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

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There are large income-based disparities in households' use of / outcomes with financial products. Low-income neighborhoods have:

- More unbanked households
- Reduced access to credit, higher cost of credit, and higher defaults

Financial services in low-income neighborhoods appear to be of lower quality.

- More CFPB complaints against banks and other financial institutions
- Fewer bank branches per capita, and more alternative finance providers (payday lenders, pawn shops, etc.)

Consumer Outcomes w/ Financial Products

Supply-side

Firm policies, product menus, costs, regulation, etc.

Human Capital

Finance labor market

Demand-side

- Lower overall demand for products?
- Less sophisticated use?
- Greater exposure to economic shocks?

We study the effect of workforce human capital on the quality of mortgage lending services.

- Build a novel nationwide panel of mortgage loan officers using data from the Nationwide Mortgage Licensing System (NMLS).
  - Covers over 350,000 loan officers from 2014-2019
  - Includes employer, worksite, years of experience, and misconduct information

- Link loan officers to the mortgages they originate (from CoreLogic) and subsequent foreclosures (from Zillow).

- We evaluate the quality of service that officers provide based on their ability to avoid:
  1) Misconduct cases – Examples
  2) Early defaults – mortgages that foreclose within a year
  3) CFPB complaints – available at the ZIP code level

Starting Point

Mortgage lending quality appears lower in low-income ZIP codes.

- Misconduct, early defaults, CFPB complaints

Main Findings

1) There is persistent heterogeneity in loan officers’ quality/performance.
   - Good vs. bad apples

2) Lenders put their most experienced and skilled loan officers in branches that service high-income customers.
   - Hiring, promotion, and firing practices

3) The resulting allocation of human capital contributes to disparities in the quality of financial services customers receive.

Related Literature

- Broader literature on households’ access to financial services:
  - Celerier and Matray (2019), Morse (2011)
- Studies of mortgage fraud leading up to the 2008 financial crisis:
  - Griffin and Maturana (2016 a,b), Mian and Sufi (2017)
- Recent literature on financial advisor misconduct and labor markets:
  - Egan, Matvos, and Seru (2019), Dimmock, Gerken, and Graham (2018), Dimmock, Gerken, and Van Alfen (2021).
- **Nascent literature on the <u>quality</u> (not quantity) of financial services based on income:**
  - Begley and Purnanandam (2021)

Mortgage lending quality appears worse in low-income ZIP codes.

	(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 1

- Sample: ZIP code-year panel from 2014-2019
- Outcomes are scaled by the number of mortgage originations in the ZIP-year

Loan officers affect lending quality, and there is persistent heterogeneity in their performance.

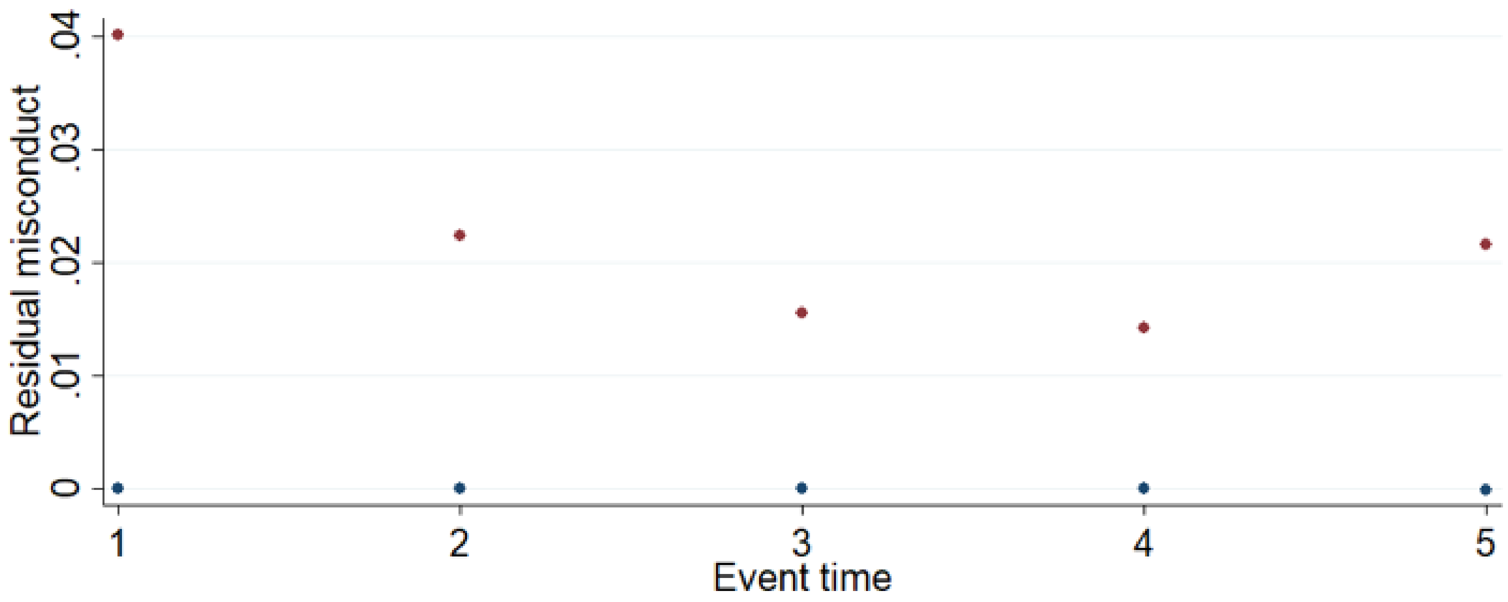
Loan officer performance is persistent.

