

Credit Without Proximity: Informational Frictions and Unequal Gains from Technology

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*Views expressed are those of the authors and do not necessarily reflect those of the Federal Reserve Bank of Richmond or the Federal Reserve System.

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- Informational frictions can distort credit allocation
- Intermediaries create value by mitigating these frictions:
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Historically, local presence enabled screening of borrowers, through “soft information”, e.g. relationships. **But:** Technology has enabled remote processing of loans. Can technology replicate the informational precision historically enjoyed by local underwriters?

Setting: U.S. residential mortgage lending

We observe all the key objects needed to study *the labor component of information production*

- every loan officer employed by each lender in the US
- who — which loan officer — screens each application
- saturated set of hard borrower information
- approval decisions and processing time
- ex post loan performance

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 - Two types of productivity: informational & physical (processing speed)
 - Lenders choose screening technology to maximize their profits. But, main cost of poor screening is *credit rationing*, which is borne by borrowers.

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 - Lenders choose screening technology to maximize their profits. But, main cost of poor screening is *credit rationing*, which is borne by borrowers.
- **Quantitative:** The model quantifies results of informational inefficiency:
 1. Technological shocks that *increase* remote processing efficiency:
 - Induce substitution away from high precision, local screening
 - *Reduce* credit access, particularly for lower income/ credit score applicants.

Reduced-Form Facts

Fact 1: Local Loan Officers' Superior Screening Performance

Regress application outcomes on loan officers' locality (same US county):

	Rejection		Default		Interest Rate	
	Home Purchase	Refinance	Home Purchase	Refinance	Home Purchase	Refinance
Local Officer	-0.643*** (0.05)	-2.855*** (0.15)	-0.463*** (0.06)	0.037 (0.08)	0.010*** (0.00)	0.037*** (0.00)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	3.7M	1.9M	2.1M	0.8M	3.4M	1.4M
R^2	0.279	0.456	0.124	0.110	0.661	0.655

► More Specifications

► Additional Heterogeneity

Fact 1: Local Loan Officers Process Loans no Slower

Processing Time Advantages

	Processing Time (Days)	
	Home Purchase	Refinance
Local Officer	-0.176 (0.15)	-1.652*** (0.13)
Controls	Yes	Yes
County-Month FE	Yes	Yes
Lender-Month FE	Yes	Yes
N	3.4M	1.4M
R ²	0.299	0.280

- Local officers process loans no slower, perhaps slightly faster

Fact 2: Lender labor choices respond to local wage differentials

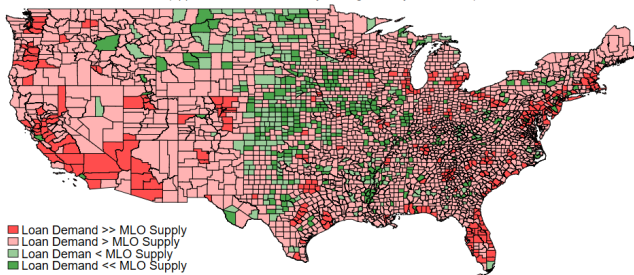
	Local Assignment		Misalignment Index		
	(1)	(2)	(3)	(4)	(5)
Finance-Sector Hourly Wage (std.)	-0.0388*** (0.010)	-0.0197** (0.009)	1.589*** (0.21)	1.814*** (0.25)	2.326*** (0.27)
Borrower / Loan Controls	Yes	Yes			
Year FE	Yes		Yes		
State $\times$ Year FE		Yes			
Lender $\times$ Year FE		Yes		Yes	Yes
MSA Controls					Yes
N	4,970,686	4,970,611	187,671	186,631	185,709
R ²	0.0263	0.1573	0.002	0.049	0.050

- Higher local wages strongly associated with greater misalignment across all specifications
- Lenders systematically avoid high-wage areas, creating supply gaps where labor is expensive

Fact 2: Spatial Misallocation of Underwriting Labor

$$\text{Misalignment}_i = \left(\frac{\text{Applications}_i}{\sum_i \text{Applications}_i} \right) - \left(\frac{\text{Loan Officers}_i}{\sum_i \text{Loan Officers}_i} \right)$$

Distribution of Loan Demand-MLO Supply Misalignment
(application count, scaled by average county MLO share)



- Systematic geographic mismatch with many high-demand counties (red) having insufficient local underwriting capacity relative to application volume

Interpreting the Local Advantage

- Local loan officers achieve lower rejection & default, higher interest rates.
 - How do local loan officers achieve a superior approved pool?
- In the paper: simple model implies either:
 1. Superior information production
 2. Sorting of good borrowers to local loan officers

note: Both are important to the lender, but have different implications for industry equilibrium.

