.e., bad loans), and 3) complaints to the Consumer Financial Protection Bureau (CFPB). Aggregating these measures to the ZIP code level, we find that income is a strong cross-sectional predictor of each: wealthier areas are associated with less misconduct, fewer bad loans, and fewer consumer complaints.

In the rest of the paper, we test whether firms' labor allocation decisions are major supply-side factors in these income-based disparities in financial services quality. We begin by documenting substantial, durable variation in loan officer quality and productivity. In panel regressions, we find that loan officer fixed effects are overwhelmingly the most important determinant of misconduct, bad loans, and sales volume.[3]

To give a sense of the magnitudes, in the case of misconduct, relative to branch-year fixed effects that capture time-varying geographic heterogeneity, loan officer fixed effects increase the adjusted R-squared by 30 percentage points. Likewise, when explaining the prevalence of bad loans, loan officer fixed effects more than double

[2] The NMLS is an exhaustive registry of all mortgage loan officers employed in the United States, and was created as a result of the Secure and Fair Enforcement for Mortgage Licensing Act of 2008 (SAFE Act).

[3] We can measure misconduct and the percentage of bad loans at the loan officer-year level, but we cannot link CFPB complaints directly to individual loan officers. Hence, we study loan officers' volume as a third metric of individual performance because it is the primary measure of productivity used by firms (incentive pay is typically a percentage of lending volume).

both the raw and adjusted R-squared.[4] The results for loan volume show similar cross-officer heterogeneity. Empirical Bayes estimates of officer fixed effects (Morris, 1983), which apply a shrinkage factor to account for measurement error, suggest that a loan officer at the 75^{th} percentile produces about twice the volume as one at the 25^{th} percentile.

We then examine whether low-income branches are systematically assigned low-performing or inexperienced officers. Across all new hires, we find that rookies (i.e., those with no prior industry experience) are more likely to work in low-income areas. Moreover, among seasoned hires, loan officers with a track record of misconduct, making bad loans, or having low volume are disproportionately assigned to branches in low-income ZIP codes.

Focusing on within-firm variation – excluding rookie assignments and exits from the profession – a similar picture emerges. Loan officers with higher volume, fewer bad loans, and no financial misconduct tend to be assigned to higher-income ZIP codes when they move branches. The converse is also true, with the worst performers being reassigned to low-income areas.

Critically, the sensitivity of this "reassignment-for-performance" relation is itself a function of an area's income. Committing misconduct in a high-income area is severely punished, with first-time offenses sharply increasing the probability of dismissal or reassignment to a lower-income branch. In contrast, misbehavior appears to be more tolerated in the lowest-income areas, where misconduct is relatively unlikely to result in dismissal. These dynamics lead to the worst performers being disproportionately represented in low-income areas.

We also find evidence of spillover effects: loan officers' volume, loan quality, and

[4] Because our panel is relatively short (6 years), one possibility is that the variation in average quality described above conflates differences due to relatively static (e.g., ability, education) and dynamic (e.g., experience) factors. As it turns out, while experience is positively related to sales volume and negatively related to misconduct and bad loans, the incremental R-squared of loan officer fixed effects is nearly identical when we control for years in the industry.

tendency to commit misconduct are affected by their peers' quality, which we measure based on performance at *prior jobs.* These spillover effects amplify the impact of reallocating underperforming workers to low-income areas. The combined impact of financial firms' hiring, promotion, and firing practices on the spatial distribution of human capital is large. For example, doubling a ZIP code's income is associated with resident loan officers having roughly 20% less prior misconduct, and a 45% stronger track record in terms of loan volume.

Overall, our findings indicate that human capital is a critical component in providing financial services, and consequently, that internal labor market decisions contribute to the disparities between high- and low-income areas. Due to the combination of firms' sorting policies, and the vast heterogeneity in individuals' productivity, loan officer characteristics explain between 25% and 40% of the explainable variation in the quality of financial services.[5]

Our paper contributes to the broader literature on the importance of human capital for economic development (e.g., Stokey, 1991; Gennaioli et al., 2012), for firms (e.g., Bertrand and Schoar, 2003), and for the financial industry in particular (e.g., Philippon and Reshef, 2012). While prior studies have examined the allocation of talent across firms (e.g., Abowd et al., 1999; Egan et al., 2019; Babina et al., 2020) and along corporate hierarchies (e.g., Baker et al., 1994; DeVaro and Waldman, 2012; Berk et al., 2017), less is known about the spatial allocation of talent within firms.[6] The evidence here speaks directly to this spatial distribution, indicating that among financial service firms, systematic allocation of their most talented workers to higher-income neighborhoods contributes to disparities in the

[5] These estimates reflect variance decompositions for early defaults (at the loan level) and CFPB complaints (at the ZIP code-year level using local officers' average characteristics). For misconduct (at the officer-year level) the person's prior track record accounts for almost all of the explanatory power. The relevant fraction of variation explained by loan officer characteristics is compared to that explained by local demographic factors, such as income.

[6] See Giroud and Mueller (2015), who provide evidence that financially constrained manufacturing firms reallocate capital and labor from far away or less productive plants to plants with more appealing investment opportunities.

quality of services across income strata.

Another important literature shows that access to finance facilitates economic growth (e.g., Jayaratne and Strahan, 1996) and household wealth accumulation (Célerier and Matray, 2019).[7] Yet, research also documents high rates of misconduct in financial services.[8] In the mortgage market, studies document that a significant amount of fraud and predatory lending took place in the lead up to the 2008 financial crisis (e.g., Gurun et al., 2016; Mian and Sufi, 2017; Griffin and Maturana, 2016a), and that the ensuing foreclosures had deleterious effects.[9] Together, these findings underscore the importance of delving deeper than quantities (i.e., access to finance) in order to study the *quality* of financial services. We contribute to this vein of research by using novel micro-data linking loan officers and customers to show that human capital plays an important role in the quality of mortgage lending, even though the mortgage market is transaction-oriented and competitive.[10]

Finally, our paper contributes directly to the literature on differences in the quality of financial services offered in high- versus low-income areas.[11] Begley and Purnanandam (2021) show that low-income areas targeted by the CRA have significantly more CFPB complaints, suggesting that existing policies which focus on quantities are unlikely to improve the quality of financial services in these areas. In related work, Haendler and Heimer (2021) show that customers filing CFPB complaints from low-income ZIP codes are less likely to receive financial restitution,

[7] Studies also explore various determinants of access to finance such as regulation (e.g., Campbell et al., 2015; Fuster et al., 2021), technology (e.g., Fuster et al., 2022; Howell et al., 2022), politics (Akey et al., 2021), discrimination (Butler et al., 2022), and culture (Hayes et al., 2021).

[8] For evidence of misconduct among financial advisors, see Dimmock et al. (2018), Egan et al. (2019) and Dimmock et al. (2021). Also, see evidence on the impact of fraud in securitization (Griffin and Maturana, 2016b) and the fallout from the Madoff Ponzi scheme (Gurun et al., 2018).

[9] Studies show that foreclosures negatively affect house prices (e.g., Campbell et al., 2011; Gupta, 2019), the real economy (e.g., Mian et al., 2015), crime rates (Ellen et al., 2013), public health (Currie and Tekin, 2015), and individuals' well-being (Makridis and Ohlrogge, 2022).

[10] For evidence that corporate loan officers affect loan terms and outcomes in the more relationship-oriented syndicated loan market, see Engelberg et al. (2012), Bushman et al. (2021), Herpfer (2021), and Carvalho et al. (2022).

[11] For evidence of disparities in access to quality goods and services in other contexts, see e.g., work on supermarkets (Matsa, 2011a,b).

and that this gap increases under industry-friendly political regimes. We contribute to this literature by showing that financial firms' labor allocation decisions lead to dramatic differences in their human capital across ZIP codes, and that this geographic allocation of talent is a major supply-side obstacle to providing quality financial services in low-income areas. Our results suggest that sorting in finance labor markets may reinforce existing levels of economic inequality, and that policies seeking to improve financial services in low-income areas should take into account the importance of human capital.

II. Data

To conduct our empirical analysis, we first build a novel nationwide panel of mortgage loan officers using licensing and registration information from the Nationwide Mortgage Licensing System (NMLS). We then merge on data from CoreLogic to identify the loans originated by these loan officers, and information from Zillow on foreclosures. In this section, we discuss the key data sources and merges.

A. NMLS Loan Officer Data

The Secure and Fair Enforcement for Mortgage Licensing Act (SAFE Act) was passed in 2008 to protect consumers and reduce fraud in the mortgage market. The law requires all residential mortgage loan originators (i.e., loan officers) to be licensed/registered, and for these licenses/registrations to be recorded in the Nationwide Mortgage Licensing System.[12] By 2012, all state and federal regulators had implemented licensing/registration regimes and integrated them with the

[12] All loan officers working for federally insured depository institutions, credit unions, and their subsidiaries must be federally registered. All other loan officers, such as those working at mortgage companies, must be state-licensed.

NMLS, making it a comprehensive registry of mortgage lenders and their loan officers.[13]

We obtain access to data from NMLS Consumer Access^{SM} through an agreement with the State Regulatory Registry, a subsidiary of the Conference of State Bank Supervisors (CSBS) tasked with operating the NMLS.[14] Specifically, we obtain historical snapshots taken at the end of each calendar year from 2012 to 2019 on licenses, registrations, and other information for individual loan officers. Each loan officer is assigned a unique NMLS ID that stays with them over time and across employment spells, which allows us to accurately track them throughout their career in the mortgage industry. From these data, we construct a national panel of mortgage loan officers with information on their employment history, physical job location, and any legal/regulatory disciplinary actions they have faced.