Panel A: Persistence in loan officer performance	(1) Misconduct	(2) Early default	(3) Log(loan volume)
Prior misconduct$_{std}$	0.0094***		
	(0.0026)		
Prior early default$_{std}$		0.0002***	
		(0.0000)	
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

Table 3

- Sample: Loan officer-year panel from 2015-2019 (need 1 lag)

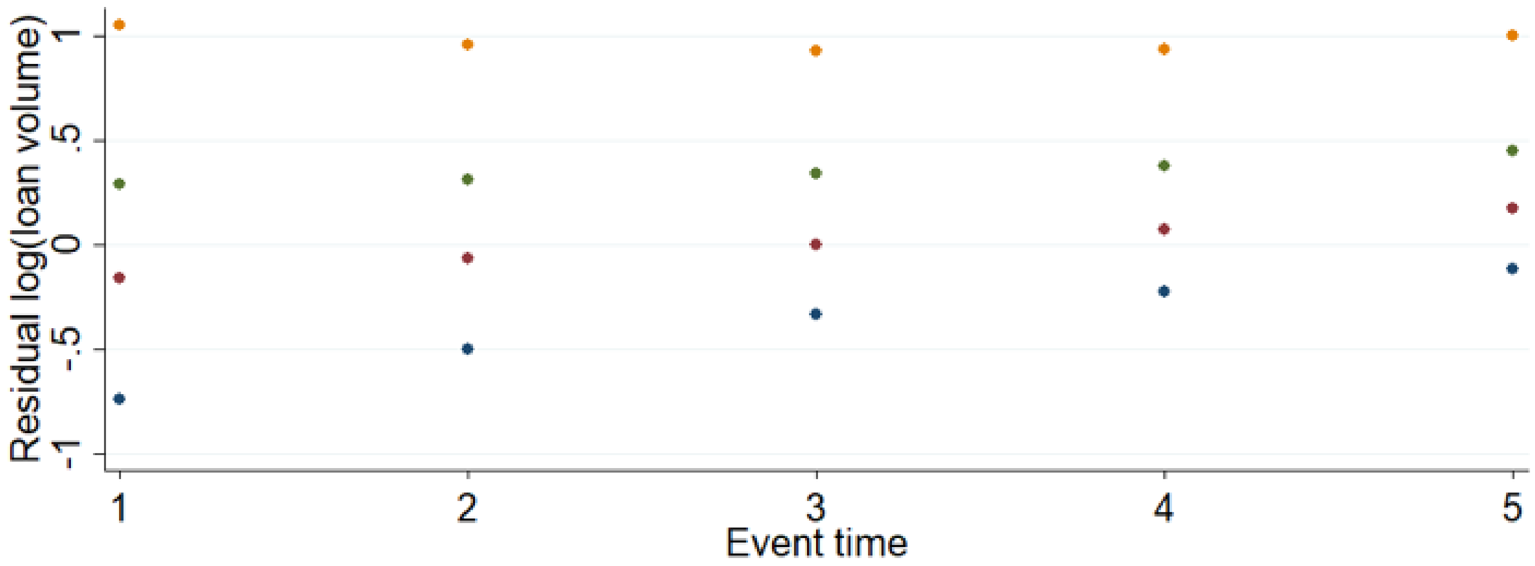
In fact, it is *very* persistent.