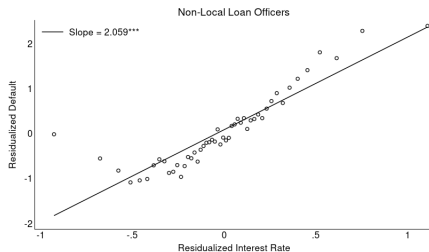
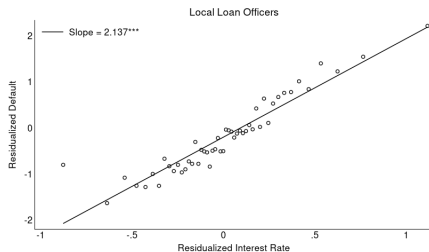
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- First: additional empirics in the paper:
 - Local loan officers use more soft information
 - Local advantage largest in riskiest segments
 - Additional test using wages to shift prevalence of local loan officers.
- Second, an additional implication from the theory: screening information advantages should show up in rejection decisions, but not prices.

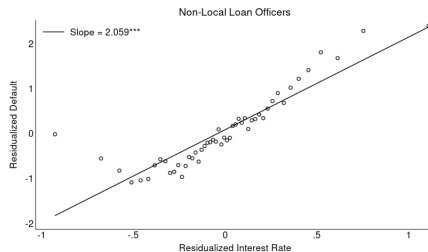
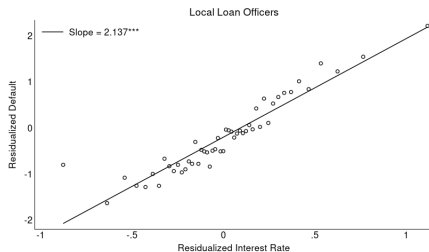
Local Advantage Does not Appear in Prices

Residualized correlation between price and default: "How much unobserved heterogeneity is reflected in prices?"



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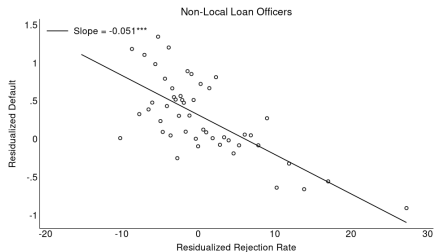
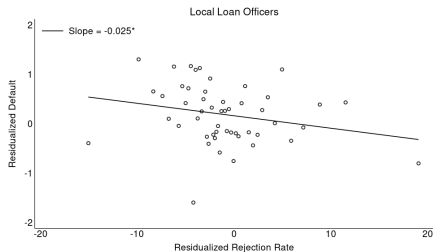
Residualized correlation between price and default: "How much unobserved heterogeneity is reflected in prices?"



- Local information advantage not reflected in loan pricing. Why?
 - Lenders post rate sheets and loan officers quote rates: before screening
 - Limited ability to reprice after screening (regulatory constraints)
 - Lenders cannot easily adjust rates to reflect risk discovered later
 - rely on approval/rejection decisions to manage borrower risk

Local Advantage Appears in Rejections

Local screening → Fewer additional defaults per additional approval.