B. Mortgage Transaction Data

Our mortgage transaction data come from CoreLogic, a leading provider of data on real estate and mortgage transactions. The data cover nearly all U.S. residential mortgages originated since the early 2000s. We extract property information (such as location) and basic mortgage characteristics (such as mortgage amount). Most importantly, starting in 2014, the CoreLogic data include a unique loan officer identifier (NMLS ID) with each transaction.

For our main analysis, we aggregate each loan officer's mortgage transactions by year to match the frequency of our NMLS panel.[15] Specifically, we calculate the total number of mortgage originations and total dollar volume for each loan officer-

[13] We confirm that the NMLS data are indeed comprehensive by matching the lending institutions in NMLS to the lenders in the Home Mortgage Disclosure Act (HMDA) data. Based on company names and addresses, we are able to match over 97% of HMDA lenders to NMLS.

[14] For information on NMLS Consumer Access^{SM}, see `https://nmlsconsumeraccess.org/`.

[15] The one exception is when we use transaction level data on mortgages and foreclosures to examine loan performance in Table 10.

year. As we collapse the data to the loan officer-year level, we also compute variables describing the loan officer's customer base. We assign ZIP code level information on income, bachelor's degree share, minority share, unemployment rate, and population density to each customer taking out a loan from the officer, and then average across customers to compute our *Customer base controls.* We then merge the CoreLogic information with our NMLS loan officer panel by NMLS ID and year. The merged data set includes each loan officer's employment history, disciplinary actions, sales performance, and customer base characteristics from 2014 to 2019.

C. Foreclosure Data

We use information on foreclosures from Zillow's Transaction and Assessment Database (ZTRAX) to measure the quality of loans made by each loan officer. For each mortgage that ends in foreclosure, ZTRAX collects information including delinquency date, unpaid loan balance, and property identifiers. We use these identifiers to merge ZTRAX foreclosures with CoreLogic mortgages based on state and county FIPS codes and parcel IDs. Therefore, we are able to link each loan officer's mortgage originations to foreclosure information, and compute measures of the officer's loan quality. Similar to the sales performance measures, we aggregate the foreclosure information to the loan officer-year level. Specifically, we calculate the percentage of loans made that year that end in foreclosure within 12 months of the origination date. We focus on these "early defaults" because they speak directly to the loan origination process, rather than defaults over longer time horizons which could be driven by subsequent events or economic trends.

D. Other Data

We supplement our main data set with information from two additional sources. First, we use rolling 5-year American Community Survey (ACS) data to measure per capita income and other demographic information at the ZIP code-year level. Second, we augment our data with information on complaints made to the Consumer Financial Protection Bureau. Similar to Begley and Purnanandam (2021), we focus on complaints that are related to mortgages and have an available five-digit ZIP code. We aggregate these CFPB complaints against mortgage lenders between 2014 and 2019 to the five-digit ZIP code-by-year level and scale complaints by the total number of mortgages originated in the same ZIP code-year.

III. Geographic Variation in the Quality of Financial Services

We begin by verifying prior literature indicating that financial services quality correlates with income. We conduct this exercise at the ZIP code-year level by testing whether neighborhoods with lower per capita income have higher fractions of loan officer misconduct, early defaults, and CFPB complaints against mortgage lenders.

Table 1 presents the results. In column 1, the dependent variable is the volume-weighted average misconduct rate across all loan officers servicing the ZIP code that year, where the misconduct rate is each officer's number of misconduct events scaled by the number of loans. The independent variable is the natural logarithm of per capita income in the ZIP code. We find a negative and significant coefficient, showing that loan officers serving low-income neighborhoods commit more misconduct.[16]

In column 2, the dependent variable is the early default rate in the ZIP-code year (the percentage of mortgage loans that end in foreclosure within 12 months of

[16] The misconduct events we observe in the NMLS data are cases where a regulatory or legal action was taken against a loan officer. These events are rare, but represent clear breaches of laws or regulations. Broadly speaking, loan officer misconduct includes unauthorized activity, misrepresentation of information to customers, and licensing requirement violations. Internet Appendix Section II provides additional details, including examples of misconduct.

origination). We find a similar pattern, whereby lower-income areas have more early defaults. Lastly, in column 3, we follow Begley and Purnanandam (2021) and use the frequency of CFPB complaints against mortgage lenders in the ZIP code-year to measure financial services' quality. We find that ZIP code income is negatively correlated with CFPB complaints. Our results here show that lower-income neighborhoods indeed experience lower quality financial services as measured by misconduct, early defaults, and CFPB complaints. In the rest of the paper, we focus on the role played by labor markets in generating and sustaining these income-based disparities.

[Insert Table 1 Here]

IV. The Importance of Human Capital in Financial Services

In this section, we document the importance of human capital in financial services using our comprehensive panel of mortgage loan officers. These officers serve as the primary point of contact for customers looking to take out a mortgage, and their responsibilities include presenting information about mortgage products and pricing to prospective applicants, answering questions, aiding applicants in filling out applications, and following up regarding documentation. Loan officers also influence mortgage approval decisions through the information they provide to underwriting departments, either in terms of soft information or hard information of varying quality (e.g., Saengchote, 2013; Frame et al., 2022). A high-performing loan officer exerts effort to grow their loan volume (for example, by providing aid to marginal applicants, or through referrals from satisfied customers or intermediaries like real estate agents) while at the same time avoiding financial misconduct and costly defaults.

We start by providing summary statistics on loan officer job performance and career trajectories. Then we evaluate the importance of human capital by examining the degree of persistence in individual workers' performance, and by formally estimating the importance of person fixed effects in this industry. Finally, we document significant returns to experience, and positive correlations between loan officers' volume and their lending quality. Each set of results provides evidence that human capital is important in mortgage lending; in other words, loan officers matter.

Table 2 presents summary statistics from our loan officer-year panel with information on work histories, misconduct, loan volume and performance, and customer base demographics from 2014 to 2019 (see Appendix A for variable definitions). Our sample includes over 350,000 mortgage loan officers working at 15,000 lending institutions. The average loan officer makes roughly 25 loans per year totaling just over $6 million. The incidence of misconduct is low, at only 0.21% for each $1 million dollars of lending volume. Early defaults are also infrequent, with 0.20% of originated loans foreclosing within one year. Despite their infrequent nature, these measures are signals of a loan officer's low effort or ability, because they represent cases where officers violated laws/regulations or exhibited particularly poor judgement during the origination process. The average loan officer has been working at their firm for just under 6 years, and at any point in time 4% of loan officers are rookies with no prior experience in the industry.

[Insert Table 2 Here]

We start our analysis by examining how persistent loan officers' performance is in terms of lending volume, early defaults, and misconduct. Figure 1 presents a visual depiction of the persistence in the data. The top plot shows lending volume. To construct the plot, we regress loan officers' volume on branch-year fixed effects to control for any firm, location, or time-varying factors affecting productivity. We then focus on the residuals and form portfolios of high- versus low-performers each year, which we hold fixed and track performance for over the next five years. For instance, we sort loan officers into four portfolios based on their residual log(loan volume) in 2014, and then we track the portfolios' performance by computing these workers' average residual in each subsequent year. We repeat this portfolio formation process for each year in our sample and plot the portfolios' average performance in event time.

Three features stand out in the top plot of Figure 1. First, there is a great deal of cross-sectional dispersion in loan officer productivity. The residual log(loan volume) ranges from -75% for the "low productivity" portfolio to over 100% in the "very high productivity" portfolio. Second, there is some convergence among the four portfolios over time, consistent with noise, luck, or time-varying skill/effort making performance in the formation period an imperfect predictor of future performance. Finally, productivity levels remain markedly different across portfolios, indicating significant persistence in performance. In other words, even holding the work environment constant, some loan officers are simply more productive than others year after year.

[Insert Figure 1 Here]

In the middle and bottom plots of Figure 1, we sort loan officers into two groups based on whether or not they had an early default or misconduct event during the formation year (time zero). We then follow the same procedure to produce the plots, and see that officers with early defaults or misconduct in the formation year remain more likely than their peers to make the same mistakes in future years. Taken together, the plots in Figure 1 show that loan officer performance is highly persistent.

In Table 3 Panel A, we test the patterns documented in Figure 1 more formally. We run OLS regressions of loan officer performance on lagged performance in terms of misconduct, early default, and log(loan volume) in columns 1-3, respectively. In each case, we find that past performance is a strong predictor of current performance, even after controlling for loan officers' work environment with branch-year fixed effects.

[Insert Table 3 Here]

In Table 3 Panel B, we assess the importance of human capital by estimating models of loan officer performance without, and then with, person fixed effects. Throughout these tests, we include branch-year fixed effects as well as our *Customer base controls* to absorb any remaining within-branch variation in loan officers' clientele. For misconduct, columns 1 and 2 show that the inclusion of loan officer fixed effects increases the adjusted R-squared by over 30 percentage points. For early defaults, columns 3 and 4 show that the adjusted R-squared more than doubles. Finally, columns 5 and 6 show that loan officer fixed effects increase the adjusted R-squared for loan volume from 48% to 78%. These large increases in explanatory power provide evidence that human capital plays a critical role in determining outcomes in financial services.

Our next test transitions from assessing the explanatory power of loan officer fixed effects to evaluating their economic magnitude in order to better understand the heterogeneity in loan officers' productivity. However, using standard fixed-effects estimation may overstate the true dispersion in loan officers' productivity because the fixed effects themselves are measured with noise. Therefore, we provide estimates of loan officers' impact using the empirical Bayes method (Morris, 1983) that has become standard in the literature on teacher performance and personnel economics (e.g., Kane et al., 2008; Rockoff and Speroni, 2010; Engelberg et al., 2016). By design, the empirical Bayes approach shrinks estimated fixed effects to account for the noise in each loan officer's productivity. For example, a loan officer with consistently above-average performance over his or her career would have little shrinkage. By contrast, a loan officer with similar average performance but high variability in performance would have his or her estimated effect reduced to reflect uncertainty over whether the positive effect could truly be attributed to the loan officer.