1) Residualize outcomes wrt branch-year

2) Sort officers into high/low portfolios at t=0

3) Track the portfolios for five years



See Early Defaults

Loan officer fixed effects have tremendous explanatory power.

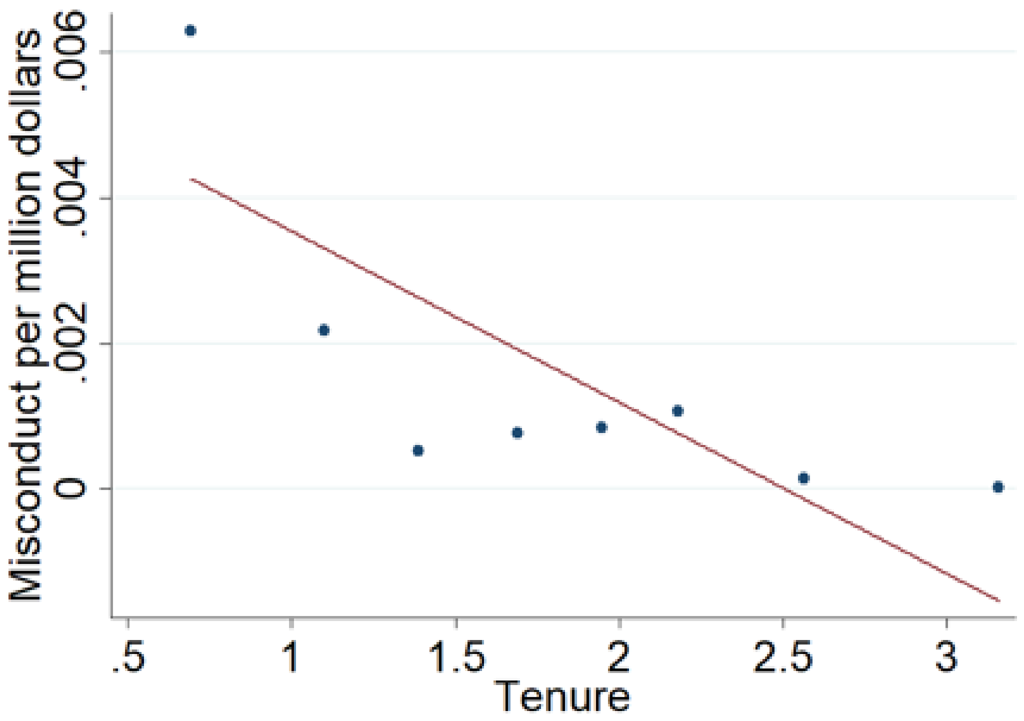
Panel B: Loan officer fixed effects

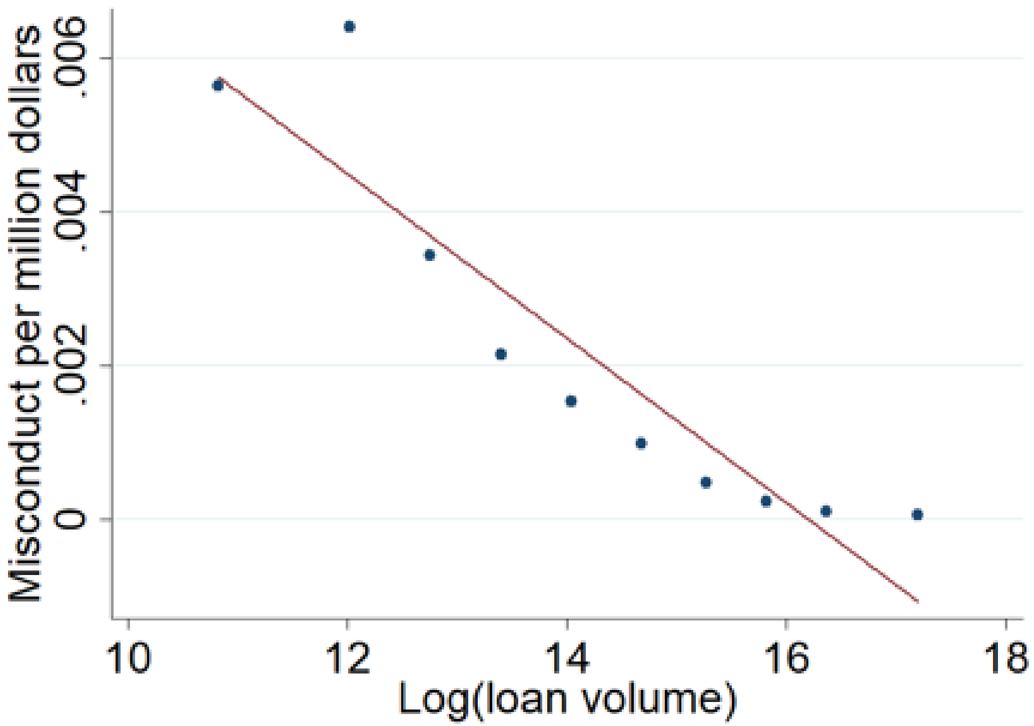
	(1)	(2)	(3)	(4)	(5)	(6)
	Misconduct		Early Default		Log(loan volume)	
Customer base controls	Y	Y	Y	Y	Y	Y
Branch x year FE	Y	Y	Y	Y	Y	Y
Loan officer FE	N	Y	N	Y	N	Y
Observations	949,071	837,377	949,071	837,377	949,071	837,377
R-squared	0.1508	0.5960	0.2278	0.5130	0.5821	0.8837
Adjusted R-squared	-0.0587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

Table 3

- Sample: Loan officer-year panel from 2014-2019

Experienced, high-volume officers deliver higher quality lending.





- The patterns look similar for *Early defaults* (here)

Next, we look at how firms allocate this human capital to high vs. low-income areas.

- Hiring
- Promotions
- Firing
- Equilibrium allocation

Firms are more likely to **hire** experienced and skilled loan officers in wealthy areas.

	(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 4

- Column 1 sample: all new hires
- Column 2-4 sample: seasoned hires