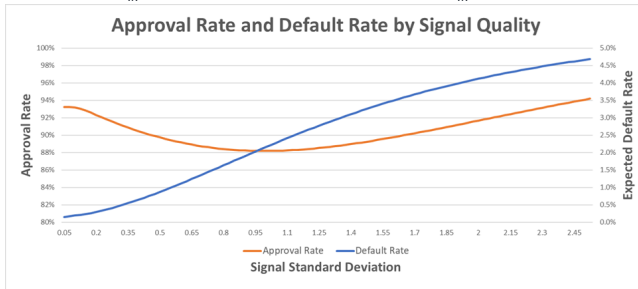
Model Sketch

Timing within a market (credit quality $\times$ product type $\times$ county $\times$ year-quarter)

1. **Pricing & hiring:** Lenders post wages for loan officers, rates for borrowers.
2. **Application:** Borrowers observe rates and apply to a lender based on prices and lender characteristics.
3. **Labor market clearing:** Loan officers choose which bank to work for, given wages and their personal tastes.
4. **Screening:** Lenders assign applicants to loan officers, who provide (noisy) signals of their riskiness
5. **Origination:** Lenders approve if expected default losses are less than or equal to their posted net interest margin..

Identification Intuition: Information Parameter

- Limiting cases of the model:
 - **Perfect screening:** zero default in equilibrium.
 - **Perfectly uninformative screening.** Either:
 - Zero rejection in equilibrium, or
 - Market breakdown
- In between: bank's chosen tradeoff between Type I and Type II errors pins down the ratio of $\frac{dp_{ijk}}{d\sigma_{ik}}$ (*rejection advantage*) to $\frac{dd_{ijk}}{d\sigma_{ik}}$ (*default advantage*):



Model Results and Counterfactual

The perfect information benchmark

The model gives us a “perfect information” benchmark

- Gives us a measure of “credit rationing” and “excess origination”:

In the baseline, substantial credit rationing, moderate excess origination.

Market	Risk Tier	Rationing	Excess Orig:
Refi	Subprime	15.3	2.4
	Near-Prime	8.4	2.0
	Prime	3.6	0.5
Purchase	Subprime	10.3	10.6
	Near-Prime	5.6	4.3
	Prime	2.3	0.8

Baseline: Local vs Remote Screening

Local officers mitigate credit rationing by ~50%

Credit Rationing and Pooled Origination by Officer Type					
Market	Tier	Rationing		Excess Orig.	
		Local	Remote	Local	Remote
Refi	Subprime	8.7	17.8	2.0	2.5
	Near-Prime	5.0	9.9	1.6	2.2
	Prime	1.9	4.4	0.4	0.6
Purchase	Subprime	10.1	10.4	8.6	12.2
	Near-Prime	5.1	6.0	3.2	5.1
	Prime	1.5	2.8	0.6	0.9

Technology Shock: Impact on Lending Outcomes

Shock: 20% increase in remote officer efficiency → 20% lower unit cost for processing loans with a remote officer

2 shock versions

- Version 1: shock only traditional "brick and mortar" lenders.
- Version 2: shock all lenders, including "fintechs"

Change in Rationing and Pooled Origination (pp)			
	Reject	Rationing	Excess Orig
Shock 1: Only Brick & Mortar			
Refi Subprime	+0.32	+0.34	+0.02
Purchase Subprime	-0.16	+0.44	+0.60
Shock 2: All lenders			
Refi Subprime	+1.13	+1.13	-0.01
Purchase Subprime	+1.29	+2.02	+0.73

Key Outcomes:

- Expected defaults rise—largest in subprime purchase.
- Modest rate reductions reduce typical monthly payment by <\$25.
- Shocking only brick-and-mortar gives the worst tradeoff: smaller payment savings relative to default increase.

Changes in Expected Default Rates and Monthly Payments

	Default (pp)		Payment (\$)	
	S1	S2	S1	S2
Refi Subprime	+0.06	+0.03	-3.07	-16.55
Purchase Subprime	+0.25	+0.28	-4.74	-23.23
Near-Prime Purchase	+0.07	+0.13	-3.10	-16.43

Conclusion

Conclusion: Key Takeaways

- **Informational frictions are first-order** in mortgage markets, with substantial credit rationing (up to 15% in subprime segments)
- **Local underwriting matters:** local officers eliminate 50% of rationing through superior screening precision
- **Technology creates tradeoffs:** remote efficiency gains improve cost savings but degrade information quality
- **General Lesson:** In markets with ex-ante imperfections, like informational frictions, technical efficiency gains can endogenously amplify pre-existing inefficiencies, leading to negative welfare effects.