We calculate our empirical Bayes estimates using a mixed multilevel model with branch-year fixed effects and loan officer random effects. Since misconduct and early defaults are relatively rare, we focus on loan volume. Figure 2 plots the distribution of loan officer effects on volume estimated using empirical Bayes in blue, and traditional fixed effects in red. As expected, the empirical Bayes method narrows the distribution. The interquartile range for the empirical Bayes estimates using log(loan volume) as the dependent variable is 0.97 (-0.29, 0.68), suggesting that the 75th percentile loan officer is roughly twice as productive as the 25th percentile loan officer in terms of sales.

[Insert Figure 2 Here]

Lastly, we document a few simple correlations that add to the evidence on human capital's importance in this setting. First, misconduct rates and early default rates decrease with loan officers' tenure with the firm, suggesting significant returns to experience among loan officers. Figure 3 presents these patterns in the top left and right plots, respectively. Second, both misconduct rates and early default rates are negatively correlated with loan officers' volume (see the bottom plots in Figure 3). Given that time constraints likely impose an inherent trade-off between quantity and quality, these patterns suggest that certain loan officers are more skilled than others.

[Insert Figure 3 Here]

Taken together, the results in this section show that loan officer performance is persistent, exhibits substantial heterogeneity across officers, and improves with experience. Each of these findings supports the notion that human capital plays a major role in the provision of quality financial services. We next turn our attention to how firms allocate this human capital.

V. Lenders' Allocation of Human Capital Across ZIP Codes

In this section, we examine how financial institutions allocate their human capital across ZIP codes through hiring, promotion, and retention/firing practices. We also document that under-performing loan officers who experience a job separation tend to be re-employed in lower-income ZIP codes, and that they have negative spillover effects on their new colleagues' performance. We then document the equilibrium (i.e., average) allocation of human capital driven by these practices – a strong relation between a ZIP code's per capita income and the characteristics of the loan officers servicing it, even within firms.

A. *Hiring Practices*

We start by evaluating how firms' hiring practices differ when they are hiring a loan officer to work at a branch in a high- versus low-income area. For these tests, we use our national panel of mortgage loan officers, and focus on new hires. We test whether the ZIP code's income affects the type of loan officers that firms hire along four dimensions: 1) whether the loan officer is a rookie (no prior industry experience), 2) their past misconduct, 3) their history of making bad loans (early defaults), and 4) their prior sales record.

Table 4 presents these tests. In column 1, we use the sample of all new hires (rookies and seasoned hires), and regress an indicator for the loan officer being a rookie on the ZIP code's *Log(income)* and firm-year fixed effects. The results show that firms are less likely to hire rookies at branches in high-income areas: doubling the ZIP code income reduces the chances of the new hire being a rookie by 4.6 percentage points (26% of the sample mean for new hires).

Columns 2-4 of Table 4 focus on the sample of seasoned hires, where we can observe the hired officers' prior track record in the industry. The results in column 2 show that loan officers hired in higher-income ZIP codes have less prior misconduct. In column 3, the dependent variable is a measure of whether the officer has made bad loans in the past (the fraction of their loans that foreclosed within a year of origination). The results show that loan officers with a history of making bad loans are significantly less likely to be hired at branches in high-income areas relative to the same firm's branches in low-income areas. The results in columns 2 and 3 are economically meaningful: doubling ZIP code income reduces the chances of hiring a loan officer with prior misconduct and prior early default by 32% and 27%, respectively, relative to the sample means presented in the bottom row. In column 4, we find that firms are more likely to hire seasoned loan officers with a strong sales record to work in high-income ZIP codes: a 1% increase in *Log(income)* corresponds to hired officers having 0.3% higher prior lending volume.

[Insert Table 4 Here]

Overall, the tests in Table 4 document a clear pattern. In high-income areas, firms tend to hire loan officers with more experience, lower misconduct, higher loan volume and higher loan quality. In contrast, firms tend to hire people without experience (rookies) to become loan officers in low-income areas, and their seasoned hires are more likely to have a track record of misconduct, and poor performance in terms of loan volume and quality. While these hiring outcomes are likely a function of both local labor supply and firm decision-making, they are striking, and represent an obstacle to providing quality financial services in low-income areas. Our subsequent tests examine promotion and retention/firing practices to more directly examine within-firm decision-making regarding the spatial allocation of human capital.

B. Promotion Practices

Our next tests examine the flow, and allocation of human capital within firms by studying promotion practices. We evaluate whether firms systematically promote their highest performing loan officers to branches in higher-income areas. Specifically, we test whether loan officers' tenure with the firm, misconduct, loan quality, and loan volume affect the likelihood that they move within the firm to a branch in a higher-income ZIP code.

Table 5 presents these tests. The dependent variable is an indicator for the loan officer moving to a different branch within the firm that is located in a higher-income ZIP code in the next year (for brevity, we refer to this as a promotion). We regress this indicator on measures of loan officer experience and performance, customer base controls, and branch-year fixed effects. Importantly, this specification controls for any differences in local mortgage demand, worker incentives, promotion opportunities, etc., that vary at the branch-year level, and allows us to evaluate whether firms promote *relatively* stronger-performing officers to service higher-income areas.

The results in column 1 show a strong relation between a loan officer's tenure with the firm and the likelihood of promotion. As loan officers gain experience, they work their way up to branches in higher-income ZIP codes. The results in column 2 show that loan officers who commit misconduct are significantly less likely to move up within firms. In column 3, we find a statistically insignificant relationship between loan officers' early default rates and promotion. However, the results in column 4 show a strong relationship between loan officers' volume and promotion: doubling an officer's volume leads to a 0.08% increase in the likelihood of promotion that year (13% of the average annual promotion rate). The results in column 5 confirm that these patterns hold when all of the aspects of loan officer experience and performance are included together in the same specification.

[Insert Table 5 Here]

The results in Table 5 show a consistent pattern: firms systematically promote their most experienced and highest-performing loan officers from branches in lower-income ZIP codes to branches in higher-income ZIP codes. Over time, these promotion practices should funnel the best loan officers to high-income areas and leave lower-performing officers in low-income areas, a pattern we document directly in Subsection V.F.

C. Do Firms Fire Their Underperforming Loan Officers?

We next study how firms' policies toward retaining/firing underperforming workers affect their spatial allocation of human capital. In these tests, we evaluate how sensitive worker-firm separations are to loan officers' performance in terms of misconduct, loan quality, and loan volume. We also test whether, within a given firm, there appears to be more tolerance for poor performance at branches in lower-income areas. Our tests speak to variation in the standards that firms uphold, and how competitive loan officer positions are in high- versus low-income branches.

Table 6 presents these tests. The dependent variable, *Separation*, is an indicator for the loan officer leaving the firm the following year. In column 1, we regress *Separation* on our measure of loan officer misconduct, as well as customer base controls and branch-year fixed effects. The results show a positive relationship, demonstrating that firms discipline their loan officers for misconduct. Indeed, for the average officer committing misconduct, the variable *Misconduct* increases from 0 to 1.4 cases per million dollars lent, which implies a 1.98 percentage point increase in the probability of separation (11% of the average separation rate). In column 2, we add an interaction term between misconduct and an indicator for the officer working in a high-income ZIP code (above the sample median). The results are striking: misconduct strongly predicts separation at branches in high-income ZIP codes, but does not significantly predict separation in low-income ZIP codes. These results provide evidence that firms are more tolerant of misconduct at branches in low-income areas.

Columns 3 and 4 of Table 6 examine the relationship between loan officers' performance in terms of loan quality and the likelihood of separation. The results in column 3 show that loan officers with a higher percentage of early defaults are more likely to experience a separation. Including the interaction term in column 4 shows that the performance–separation relation is again much stronger at branches in high-income ZIP codes.

Columns 5 and 6 test whether loan officers with poor sales performance are more likely to experience a separation. The results in column 5 show a strong negative relationship between loan officers' volume and the likelihood of separation: doubling loan volume reduces an officer's likelihood of separation by 2.5 percentage points (14% of the average separation rate). The interaction term in column 6 again shows that this relationship is even stronger at branches in high-income areas.[17]

[Insert Table 6 Here]

The results in Table 6 show an important pattern: firms tolerate significantly more misconduct and poor performance from their loan officers working at branches in low-income areas than they do in high-income areas. Importantly, the inclusion of customer base controls and branch-year fixed effects in our tests ensures that this result is not simply a byproduct of higher overall misconduct/default rates in low-income areas. Even within branches, relatively worse performers are more likely to experience a separation when it is a high-income branch, suggesting that these positions are more competitive, and that as a result, firms set a higher standard of performance at these branches, which ultimately benefits high-income customers.

[17] In untabulated results, we also find that loan officers with longer tenure are less likely to leave the firm, and that this relationship is significantly stronger in high-income areas.

D. Where do Displaced Loan Officers End Up?

After documenting that firms dismiss underperforming loan officers, we now examine these officers' career trajectories. Specifically, we test whether loan officers experiencing a job separation following poor performance regain employment in high- versus low-income areas.

Our tests in Table 7 focus on the subsample of loan officers who separate from their current employer. The dependent variable is an indicator for the loan officer working at a branch next year that is located in a lower-income ZIP code than their current pre-separation branch. We regress this indicator on measures of loan officer experience and performance, customer base controls, and branch fixed effects. These fixed effects allow us to compare the trajectories of two loan officers who are both leaving the same branch, but differ in their experience and performance.[18]

The results in column 1 show a strong negative relationship between a loan officer's tenure and the likelihood that they are reemployed in a lower-income ZIP code after separation. Column 2 shows that loan officers who commit misconduct are significantly more likely to move down to a lower-income area. For example, comparing an officer with no misconduct to the typical officer with misconduct (whose average *Misconduct* is 1.4 cases per million dollars lent) implies a 1.42 percentage point increase in the probability of moving down to a lower-income area (20% of the average rate).