Firms **promote** their best loan officers into wealthy areas.

	(1)	(2)	(3)	(4)	(5)
			Move up within firm		
Log(tenure)	0.0011***				0.0009***
	(0.0001)				(0.0001)
Misconduct_{std}		-0.0001**			-0.0001*
		(0.0000)			(0.0000)
$\text{Early default}_{std}$			0.0000		0.0000
			(0.0001)		(0.0001)
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 5

- *Move up within firm* = Indicator for moving to firm's branch in a higher income ZIP code
- Sample: Loan officer-year panel from 2014-2019

Firms **fire** underperforming loan officers, particularly in wealthy areas.

	(1)	(2)	(3)	(4)	(5)	(6)
			Separation			
Misconduct_{std}	0.0023*	0.0007				
	(0.0013)	(0.0007)				
$\text{Misconduct}_{std} \times$ high income		0.0073***				
		(0.0013)				
$\text{Early default}_{std}$			0.0015***	0.0005		
			(0.0005)	(0.0006)		
$\text{Early default}_{std} \times$ high income				0.0017*		
				(0.0009)		
Log(loan volume)					-0.0248***	-0.0191***
					(0.0003)	(0.0004)
Log(loan volume) $\times$ 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 6

- *Separation* = indicator for not working at the firm next year
- Sample: Loan officer-year panel from 2014-2019

Underperforming officers are reemployed in lower income areas.