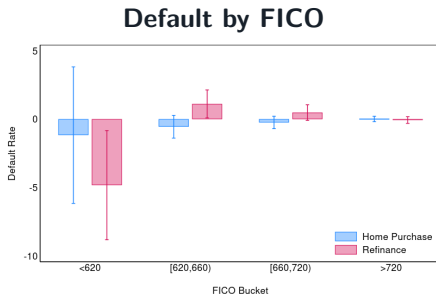
Additional Results

Additional Specifications

	Rejection		Default		Interest Rate	
	Home Purchase	Refinance	Home Purchase	Refinance	Home Purchase	Refinance
Local Officer	-0.202*** (0.03)	-0.655*** (0.10)	-0.344*** (0.05)	0.000 (0.08)	-0.002* (0.00)	0.009*** (0.00)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
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Loan Officer FE	Yes	Yes	Yes	Yes	Yes	Yes
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► Back

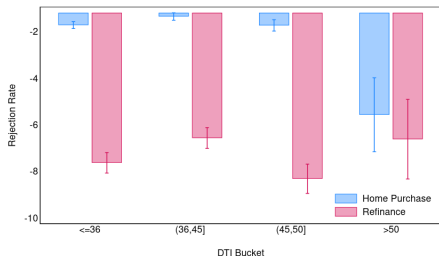
Fact 1d: High-Credit-Risk Borrowers Benefit More



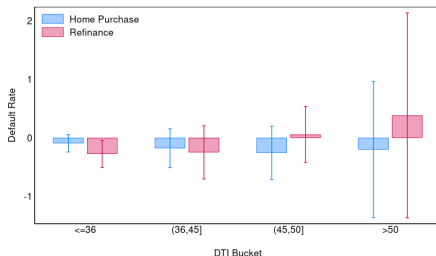
- Local officers consistently reject fewer applications across all FICO buckets
- Largest gaps in subprime ranges (FICO $\leq$ 620)
- No evidence of a performance penalty - similar or better default outcomes despite higher approval rates

Fact 1d: High-Credit-Risk Borrowers Benefit More

Rejection by DTI



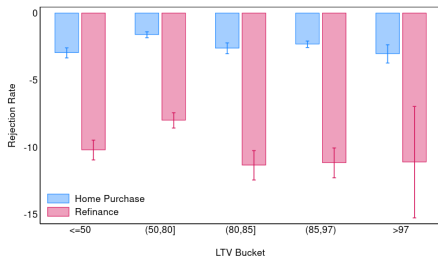
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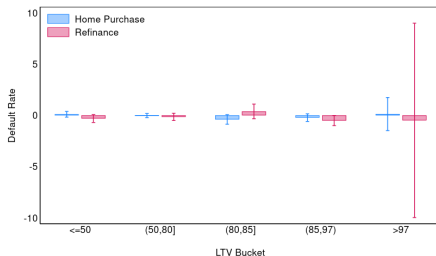
- Local officers particularly lenient for high-DTI home-purchase borrowers (50%)
- Similar loan performance despite approving more marginal-looking borrowers
- Unobserved heterogeneity is evenly distributed across DTI buckets in refinance

Fact 1d: High-Credit-Risk Borrowers Benefit More

Rejection by LTV



Default by LTV



- Unobserved heterogeneity is evenly distributed across LTV buckets

Theory Appendix

Setup: Borrower Demand

Borrower η in market i has default type x_η price sensitivity θ_η . chooses a lender j to maximize indirect utility:

$$u_{ij\eta} = -\theta_\eta r_{ij} + \xi_{ij} + \epsilon_{ij\eta},$$

- r_{ij} : posted interest rate.
- θ_η : borrower-specific price sensitivity.
- ξ_{ij} : lender–market demand shifter (incl. branch/local-preference term ζ_{ij}).
- $\epsilon_{ij\eta}$: i.i.d. Type I extreme value shock.

Implies Standard mixed logit market share (à la Berry et al. 1995):

$$s_{ij}(r_{ij}) = \int \frac{\exp\{-\theta r_{ij} + \xi_{ij}\}}{\sum_j \exp\{-\theta r_{ij} + \xi_{ij}\}} F_i^\theta(d\theta),$$

where F_i^θ is the distribution of θ in market i .