[Insert Table 7 Here]

The results in column 3 show a statistically insignificant relationship between loan officers' early defaults and next work location, while the results in column 4 show a strong negative relationship between officers' volume and their likelihood of working

[18] We focus on officers experiencing a separation because across-firm downward moves make up the majority of downward moves. The tests use branch rather than branch-year fixed effects to avoid dropping a large number of singletons in the estimation. However, the results are similar if we use all loan officer-years – see Table IA.1 in the Internet Appendix.

in a lower-income ZIP code next year. Doubling a loan officer's pre-separation volume reduces their likelihood of moving down by 1.37 percentage points (20% of the average rate). Column 5 confirms that these patterns hold when the various aspects of loan officer experience and performance are included together in one specification.

Our findings here are consistent with studies showing that labor markets discipline underperforming corporate executives (Kaplan, 1994), hedge fund managers (Ellul et al., 2020), and financial advisors (Egan et al., 2022). Evidence on this front is less clear in banking, where Gao et al. (2020) find that corporate bankers face consequences when loans perform poorly, but Griffin et al. (2019) find that bankers signing problematic RMBS deals did not experience adverse labor market outcomes. Overall, our results show that labor markets discipline underperforming mortgage loan officers, and that their career trajectories lead them to work in lower-income neighborhoods.

E. Spillover Effects in Human Capital

We next explore spillover effects in workers' job performance (e.g., Dimmock et al., 2018). Specifically, we examine the impact on a focal loan officer's performance when colleagues with a poor track record join/leave the branch. Table 8 examines spillovers in misconduct, early defaults, and lending volume. The key independent variables are the fraction of the focal officer's colleagues with poor performance at their *prior* job assignments, which we then standardize to have a mean of zero and standard deviation of one. We run OLS regressions of loan officers' performance on these measures of their colleagues' prior assignment performance, along with customer base controls, firm-year fixed effects, branch ZIP fixed effects, and loan officer fixed effects.[19]

[Insert Table 8 Here]

[19] We use firm-year rather than branch-year fixed effects in these tests because the "Fraction of colleagues" variables are essentially branch-year level variables. To control for any location effects, we add ZIP code fixed effects based on the branch location.

In column 1, we find a strong positive relationship between the fraction of colleagues with prior assignment misconduct and the focal officer's likelihood of misconduct this year. In column 2, we find similar results for early defaults. In column 3, we find that a higher fraction of colleagues with low sales at prior assignments (in the bottom 10% relative to peers) leads to the focal officer having lower sales volume. The results suggest economically meaningful effects. Taking column 1 as an example, a standard deviation increase in the fraction of colleagues with prior assignment misconduct leads to an increase in the focal officer's misconduct rate of 10 basis points, which is large relative to the sample mean.

We also implement a difference-in-differences approach using loan officer retirement events that reduce the level of experience and expertise at a branch. The results, reported in Table IA.2 in the Internet Appendix, show that following the retirement of an experienced loan officer, *Misconduct* and *Early default* increase and *Log(loan volume)* decreases at the branch. To the extent that loan officers' motives for retirement are personal/idiosyncratic, these results suggest that reductions in human capital cause a reduction in the quality of financial services offered, due to the combination of this experience being hard to directly replace and any positive spillovers it has on junior colleagues.

In sum, our results show that the likelihood of committing misconduct, making bad loans, and generating low sales depends not only on one's own characteristics, but also the prior experiences and performance of co-workers. Importantly, these findings suggest that productivity spillovers within branches likely amplify the effects of firms' labor allocation decisions for end consumers of their services.

F. *The Equilibrium Allocation of Human Capital*

At this point, we characterize the allocation of human capital within firms that results from labor supply and firms' hiring, promotion, and retention/firing practices. To do this, we examine the within-firm relation between ZIP code income and the characteristics of the loan officers at particular branches. We again focus on loan officers' experience and measures of past performance based on misconduct, loan quality, and loan volume.

Table 9 presents the results. Column 1 shows a strong negative relationship between ZIP code income and the likelihood that a loan officer is a rookie: doubling income levels reduces the incidence of rookies by 0.59 percentage points (15% of the sample mean). Columns 2 and 3 show that officers working in higher-income ZIP codes are also less likely to have a track record of committing misconduct or making bad loans. Compared to a customer visiting a firm's branch in a low-income neighborhood, a customer visiting their branch in an area with twice the income level will encounter officers with 19% less prior misconduct and 22% fewer bad loans (relative to the respective sample means). In column 4, we find that a 1% increase in ZIP code income corresponds to a loan officer with 0.45% higher historical sales.[20]

[Insert Table 9 Here]

In sum, the results in Table 9 show that even within firms, loan officers working at branches in higher-income ZIP codes are more experienced and have better track records. Although we do not observe loan officers' exact contributions to firms' profits, these patterns may well reflect profit-maximizing labor allocation decisions, where firms match their most skilled employees to the positions that handle the most volume. Yet, as we document in Section VI below, this allocation of human capital leads to financial firms providing lower quality services in low-income areas.

[20] We also confirm in a robustness check that these same patterns hold after adjusting loan officers' prior performance for their previous work locations (see Table IA.3).

VI. Human Capital and Disparities in the Quality of Financial Services

Our prior tests in Sections IV and V document the importance of person fixed effects (human capital) in the provision of financial services, and that firms allocate their best workers to high-income areas. In this section, we work to deepen the connection between labor markets and consumer outcomes by directly evaluating the effect of loan officer characteristics on outcomes at the most granular level the data allow. We use three measures of financial services' quality: the rate at which loan officers commit misconduct (loan officer-year level), the likelihood that a mortgage originated by the officer forecloses within a year (loan level), and the frequency of CFPB complaints (ZIP code-year level).

Table 10 Panel A presents these tests. In column 1, we use our loan officer-year panel and regress *Misconduct* on four measures of the officer's experience and past performance: their tenure with the firm, and their track record in terms of prior misconduct, loan quality, and loan volume. We control for customer base characteristics and we use branch-year fixed effects to absorb variation in branches' operations, loan products, or culture that may affect the likelihood of misconduct. The results show that inexperienced officers and those with a history of misconduct are significantly more likely to commit misconduct this year.

In column 2, we use a merged loan level data set which links loan officers in our NMLS panel to the mortgages they originate from 2014 to 2019 (from CoreLogic) and information on foreclosures (from Zillow). We regress an indicator for the mortgage ending in foreclosure within a year (*Early default*) on our four key loan officer characteristics, as well as loan-level controls, firm fixed effects, and property ZIP code-year fixed effects. The results show that "bad loans" are more likely if the loan officer is inexperienced, has a prior record of misconduct, has a history of making bad loans, or has a track record of low loan volume. All of these effects are statistically significant, and they provide evidence that less experienced and less skilled loan officers have a tendency to make bad loans that are potentially harmful to the local economy and consumers.[21]

In column 3, we measure the quality of financial services at the ZIP code-year level based on complaints made to the CFPB. Our dependent variable is the number of mortgage-related complaints in the ZIP code scaled by the total number of mortgages originated in the ZIP code that year.[22] We regress *CFPB complaints* on the average characteristics of the loan officers who serviced that ZIP code during the year (weighted by loan volume), as well as customer base controls and fixed effects for MSAs and years. The results show that there are significantly more complaints in a ZIP code when it is serviced by loan officers who are inexperienced, or have worse track records based on misconduct, loan quality, and loan volume.

[Insert Table 10 Here]

Finally, we quantify the overall importance of human capital in the income-based disparities we document. To do so, we carry out a variance decomposition. We first difference out the MSA and year effects for our measures of financial services quality. We then take the residual and use an analysis of covariance (ANCOVA) framework to decompose the variation and attribute it to various factors.

We present the results in Table 10 Panel B. The factors include the local ZIP code income and the four main loan officer characteristics. The percentages reported correspond to the fraction of the total Type III partial sum of squares. That is, we divide the partial sum of squares for each effect by the aggregate partial sum of squares across all five factors. This provides a normalization that forces the columns

[21] For evidence on the negative effects of foreclosures, see for example, Campbell et al. (2011), Gupta (2019), Mian et al. (2015), Ellen et al. (2013), Currie and Tekin (2015), and Makridis and Ohlrogge (2022).

[22] We follow the same data procedure as in Table 1 column 3 by excluding CFPB complaints which do not have a five-digit ZIP code.

to sum to one. Intuitively, the percentages in the table correspond to the fractions of the model sum of squares attributable to each factor.

In column 1, the dependent variable is *Misconduct*. We observe that prior misconduct explains over 99% of the "explainable" variation in future misconduct, whereas local income only explains 0.02%. In column 2, we focus on *Early default* and find that local income explains around 61% of the relevant variation, whereas loan officer characteristics explain around 39% (with 17% coming from tenure and 21% from the loan officers' track record of defaults). In column 3, we decompose *CFPB complaints*. Here, we find that local income accounts for 74% of the explanatory power. Overall, these results indicate that when taking into account local income levels and loan officer characteristics, human capital can explain between 25% and 40% of the explainable variation in the quality of financial services (or nearly 100% in the case of severe misconduct).

VII. Conclusion

We use a comprehensive data set covering over 350,000 U.S. mortgage loan officers and the loans they originate from 2014 to 2019 to explore the role of human capital in mortgage lending. We document that loan officer performance is persistent, exhibits tremendous heterogeneity across officers, and improves with experience. The patterns in the data provide evidence that human capital is a critical component in providing quality financial services, even in competitive and transaction-oriented markets.