	(1)	(2)	(3)	(4)	(5)
	Move down to lower income area				
Log(tenure)	-0.1186***				-0.1156***
	(0.0014)				(0.0014)
Misconduct_{std}		0.0010**			0.0006
		(0.0005)			(0.0005)
$\text{Early default}_{std}$			-0.0000		-0.0003
			(0.0006)		(0.0005)
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 7

- *Move down to lower income area* = indicator for being reemployed in lower income ZIP
- Sample: Loan officers experiencing a separation from their firm (2014-2019)

New: Reemploying “bad actors” has negative peer effects

	(1) Misconduct	(2) Early default	(3) Log(loan volume)
Fraction of colleagues with prior assignment misconduct$_{std}$	0.0010**		
	(0.0004)		
Fraction of colleagues with prior assignment early default$_{std}$		0.0001***	
		(0.0000)	
Fraction of colleagues with prior assignment low loan volume$_{std}$			-0.0339***
			(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

In equilibrium, experienced and skilled loan officers end up working in high income areas.

	(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 8

- Doubling ZIP code income reduces the chances of working with an officer with no experience, prior misconduct, or prior early defaults by 15%, 19%, and 22%.
- Sample: Loan officer-year panel from 2014/15-2019

Finally, does this allocation of human capital affect the quality of financial services?

Yes, it does.

Table 10 - The impact of human capital on the quality of mortgage lending

Panel A: Quality of financial services	(1) Misconduct	(2) Early default	(3) CFPB complaints
Log(tenure)	-0.00066***	-0.00008***	-0.00045***
	(0.00019)	(0.00001)	(0.00008)
Prior misconduct$_{std}$	0.00941***	0.00002**	0.00001***
	(0.00265)	(0.00001)	(0.00000)
Prior early default$_{std}$	-0.00003	0.00011***	0.00012***
	(0.00010)	(0.00002)	(0.00003)
Lag log(loan volume)	0.00019**	-0.00004***	-0.00030***
	(0.00007)	(0.00001)	(0.00005)
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	0.2671	0.0120	0.0996
Dep. var. mean	0.0021	0.0018	0.0016

- Samples: Col 1; Loan-officer year panel, Col 2; Loan-level data, Col 3; ZIP-year panel

Three Takeaways:

1) The human capital component of financial services is critical.
   - Performance varies quite dramatically across loan officers.

2) Financial institutions put their most experienced and skilled workers in branches that service high-income customers.

3) This allocation of human capital is an important supply-side factor contributing to income-based disparities in financial services.

Thank You!

Additional Material

Examples of loan officer misconduct:

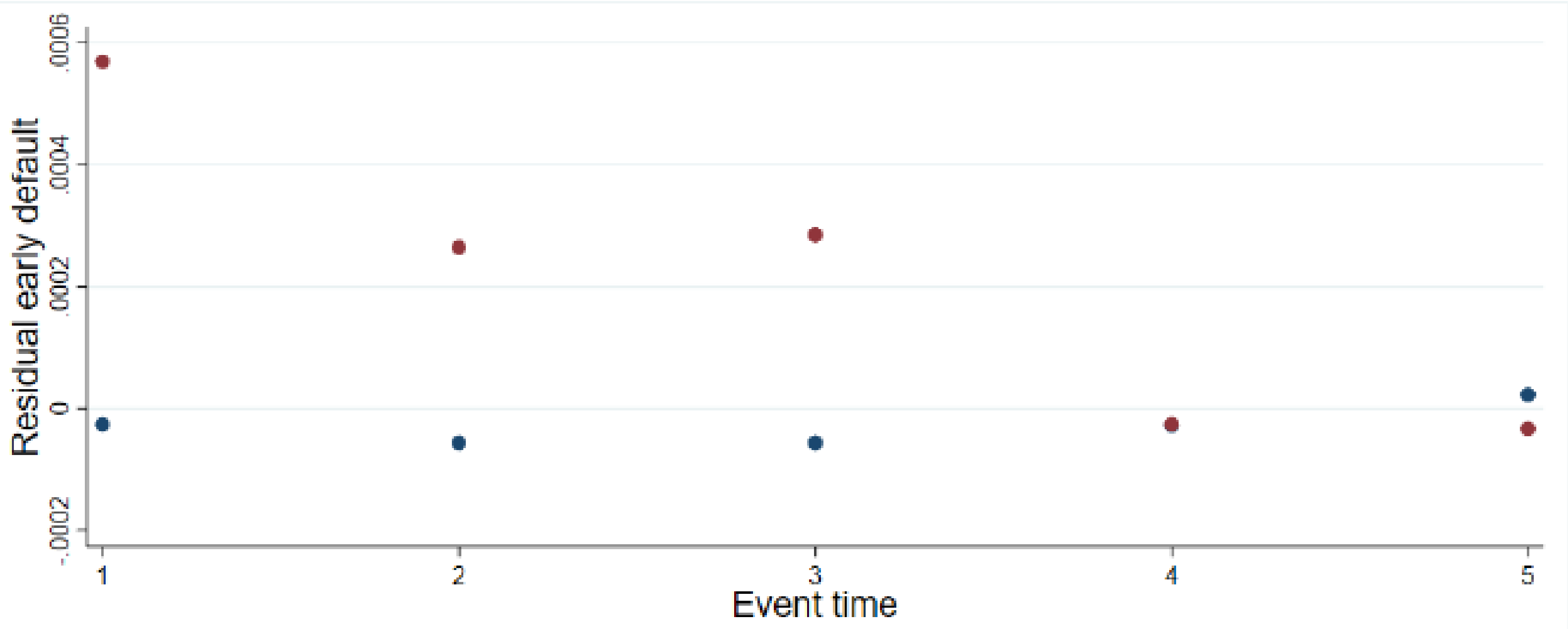
- Originating loans without a proper/current license
  - Failure to renew a license
  - Failure to complete mandatory training/continuing education
- Forging customers’ or managers’ signature on documents
- Customer lawsuits

(go back)

Summary Statistics

	(1) N	(2) Mean	(3) SD	(4) P25	(5) P50	(6) P75
Loan officer-year panel						
Misconduct	1,110,423	0.0021	0.1637	0	0	0
Early default	1,110,423	0.0020	0.0204	0	0	0
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
Log(income)	1,110,423	10.4666	0.3975	10.1866	10.4530	10.7249
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 low income area (conditional on separation)	203,322	0.0695	0.2543	0	0	0
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
Log(tenure)	1,110,423	1.6112	0.7649	1.0986	1.3863	2.0794
High income	1,110,423	0.5232	0.4995	0	1	1
Customer base controls (average at customer-ZIP level)						
Income	1,110,423	10.3878	0.2630	10.2154	10.3746	10.5459
Education	1,110,423	33.4533	12.2978	24.9000	32.1464	40.6750
Minority share	1,110,423	31.5472	19.0048	17.0250	29.0000	41.9125
Unemployment rate	1,110,423	6.3922	2.4015	4.7941	6.0000	7.5800
Population density	1,110,423	6.7817	1.3389	6.0609	6.9734	7.6839

Persistence in Early Defaults (Portfolio Approach)