Higher r_{ij} leads to lower price sensitivity applicants. $\text{corr}(\theta, x) < 0 \rightarrow$ adverse selection.

Adverse Selection - Details

It is helpful to denote the θ -specific market share:

$$s_{ij}(\theta, r_{ij}) = \frac{-\theta r_{ij} + \xi_{ij}}{\sum_j -\theta r_{ij} + \xi_{ij}}$$

Given posted rate r_{ij} , selected distribution of rates follows:

$$F_{ij}^\theta(t; r_{ij}) = (s_{ij}(r_{ij}))^{-1} \int_{-\infty}^t s_{ij}(\theta, r_{ij}) F_i^\theta(d\theta).$$

The distribution of default types follows:

$$F_{ij}^x(t; r_{ij}) = (s_{ij}(r_{ij}))^{-1} \int_{-\infty}^t \int_{-\infty}^{\infty} s_{ij}(\theta, r_{ij}) F_i^{x,\theta}(dx, d\theta)$$

In the special case where $x \perp\!\!\!\perp \theta$, the joint distribution is multiplicatively separable, and the integral immediately collapses to $F_i^x(t)$. [► Back](#)

Labor Cost - Details

Mass $\bar{L}$ of potential loan officers indexed by λ picks between working as a mortgage originator, or for one of $N_{i,oo}$ outside options in location i that pay an average (amenity) wage of $w_{i,oo}$. The CDF of A_{ij} is given by:

$$\mathbb{P} \left(\bigcap_{\forall i,j,k} \{a_{ijk} \leq t_{ijk}\} \right) = \exp \left\{ - \sum_k \left[\left(\sum_{i,j} t_{ijk}^{\frac{\epsilon}{(1-\rho)(1-\phi)}} \right)^{1-\rho} - N_{k,oo} t_{k,oo}^{\frac{\epsilon}{1-\phi}} \right]^{1-\phi} \right\}$$

with composite parameter $\varrho := \frac{\epsilon}{(1-\rho)(1-\phi)}$.

Labor Cost - Details

Implied cost function to process $\tilde{l}_{ijk}$ loans with loan officer of type k :

$$C_{ijk}(\tilde{l}_{ijk}) = \underbrace{\bar{L}\Psi_k e_{ijk}^{-1}}_{A_{ijk}^{-1}} \tilde{l}_{ijk}^{1+\varrho^{-1}}$$

where the local wage index Ψ_k follows:

$$\Psi_k := \left\{ \left(\sum_{i,j} w_{ijk}^{\frac{\epsilon}{(1-\rho)(1-\phi)}} \right)^\rho \left[\left(\sum_{i,j} w_{ijk}^{\frac{\epsilon}{(1-\rho)(1-\phi)}} \right)^{1-\rho} + (N_{k,oo} w_{k,oo})^{\frac{\epsilon}{1-\phi}} \right]^\phi \times \right. \\ \left. \left(\sum_k \left[\left(\sum_{i,j} w_{ijk}^{\frac{\epsilon}{(1-\rho)(1-\phi)}} \right)^{1-\rho} + (N_{k,oo} w_{k,oo})^{\frac{\epsilon}{1-\phi}} \right]^{1-\phi} \right) \right\}^{\frac{1}{\varrho}}$$

Note: for simplicity, we work with the case where loan officers are an atomistic share of the labor market, i.e. $\bar{L}, N_{i,oo} \rightarrow \infty$

Solution to Lender's Problem: Full Pricing

With heterogeneous screening efficiency, r_{ij} solves:

$$\sum_{k=1}^K \mathcal{S}_{ijk} p_{ijk} \left[r_{ij} (1 + \varepsilon_{p_{ijk},r} + \varepsilon_{s_{ij},r}) - f_{ij} (\varepsilon_{p_{ijk},r} + \varepsilon_{s_{ij},r}) - d_{ijk} (\varepsilon_{p_{ijk},r} + \varepsilon_{s_{ij},r} + \varepsilon_{d_{ijk},r}) - \varepsilon_{s_{ij},r} \bar{c}_{ij} (r_{ij} - f_{ij} - d_{ijk}) \right] = 0.$$