We then evaluate how financial firms allocate their human capital across geographic areas based on local income levels. We document that firms' hiring and promotion policies disproportionately assign workers with less experience or poor track records to branches in low-income ZIP codes. Firms also appear to be more tolerant of loan officers having low sales numbers, writing bad loans, or committing misconduct in low-income branches.

Overall, our results show that firms' labor allocation decisions lead to substantial differences in worker quality across ZIP codes, and that this spatial distribution of talent is a critical supply-side factor contributing to the large disparities in financial services quality across income strata. Our findings suggest that sorting in finance labor markets may reinforce existing levels of economic inequality, and that policies seeking to improve financial services in low-income areas should consider the importance of human capital.

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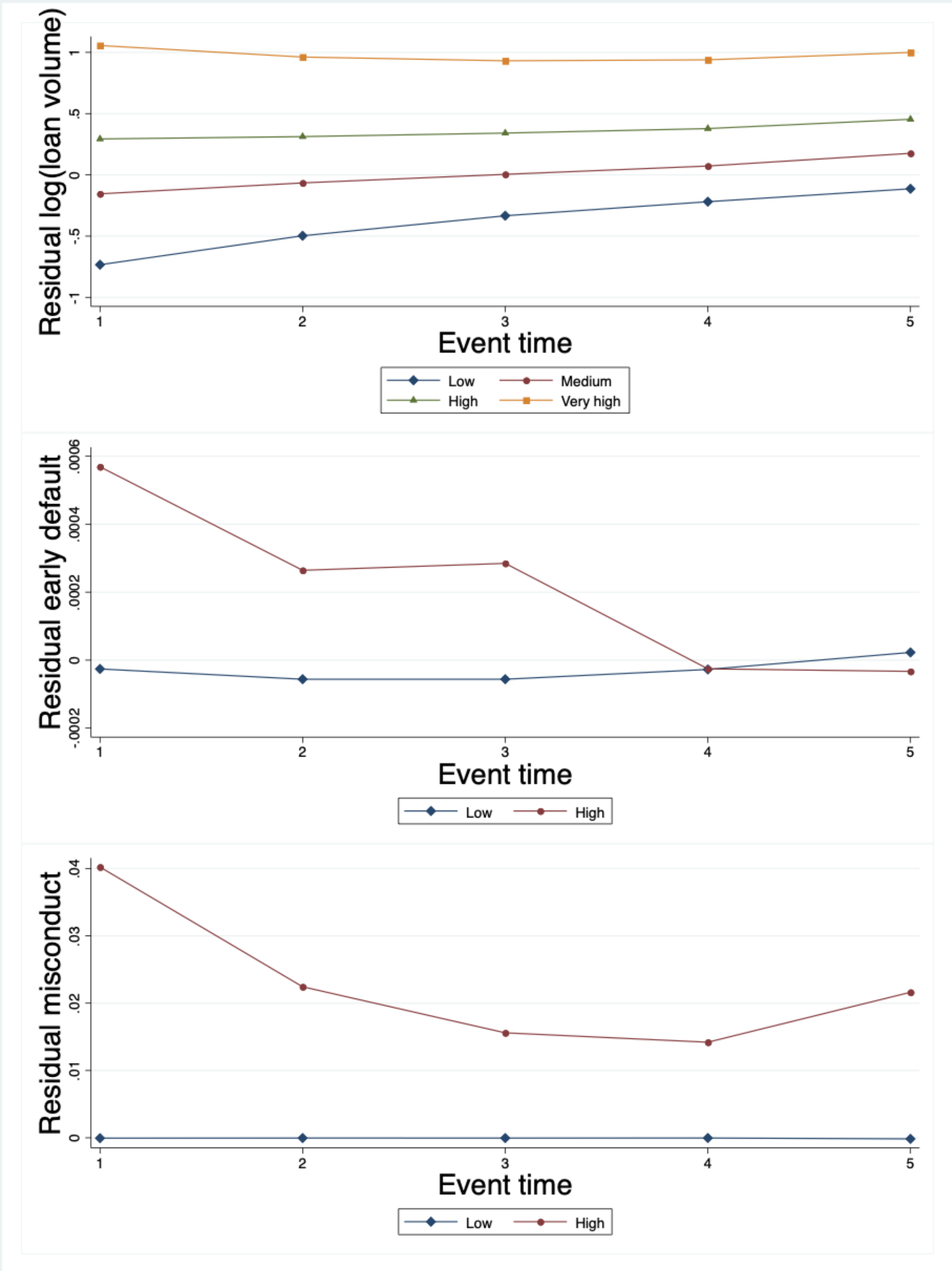

Figure 1: Persistence in loan officer performance
This figure shows the persistence in loan officers' performance in terms of loan volume, loan quality, and misconduct. We regress loan officers' volume/defaults/misconduct on branch-year fixed effects and collect the residuals. For each calendar year, we use the residuals to sort officers into high/low performer portfolios, which we then hold fixed for five years, tracking (residual) performance of the officers in event time. We conduct this exercise each calendar year and average portfolio outcomes across event time. In the top plot, we sort loan officers into four groups based on their quartile of residual log(loan volume) in the formation year, and track them for the next five years. In the middle plot, we track two portfolios formed based on whether or not loan officers had any early defaults (loans ending in foreclosure within a year) during the formation year. In the bottom plot, we track two portfolios formed based on whether or not the loan officer committed misconduct in the formation year.

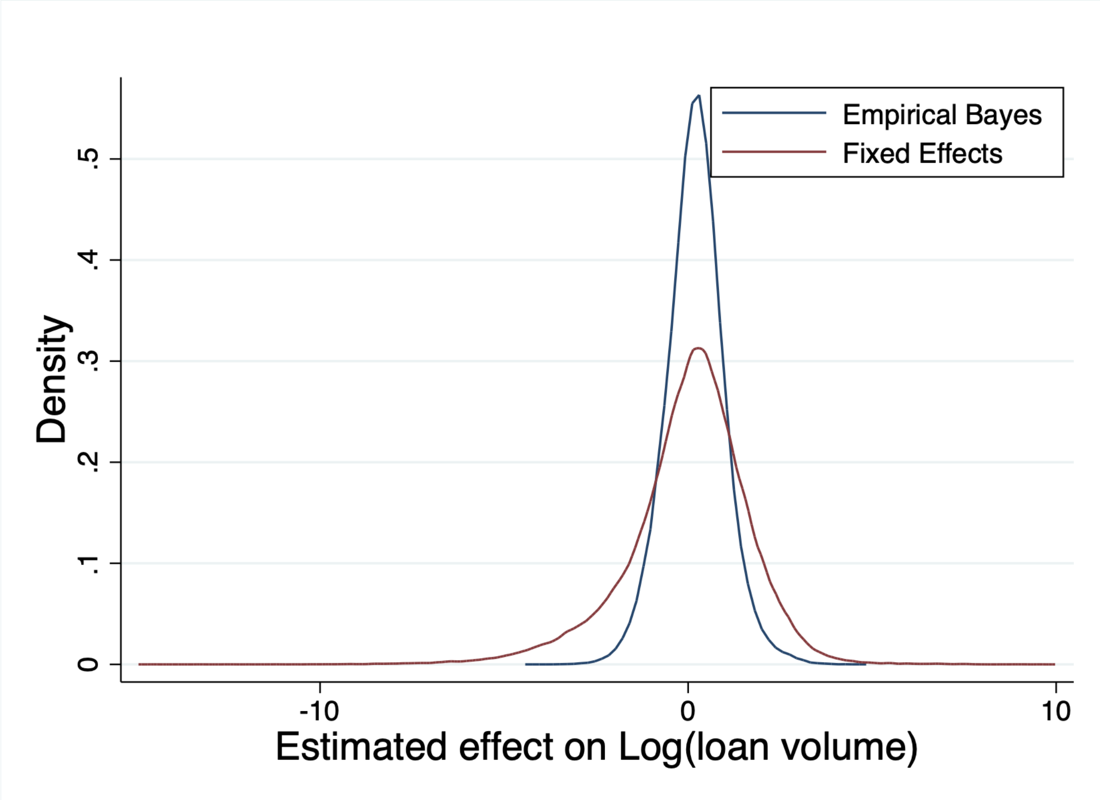

Figure 2: Empirical Bayes estimates of loan officers' effect on sales
This figure shows the distribution of loan officers' estimated effect on Log(loan volume) using empirical Bayes (in blue) and traditional fixed effects (in red). Both sets of estimates control for branch-year fixed effects.