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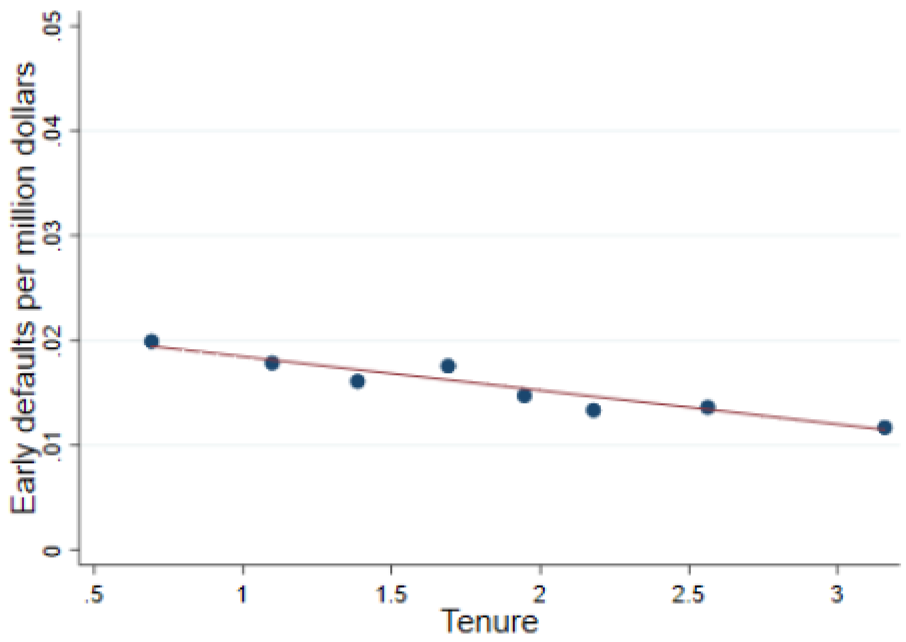
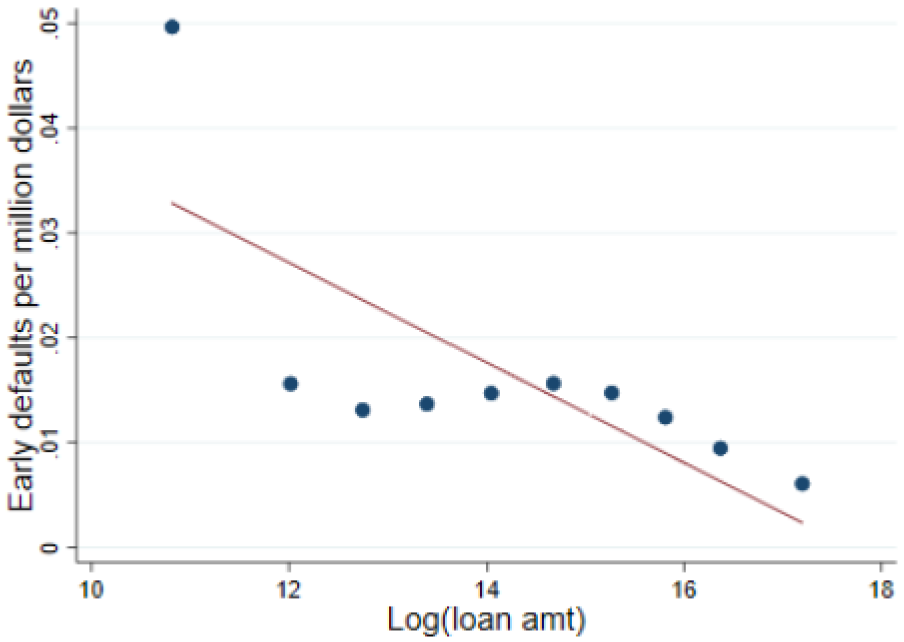
Experience, Volume, and Early Defaults





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Variable Definitions

Variables	Definition
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
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)*
Rookie	Equals one if it is the loan officer's first year in the industry, zero otherwise
Log(income)	Natural logarithm of per capita income at the ZIP code level
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
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
Separation	Equals one if the loan officer leaves the company in the next year and 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
Log(tenure)	Natural logarithm of the number of years with the current firm
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
CFPB complaints	Number of CFPB complaints in the ZIP code against mortgage lenders, scaled by total number of originated mortgages that year
Customer-ZIP income	Natural logarithm of average customer ZIP code level per capita income from ACS.
Education	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.
Population density	Natural logarithm of average customer ZIP code level population per square mile from ACS.

Are these income-based disparities due to **Supply** or **Demand**?

- Demand-side factors:
  - Low income households may have greater exposure to negative economic shocks
  - Lower demand for financial services
  - Less sophisticated use of the same product offerings

- Supply-side factors:
  - Predatory lending
  - Taste-based or statistical discrimination
  - Incentives due to regulation
  - **Differences in workforce human capital (and how workers are deployed)**

Financial services in low-income neighborhoods <u>appear</u> to be of lower quality.

Low-income neighborhoods have:

- Fewer bank branches per capita
- More unbanked households
- Reduced access to credit, higher cost of credit, and higher defaults
- More CFPB complaints against banks and other financial institutions
- More non-bank alternative finance providers (payday lenders, pawn shops, etc.)