with:

$$\bar{c}_{ij} = \left(\frac{\mathcal{M}_i s_{ij}}{\sum_{k=1}^K \mathcal{A}_{ijk}^e} \right)^{1/\varrho} \quad \mathcal{S}_{ijk} \propto \mathcal{A}_{ijk}^e \quad \mathcal{A}_{ijk} = \underbrace{A_{ijk}}_{\text{Processing Efficiency}} \underbrace{p_{ijk}(r_{ij} - f_{ij} - d_{ijk})}_{\text{Info Efficiency}}$$

Note that: $A_{ijk} \propto \frac{\Psi_i}{e_{ijk}^{1+\varrho-1}}$, where Ψ_i is the local wage index.

Calibration Details - Parameterization and External

Parameterization to take model to the data:

- Borrower types $\begin{matrix} \theta_\eta \\ x_\eta \end{matrix} \sim \mathcal{N} \left(\begin{matrix} \mu_\theta & \sigma_\theta^2 & \gamma\sigma_\theta\sigma_i^x \\ \mu_i^x, \gamma\sigma_\theta\sigma_i^x & (\sigma_i^x)^2 \end{matrix} \right).$
- $d_i = \mathbf{1}_{\{x_\eta + \epsilon_\eta + \epsilon_{i,t} \geq 0\}}$, for iid standard normal idiosyncratic shock ϵ_η and aggregate shock ϵ_t .
- Set $\mu_\theta = 165$; $\sigma_\theta \approx 41$ (Buchak et al. 2018)
- Set $\varrho = 8$ (Giroud et. al 2024)
- Set $f_{ij} = 2.75\%$ (Janus Henderson Investors 2019)
- Set $lgd = 17.7\%$, calculated using Fannie Mae data

Calibration Details - Internal

Internally calibrated parameters:

- Calibrate to match average market, stats in the paper
- Revenue efficiency parameters (A) and demand shifters (ξ) recovered using standard techniques
- Jointly set:
 - Signal precisions σ_k ; Default-price correlation γ ; Borrower default type distributions μ_i^x, σ_x^i ; Aggregate shocks $\epsilon_{i,t}$to match expected default rates, realized default rates, approval rates, rejection/default local advantages, and the correlation between rates and default. Model is just identified, fit is exact.
- **Untargetted moments:** Model correctly predicts higher rejection advantage for refi; higher default advantage for purchase; higher rejection/default advantage for subprime.

Calibration Details - Internal Parameter Values

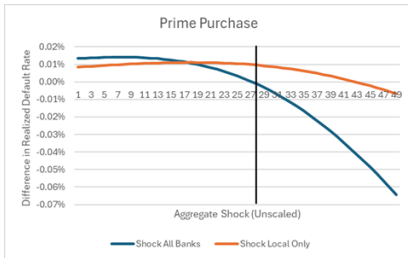
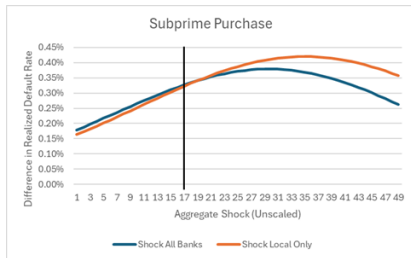
Internally calibrated parameters:

- $\gamma = -.4$ implies adverse selection
- $\sigma_{\text{local}} = 1.45$; $\sigma_{\text{distant}} = 2.45$ implies significant local information advantage.
- Other Parameters:

Market	Risk tier	Baseline risk measures		
		Default rate	Dispersion	Aggregate shock
Refi	Subprime	31.6%	4.41	-0.99
	Near-Prime	12.9%	5.16	-1.98
	Prime	8.0%	9.19	-2.95
Purchase	Subprime	7.9%	1.21	0.12
	Near-Prime	3.9%	1.92	-0.68
	Prime	2.1%	4.75	-2.30

Technology Shock and Aggregate Risk

Realized default rates rise under moderate aggregate stress;
local information advantage persists even under GFC-sized shocks.



*technology-driven increase in realized defaults across aggregate states