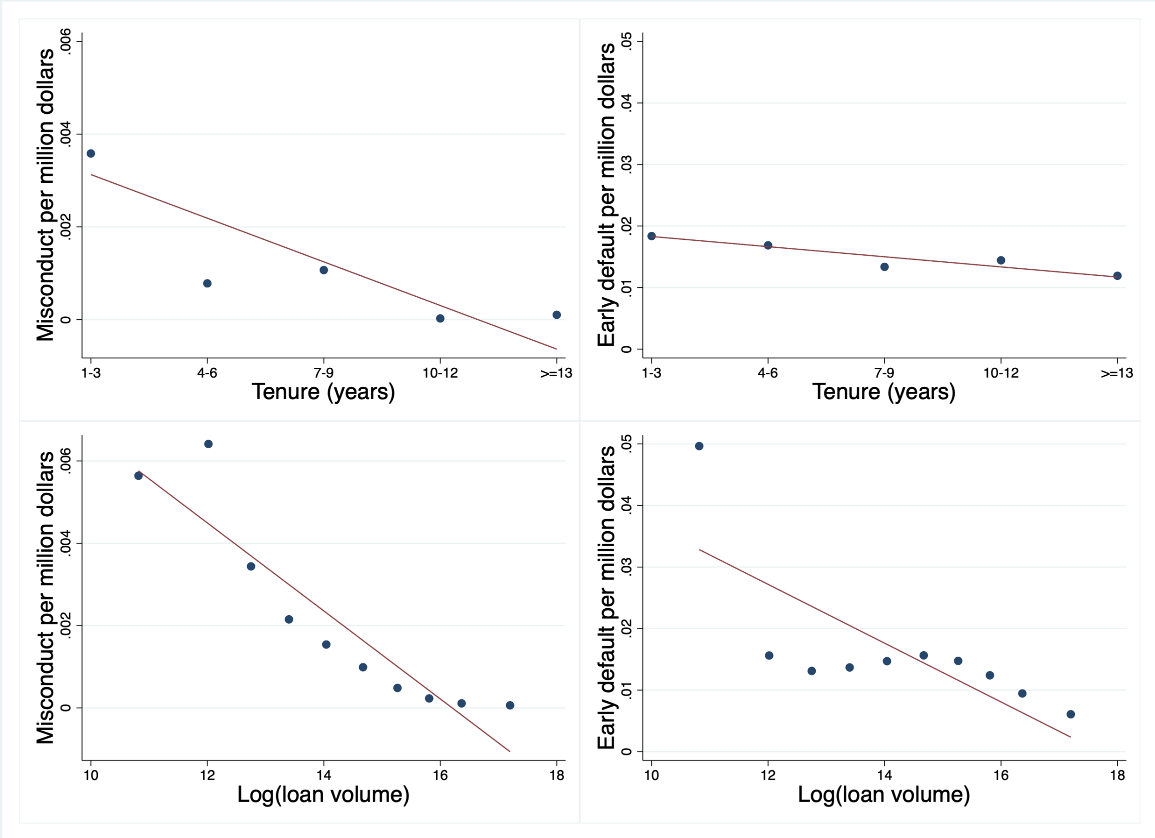

Figure 3: Loan officer experience, productivity, and lending quality
This figure shows how loan officers' experience and lending volume (i.e., productivity), relate to the quality of the financial services they provide. We measure the quality of loan officers' work based on the frequency with which they commit misconduct, and whether their loans foreclose within a year (both in terms of occurrences per million dollars lent). The top left and right plots show how loan officer tenure correlates with misconduct and early defaults, respectively. Similarly, the bottom left and right plots show how loan officers' volume correlates with misconduct and early defaults.

Table 1: ZIP code income and the quality of financial services

This table reports OLS regressions examining the effect of local income levels on the quality of financial services. The sample includes all ZIP code-years from 2014 to 2019. In columns 1, 2, and 3 respectively, the dependent variable is the instances of loan officer misconduct, the number of early defaults (foreclosure within a year), and the number of CFPB complaints against mortgage lenders, respectively, each scaled by the number of mortgages originated in the ZIP code that year. The key independent variable is the natural logarithm of per capita income in the ZIP code. The standard errors are clustered at the ZIP code level, and statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

	(1) Misconduct	(2) Early default	(3) CFPB complaints
Log(income)	-0.0006***	-0.0024***	-0.0025***
	(0.0002)	(0.0001)	(0.0001)
Year FE	Y	Y	Y
MSA FE	Y	Y	Y
Observations	146,979	146,979	146,979
R-squared	0.0220	0.0312	0.1161
Dep. var. mean	0.0020	0.0025	0.0025

Table 2: Summary statistics

This table presents descriptive statistics for our loan officer-year panel. Columns 1-6 present the sample size (N), mean, standard deviation (SD), 25th percentile (P25), 50th percentile (P50), and 75th percentile (P75), respectively. All the variables are defined in Appendix A.

	(1) N	(2) Mean	(3) SD	(4) P25	(5) P50	(6) P75
Loan officer characteristics						
Misconduct	1,110,423	0.0021	0.1637	0	0	0
Early default	1,110,423	0.0020	0.0204	0	0	0
Loan volume (million $)	1,110,423	6.1694	10.2485	0.3445	1.7326	7.4055
Log(loan volume)	1,110,423	14.2357	1.9362	12.7499	14.3651	15.8177
Prior misconduct	755,850	0.0101	0.2275	0	0	0
Prior early default	755,850	0.0063	0.0220	0	0	0
Lag log(loan volume)	755,850	14.4663	1.8414	13.1022	14.6725	15.9320
Tenure	1,110,423	5.9375	6.6280	2	3	7
Log(tenure)	1,110,423	1.6112	0.7649	1.0986	1.3863	2.0794
Rookie	1,110,423	0.0398	0.1954	0	0	0
Move up within firm	1,110,423	0.0062	0.0786	0	0	0
Separation	1,110,423	0.1801	0.3842	0	0	0
Move down to lower income area (conditional on separation)	203,322	0.0695	0.2543	0	0	0
Branch location characteristics						
Income (thousand $)	1,110,423	35.2544	14.6244	24.7275	32.2454	42.1836
Log(income)	1,110,423	10.4666	0.3975	10.1866	10.4530	10.7249
High income	1,110,423	0.5232	0.4995	0	1	1
Fraction of colleagues with prior assignment misconduct	823,937	0.0017	0.0216	0	0	0
Fraction of colleagues with prior assignment early default	823,937	0.0389	0.1186	0	0	0
Fraction of colleagues with prior assignment low loan volume	823,937	0.0857	0.1849	0	0	0.0851
Customer base controls (average at customer-ZIP level)						
Log(customer-ZIP income)	1,110,423	10.3878	0.2630	10.2154	10.3746	10.5459
Bachelor's degree share	1,110,423	0.3345	0.1230	0.2490	0.3215	0.4068
Minority share	1,110,423	0.3155	0.1900	0.1703	0.2900	0.4191
Unemployment rate	1,110,423	0.0639	0.0240	0.0479	0.0600	0.0758
Log(population density)	1,110,423	6.7817	1.3389	6.0609	6.9734	7.6839

Table 3: Persistence and person fixed effects in loan officer performance

This table reports OLS regressions testing whether loan officers' performance is persistent, and assessing the overall importance of loan officer fixed effects. The unit of observation is at the loan officer-year level. The tests in Panel A regress measures of loan officer performance on past performance. The dependent variables in columns 1 to 3 are *Misconduct*, *Early default*, and *Log(loan volume)*, respectively. In Panel B, we regress each measure of loan officer performance on customer base controls and branch-year fixed effects, and then include loan officer fixed effects to assess their importance. Customer base controls include average customer ZIP code level income, bachelor's degree share, minority share, unemployment rate, and population density. All variables are defined in Appendix A. The standard errors are clustered at the loan officer level, and statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

Panel A: Persistence in loan officer performance

	(1) Misconduct	(2) Early default	(3) Log(loan volume)
Prior misconduct	0.0396***		
	(0.0112)		
Prior early default		0.0085***	
		(0.0013)	
Lag log(loan volume)			0.6354***
			(0.0016)
Branch x year FE	Y	Y	Y
Observations	629,255	629,255	629,255
R-squared	0.2670	0.2372	0.7355
Dep. var. mean	0.0020	0.0025	14.4663

Panel B: Loan officer fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Misconduct		Early Default		Log(loan volume)	
Customer base controls	Y	Y	Y	Y	Y	Y
Branch x year FE	Y	Y	Y	Y	Y	Y
Loan officer FE	N	Y	N	Y	N	Y
Observations	949,071	837,377	949,071	837,377	949,071	837,377
R-squared	0.1508	0.5960	0.2278	0.5130	0.5821	0.8837
Adjusted R-squared	-0.0587	0.2437	0.0373	0.0883	0.4790	0.7823

Table 4: Firms are more likely to hire experienced and skilled loan officers in wealthy areas

This table reports OLS regressions examining the effect of ZIP code income levels on the characteristics of the loan officers that firms hire to work at local branches. In column 1, we study all new hires (loan officer-years where tenure with the firm equals one), and the dependent variable is an indicator for the new hire having no prior experience in the industry (*Rookie*). In columns 2 to 4, we study only seasoned hires (where the officer has prior industry experience), and the dependent variable is *Prior misconduct*, *Prior early default*, and *Lag log(loan volume)*, respectively. The key independent variable is always the natural logarithm of per capita income in the ZIP code where the branch is located. All variables are defined in Appendix A. The standard errors are clustered at the loan officer level, and statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

	(1) Rookie	(2) Prior misconduct	(3) Prior early default	(4) Lag log(loan volume)
Log(income)	-0.0463***	-0.0089**	-0.0025***	0.3061***
	(0.0024)	(0.0038)	(0.0003)	(0.0121)
Firm x year FE	Y	Y	Y	Y
Observations	235,913	141,616	141,616	141,616
R-squared	0.1903	0.0720	0.1114	0.3632
Dep. var. mean	0.1788	0.0275	0.0092	14.4237

Table 5: Firms promote their best loan officers into wealthy areas

This table reports OLS regressions examining the effect of loan officers' experience and performance on whether they are promoted within the firm to work in higher income areas. The sample includes all the loan officer-years in our data from 2014 to 2019. The dependent variable, *Move up within firm*, is an indicator for the loan officer working at one of the firm's other branches that is located in a higher income ZIP code next year. The key independent variables are measures of loan officer experience and performance. Customer base controls include average customer ZIP code level income, bachelor's degree share, minority share, unemployment rate, and population density. All variables are defined in Appendix A. The standard errors are clustered at the loan officer level, and statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)
			Move up within firm		
Log(tenure)	0.0011***				0.0009***
	(0.0001)				(0.0001)
Misconduct		-0.0008**			-0.0006*
		(0.0003)			(0.0003)
Early default			0.0012		0.0013
			(0.0050)		(0.0050)
Log(loan volume)				0.0008***	0.0008***
				(0.0001)	(0.0001)
Customer base controls	Y	Y	Y	Y	Y
Branch x year FE	Y	Y	Y	Y	Y
Observations	949,071	949,071	949,071	949,071	949,071
R-squared	0.3475	0.3474	0.3474	0.3474	0.3476
Dep. var. mean			0.0062		

Table 6: Firms fire underperforming loan officers, especially in wealthy areas

This table reports OLS regressions examining the effect of loan officers' job performance on job separations. The sample includes all the loan officer-years in our data from 2014 to 2019. The dependent variable, *Separation*, is an indicator for the loan officer not working at the firm the next year. The key independent variables are measures of loan officer performance, and their interaction with *high income*, which is an indicator for the officer working at a branch in a ZIP code with per capita income above the sample median. Customer base controls include average customer ZIP code level income, bachelor's degree share, minority share, unemployment rate, and population density. All variables are defined in Appendix A. The standard errors are clustered at the loan officer level, and statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Separation					
Misconduct	0.0141*	0.0041				
	(0.0078)	(0.0041)				
Misconduct × high income		0.0449***				
		(0.0079)				
Early default			0.0713***	0.0260		
			(0.0225)	(0.0304)		
Early default × high income				0.0847*		
				(0.0447)		
Log(loan volume)					-0.0248***	-0.0191***
					(0.0003)	(0.0004)
Log(loan volume) × high income						-0.0102***
						(0.0006)
Customer base controls	Y	Y	Y	Y	Y	Y
Branch x year FE	Y	Y	Y	Y	Y	Y
Observations	949,071	949,071	949,071	949,071	949,071	949,071
R-squared	0.3953	0.3954	0.3953	0.3953	0.4017	0.4019
Dep. var. mean	0.1801					

Table 7: Underperforming loan officers are reemployed in lower income areas

This table reports OLS regressions that examine loan officers' career trajectories following separations from their employer. The sample includes loan officer-years from 2014 to 2019, where the loan officer separates from the firm during the year. The dependent variable, *Move down to lower income area*, is an indicator for the loan officer being reemployed at another lender's branch located in a lower income ZIP code next year. The key independent variables are measures of loan officer experience and performance in their current job (pre-separation). Customer base controls include average customer ZIP code level income, bachelor's degree share, minority share, unemployment rate, and population density. All variables are defined in Appendix A. The standard errors are clustered at the loan officer level, and statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)
	Move down to lower income area				
Log(tenure)	-0.1186***				-0.1156***
	(0.0014)				(0.0014)
Misconduct		0.0101**			0.0064
		(0.0050)			(0.0049)
Early default			-0.0004		-0.0163
			(0.0273)		(0.0266)
Log(loan volume)				-0.0137***	-0.0092***
				(0.0005)	(0.0004)
Customer base controls	Y	Y	Y	Y	Y
Branch FE	Y	Y	Y	Y	Y
Observations	170,204	170,204	170,204	170,204	170,204
R-squared	0.3454	0.3074	0.3074	0.3117	0.3474
Dep. var. mean	0.0695				

Table 8: Spillover effects in loan officer performance

This table reports OLS regressions examining spillover effects in loan officer performance. The sample includes all the loan officer-years in our data from 2015 to 2019 (the 2014 data are used to measure officers' prior assignments). The dependent variable is *Misconduct*, *Early default*, and *Log(loan volume)* in columns 1 to 3, respectively. The key independent variables in columns 1 to 3 are the fractions of the focal officer's colleagues at the branch with misconduct, early default, and low sales (bottom 10%) at their prior job assignments, respectively. We standardize these independent variables by subtracting the mean and dividing by the standard deviation (denoted by the subscript *std*). Customer base controls include average customer ZIP code level income, bachelor's degree share, minority share, unemployment rate, and population density. All variables are defined in Appendix A. The standard errors are clustered at the loan officer level, and statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

	(1) Misconduct	(2) Early default	(3) Log(loan volume)
Fraction of colleagues with	0.0010**		
prior assignment misconduct$_{std}$	(0.0004)		
Fraction of colleagues with		0.0001***	
prior assignment early default$_{std}$		(0.0000)	
Fraction of colleagues with			-0.0339***
prior assignment low loan volume$_{std}$			(0.0023)
Customer base controls	Y	Y	Y
Firm x year FE	Y	Y	Y
ZIP FE	Y	Y	Y
Loan officer FE	Y	Y	Y
Observations	726,449	726,449	726,449
R-squared	0.3505	0.4032	0.8503
Dep. var. mean	0.0011	0.0016	14.3171

Table 9: The equilibrium allocation of loan officer human capital

This table reports OLS regressions examining the effect of ZIP code income levels on the characteristics of the loan officers working at local branches. The sample includes all the loan officer-years in our data from 2014 to 2019 (columns 2-4 require at least one prior year of data on officers). In columns 1 to 4, the dependent variable is *Rookie*, *Prior misconduct*, *Prior early default*, and *Lag log(loan volume)*, respectively. The key independent variable is always the natural logarithm of per capita income in the ZIP code where the branch is located. All variables are defined in Appendix A. The standard errors are clustered at the loan officer level, and statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

	(1) Rookie	(2) Prior misconduct	(3) Prior early default	(4) Lag log(loan volume)
Log(income)	-0.0059***	-0.0019*	-0.0014***	0.4526***
	(0.0006)	(0.0010)	(0.0001)	(0.0080)
Firm x year FE	Y	Y	Y	Y
Observations	1,110,423	755,850	755,850	755,850
R-squared	0.0777	0.0473	0.1171	0.4364
Dep. var. mean	0.0398	0.0101	0.0063	14.4663

Table 10: The impact of human capital on the quality of financial services

This table reports OLS regressions examining the effect of loan officer characteristics on the quality of financial services provided to borrowers. Panel A focuses on the OLS estimates. In column 1, the unit of observation is at the loan officer-year level, and the dependent variable is *Misconduct*. In column 2, the unit of observation is at the loan level, and the dependent variable is an indicator for the loan ending in foreclosure within a year (early default). In column 3, the unit of observation is at the ZIP code-year level, and the dependent variable is the number of CFPB complaints against mortgage lenders normalized by the number of mortgages originated. The key independent variables are the reported loan officer characteristics—in column 3, these are averaged across officers serving the ZIP code. Customer base controls in columns 1 and 3 include average customer ZIP code level income, bachelor's degree share, minority share, unemployment rate, and population density. The loan level controls in column 2 include indicators for the loan being conforming, and for various loan types such as loans insured through the Federal Housing Administration (FHA). The standard errors are clustered at the loan officer, county, and ZIP code level in columns 1-3, respectively. Panel B presents the variance decomposition of the quality of financial services by loan officer characteristics net of MSA and year fixed effects. All variables are defined in Appendix A. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

Panel A: Quality of financial services

	(1) Misconduct	(2) Early default	(3) CFPB complaints
Log(tenure)	-0.0007***	-0.0001***	-0.0004***
	(0.0002)	(0.0000)	(0.0001)
Prior misconduct	0.0260***	0.0001**	0.0000***
	(0.0083)	(0.0001)	(0.0000)
Prior early default	-0.0006	0.0056***	0.0065***
	(0.0044)	(0.0008)	(0.0018)
Lag log(loan volume)	0.0001	-0.0000***	-0.0003***
	(0.0001)	(0.0000)	(0.0001)
Customer base controls	Y		Y
Branch x year FE	Y		
Loan characteristics controls		Y	
Firm FE		Y	
ZIP x year FE		Y	
Year FE			Y
MSA FE			Y
Observations	629,255	27,811,234	118,521
R-squared	0.2649	0.0120	0.0996
Dep. var. mean	0.0021	0.0018	0.0016

Panel B: Variance decomposition

	(1) Misconduct	(2) Early default	(3) CFPB complaints
Log(income)	0.02%	61.19%	73.64%
Log(tenure)	0.41%	16.82%	19.88%
Prior misconduct	99.54%	0.29%	0.03%
Prior early default	0.00%	21.20%	6.46%
Lag log(loan volume)	0.02%	0.50%	0.05%
Observations	629,255	27,811,234	118,521

Appendix A: Variable definitions

Variables	Definition
Loan officer characteristics	
Misconduct	Number of misconduct cases in year t, scaled by total loan volume (in million $)
Early default	Percentage of loans made that end in foreclosure within a year of origination
Loan volume (million $)	Total dollar amount of loans originated
Log(loan volume)	Natural logarithm of the total dollar amount of loans originated
Prior misconduct	Cumulative number of misconduct cases up until year t-1, scaled by total loan volume (in million $) in year t-1
Prior early default	Cumulative number of loans made that end in foreclosure within a year of origination up until year t-1, scaled by total number of originations in year t-1
Lag log(loan volume)	One-period lag of *Log(loan volume)*
Tenure	Number of years with the current firm
Log(tenure)	Natural logarithm of the number of years with the current firm
Rookie	Equals one if it is the loan officer's first year in the industry, zero otherwise
Move up within firm	Equals one if the loan officer moves to a branch within the firm that is located in a higher income ZIP code next year, zero otherwise
Separation	Equals one if the loan officer leaves the company in the next year and zero otherwise
Move down to lower income area	Equals one if the loan officer working at a different bank's branch that is located in a lower income ZIP code next year, zero otherwise
Branch location characteristics	
Income (thousand $)	Per capita income at the ZIP code level
Log(income)	Natural logarithm of per capita income at the ZIP code level
High income	Equals one if the loan officer works at a branch in a ZIP code with per capita income above the sample median, zero otherwise
Fraction of colleagues with prior assignment misconduct	Fraction of the focal officer's colleagues at the branch with misconduct at their prior jobs
Fraction of colleagues with prior assignment early default	Fraction of the focal officer's colleagues at the branch with early defaults at their prior jobs
Fraction of colleagues with prior assignment low loan volume	Fraction of the focal officer's colleagues at the branch with low sales (bottom 10%) at their prior jobs
Customer base controls (average at customer-ZIP level	
Log(customer-ZIP income)	Natural logarithm of average customer ZIP code level per capita income from ACS.
Bachelor's degree share	Average customer ZIP code level fraction of population with bachelor's degree from ACS.
Minority share	Average customer ZIP code level fraction of minorities over total population from ACS.
Unemployment rate	Average customer ZIP code level unemployment rate from ACS.
Log(population density)	Natural logarithm of average customer ZIP code level population per square mile from ACS.

Can Human Capital Explain Income-based Disparities in Financial Services?

Internet Appendix

I. Supplemental tables

Table IA.1: Underperforming loan officers end up working in low income areas

This table reports OLS regressions examining the effect of loan officers' experience and performance on whether they end up working in low income areas. The sample includes all the loan officer-years in our data from 2014 to 2019. The dependent variable, *Move down to lower income area (all)*, is an indicator for the loan officer working at any branch that is located in a lower income ZIP code next year. The key independent variables are measures of loan officer experience and performance. Customer base controls include average customer ZIP code level income, bachelor's degree share, minority share, unemployment rate, and population density. All variables are defined in Appendix A. The standard errors are clustered at the loan officer level, and statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)
	Move down to lower income area (all)				
Log(tenure)	-0.0685***				-0.0667***
	(0.0005)				(0.0005)
Misconduct		0.0138***			0.0102***
		(0.0037)			(0.0036)
Early default			0.0114		0.0047
			(0.0128)		(0.0126)
Log(loan volume)				-0.0094***	-0.0064***
				(0.0002)	(0.0002)
Customer base controls	Y	Y	Y	Y	Y
Branch x year FE	Y	Y	Y	Y	Y
Observations	949,071	949,071	949,071	949,071	949,071
R-squared	0.3782	0.3544	0.3544	0.3572	0.3795
Dep. var. mean			0.0513		

Table IA.2: The effect of loan officer retirements

This table reports OLS regressions examining the effect of loan officer retirements on the quality of financial services provided to borrowers. The unit of observation is at the branch-year level. The dependent variables in columns 1-3 are *Misconduct*, *Early default*, and *Log(loan volume)*, respectively. The key independent variable, *Retirement*, takes the value of one for years after the branch has a loan officer retirement (defined as someone who retires after working at the firm for more than six years and never comes back to the industry) and zero otherwise. The standard errors are clustered at the branch level. All variables are defined in Appendix A. Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

	(1) Misconduct	(2) Early default	(3) Log(loan volume)
Retirement	0.0008***	0.0025***	-0.3637***
	(0.0002)	(0.0002)	(0.0121)
Branch FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	341,336	341,336	341,336
R-squared	0.2844	0.3408	0.8497
Dep. var. mean	0.0007	0.0047	15.0196

Table IA.3: The equilibrium allocation of human capital (residual past performance)

This table reports OLS regressions examining the effect of ZIP code income levels on the quality of loan officers working at local branches (which we measure based on residualized past performance). The sample includes all the loan officer-years in our data from 2015 to 2019 (2014 is omitted because we require past performance). In columns 1 to 3, the dependent variable is *Residual misconduct*, *Residual early default*, and *Residual log(loan volume)*, respectively. To construct these residual past performance metrics, we first regress the outcome on branch-year fixed effects and collect the residuals, which reflect whether an officer underperformed/outperformed their peers. We then calculate each officer's average of all prior residuals, and define this as their residual performance for the given outcome. The key independent variable is always the natural logarithm of per capita income in the ZIP code where the branch is located. All variables are defined in Appendix A. The standard errors are clustered at the loan officer level, and statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

	(1) Residual misconduct	(2) Residual early default	(3) Residual log(loan volume)
Log(income)	-0.0007***	-0.0002**	0.1311***
	(0.0001)	(0.0001)	(0.0166)
Firm x year FE	Y	Y	Y
Observations	642,918	642,918	642,918
R-squared	0.2674	0.0290	0.0408
Dep. var. mean	-0.0029	-0.0006	0.4554

II. Loan officer misconduct

A. Overview

Loan officer misconduct events are reported in the NMLS registration records, under regulatory actions. Misconduct events are cases where a regulatory or legal action was taken against a loan officer. Hence, the misconduct events we observe are relatively rare (e.g., compared to customer complaints against financial professionals), but they represent clear breaches of laws or regulations as determined by the relevant legal/regulatory authority. Broadly speaking, loan officer misconduct includes unauthorized activity, misrepresentation of information to customers, and licensing requirement violations. We present examples and exhibits for each broad category below.

B. Examples of misconduct

Example 1: Unauthorized activity
Jinnie J. Chao works for American Capital Corporation (ACC) as a real estate broker and holds a Mortgage Loan Originator license. A pre-approval letter was ostensibly signed by Margaret Katz (Katz), ACC's branch manager, when in fact, Chao signed Katz's name without Katz's knowledge, permission, or authorization. Chao's license was revoked, she was fined $2,500, and she cannot reapply within two years. Exhibit 1 below contains an excerpt from the regulatory action notice. To read the full document, see: https://www.nmlsconsumeraccess.org/EntityDetails.aspx/Artifact/Other.pdf?q=270050-360694

Example 2: Misrepresentation of information to customers
Eli B. Weissman is licensed as a mortgage loan originator in New York, sponsored by Jet Direct Funding Corp (JDF). Weissman utilized video commercials to advertise mortgage loans calling himself a "direct lender." The advertisement could mislead borrowers to believe that Weissman is a duly licensed mortgage banker, when in fact he originates loans under JDF. Weissman was fined $10,000. Exhibit 2 below contains an excerpt from the settlement agreement. To read the full document, see: https://www.nmlsconsumeraccess.org/EntityDetails.aspx/Artifact/Settlement.pdf?q=274203-365088

Example 3: Licensing requirement violations
Jason Lukasik held a loan originator license in Ohio during the calendar year 2014. Ohio law requires license holders to complete eight hours of approved continuing education every calendar year. However, Lukasik failed to comply with the continuing education requirement. As a result, Lukasik's license was canceled on December 31, 2014. Lukasik submitted a new application for a loan originator license, which remained pending. He was required to pay a fine of $250 and complete eight hours of continuing education for 2014. Exhibit 3 below contains an excerpt from the settlement agreement. To read the full document, see:

https://www.nmlsconsumeraccess.org/EntityDetails.aspx/Artifact/Settlement.pdf?q=272805-363596

C. Excerpts from regulatory filings

Exhibit 1: Unauthorized activity (Chao example)

On about March 18, 2014, Respondent, in connection with the activities described in Paragraph 3, above, acting on behalf of purchasers David W. and Tong L. (herein "David and Tong") for the purchase of a property located on 66th Street in Oakland, California (herein "the Property"), submitted to Henry Chan, the listing agent for the Property, a Pre-Approval Letter (herein "the Letter"), along with David and Tong's purchase offer; the Letter was ostensibly signed by Margaret Katz (herein "Katz"), ACC's Branch Manager, when in fact, Respondent signed Katz' name without Katz' knowledge, permission or authorization, in violation of Section 10176(a) and (i) of the Code.

Exhibit 2: Misrepresentation of information to customers (Weissman example)

MISREPRESENTATION OF LICENSE

4. Weissman has been sponsored as an MLO by Jet Direct Funding Corp. d/b/a Jet Direct Mortgage ("JDF"), a licensed mortgage banker, since June 25, 2016.

5. The Department determined that in August 2017, Weissman utilized video commercials ("Commercial") via youtube.com to solicit and promote mortgage loans relating to properties in New York State.

6. The Commercial prominently displayed Weissman's name, an unauthorized assumed name "Team Weissman", his NMLS No. and his contact information without JDF's information and the required disclosures.

7. Specifically, Weissman stated in the Commercial that "as a direct lender, I have learned skills to find the lowest rate possible...I built the team of experts..." and "I hope we are the team you select when you are ready to buy a home."

8. Based on the aforementioned statement, the Department has determined Weissman violated 3 NRCRR Section 420.20 (a) (3), which prohibits an MLO from misrepresenting "his or her license status, or persuade or induce a borrower to apply for a mortgage loan under the belief that such MLO is duly licensed as a mortgage banker or registered as a mortgage broker, pursuant to Article 12-D of the Banking Law."

9. Additionally, Weissman used JDF's logo displayed at the bottom of the Commercial during its entirety without disclosing JDF is a licensed mortgage banker and he is an MLO employed by JDF.

10. Based on the aforementioned, the Department has determined that Weissman violated 3 NYCRR Section 420.20 (a) (4), which prohibits an MLO from misstating his ability to act as a mortgage banker or mortgage broker pursuant to article 12-D of the Banking Law.

Exhibit 3: Licensing requirement violation (Lukasik example)

STIPULATIONS AND ADMISSIONS

This Settlement Agreement is entered into on the basis of the following stipulations, admissions and understandings:

A. DFI is authorized by R.C. 1322.10(A) to refuse to issue a loan originator license to an individual that has failed to fulfill the continuing education requirements of R.C. 1322.052 and to impose a fine for any violation of Chapter 1322.

B. R.C. 1322.052, requires every loan originator to complete at least eight (8) hours of approved continuing education every calendar year (by December 31st).

C. Applicant held a loan originator license during the 2014 calendar year.

D. Applicant admits that he failed to timely complete the required CE credit hours for the 2014 calendar year.

E. Because Applicant failed to timely comply with R.C. 1322.052, DFI has the authority to refuse to issue Applicant a loan originator license and impose a fine.

F. DFI enters into this Settlement Agreement in lieu of formal proceedings under R.C. 1322.10(A) and R.C. Chapter 119 to refuse to issue Applicant a loan originator license and impose a fine based upon Applicant's admitted violation of and noncompliance with the OMBA.

G. DFI expressly reserves the right to institute formal proceedings based upon any violation of or noncompliance with any provision of the OMBA not specifically addressed herein, whether occurring before or after the effective date of this Settlement Agreement.