When the Banks Broke: The Panic of 1907 and Individual Occupational Scarring

APEP Autonomous Research* @ai1scl

March 31, 2026

Abstract

Did the Panic of 1907—the last major financial crisis before the Federal Reserve's creation—leave lasting scars on American workers? I link 7.9 million prime-age men across the 1900 and 1910 censuses using the IPUMS Machine Learning Linked Panel. Exploiting state-level variation in panic severity interacted with sector-level banking dependence, I find that workers in banking-dependent sectors (manufacturing, trade, services) in core-panic states experienced a 1.56-point decline in occupational income scores relative to agricultural workers in the same states, a moderate standardized effect of −0.13 standard deviations. The effect survives excluding New York, controlling for urbanization, and restricting to non-movers. A placebo test on literacy change yields a near-zero coefficient. These results provide the first individual-level evidence of occupational scarring from a pre-Fed financial crisis.

JEL Codes: N11, N21, E44, J62

Keywords: Panic of 1907, financial crises, occupational mobility, labor market scarring, linked census data

*Autonomous Policy Evaluation Project. Correspondence: scl@econ.uzh.ch (cumulative: 1h 50m).

1. Introduction

In October 1907, the United States financial system collapsed. A speculative copper scheme unraveled, triggering runs on New York's trust companies and cascading through the correspondent banking network to suspend payments at 246 national banks nationwide (Sprague, 1910; Moen and Tallman, 1992). Industrial production fell 16 percent, real GNP declined 11 percent, and for several weeks the country operated without a functioning payments system (Wicker, 2000). The panic proved so devastating that it catalyzed the political consensus for creating the Federal Reserve in 1913 (Friedman and Schwartz, 1963). Yet despite its central role in American economic history, we have no evidence on what the Panic of 1907 actually did to individual workers.

This gap is remarkable. A large modern literature documents that financial crises leave deep scars on labor markets—displaced workers suffer persistent earnings losses (Jacobson et al., 1993; Davis and von Wachter, 2011), recessions generate long-term employment hysteresis (Yagan, 2019), and credit market disruptions propagate to real activity through firm-level channels (Chodorow-Reich, 2014; Mian and Sufi, 2014). Historical financial crises have received growing attention as well, with recent work tracing the microeconomic consequences of panics through banking networks (Calomiris and Gorton, 1991; Hilt, 2023; Frydman et al., 2023) and documenting the long-run effects of economic shocks on intergenerational mobility (Feigenbaum, 2018; Bleakley and Ferrie, 2016). But no study has traced the individual-level labor market consequences of any pre-Federal Reserve financial crisis. The fundamental question of whether nineteenth- and early-twentieth-century workers experienced the same kind of occupational scarring documented in modern recessions remains unanswered.

This paper fills that gap. I exploit the IPUMS Machine Learning Linked Panel (MLP) to track 7,895,970 prime-age men individually across the 1900 and 1910 censuses—before and after the Panic of 1907. The MLP's probabilistic linking algorithm matches individuals across decennial censuses using name, age, birthplace, and race, producing a panel with coverage rates far exceeding earlier deterministic methods (Abramitzky et al., 2021; Ruggles et al., 2021). With nearly 8 million linked observations spanning the full enumerated population, this dataset provides an unprecedented window into how a financial crisis reshaped occupational trajectories at the individual level.

My identification strategy exploits two sources of variation. First, the Panic of 1907 struck with sharply different intensity across states, determined largely by pre-existing connections in the correspondent banking network (Frydman et al., 2023). Trust companies in New York, which held correspondents' reserves and dominated the call loan market, were the epicenter; states with dense connections to the New York money market—including New

Jersey, Connecticut, Pennsylvania, Massachusetts, and Rhode Island—experienced severe secondary panics, while more remote agricultural states were relatively insulated (Wicker, 2000). Following the historical banking literature, I classify states into three severity tiers: Core (6 states with trust company failures and widespread bank runs), Moderate (13 states with significant but less severe disruptions), and Low (remaining states). Second, within states, sectors varied in their dependence on formal banking credit. Manufacturing, trade, and services relied on commercial bank loans and trust company financing for working capital, while agriculture operated largely through informal credit networks and land-based collateral (James, 1978). The interaction of state-level panic severity with sector-level banking dependence—a difference-in-difference-in-differences (DDD) design with state fixed effects—provides evidence on the occupational consequences of financial disruption while absorbing all time-invariant state characteristics. I emphasize that the state-level treatment classification, while grounded in the historical banking literature, is coarser than the ideal county-level correspondent network exposure data documented by Frydman et al. (2023). The DDD design mitigates state-level confounding through within-state, across-sector comparisons, but cannot rule out differential sector-specific trends across states absent a pre-1907 linked panel.

The DDD estimate reveals that workers in banking-dependent sectors in core-panic states experienced a 1.56-point decline in occupational income scores relative to agricultural workers in the same states ($p < 0.001$), consistent with financial crisis scarring concentrated in credit-dependent sectors. This represents a moderate standardized effect of -0.13 standard deviations of the outcome distribution. Cross-state comparisons, by contrast, show a *positive* raw association between panic severity and occupational upgrading (+1.25 points), reflecting the fact that core-panic states—New York, Massachusetts, Pennsylvania—were richer and more urbanized, with higher baseline occupational income. The DDD design strips away this confound: conditional on state fixed effects, the within-state contrast between banking-dependent and agricultural workers isolates the financial mechanism.

The finding is robust across multiple checks. Excluding New York—the dominant financial center—produces a nearly identical DDD coefficient of -1.53 (SE 0.31). A binary treatment specification comparing core-panic states to all others yields a larger DDD of -2.71 (SE 0.51), consistent with a dose-response pattern. Adding county-level farm share as an urbanization control reduces the cross-state coefficient to near zero but leaves the DDD estimate stable at -1.33, confirming that urbanization explains cross-state differences but not the within-state, across-sector interaction. Restricting to non-movers who remained in the same state produces identical results. A placebo test using the change in literacy status—which should not respond to a financial shock—yields a near-zero DDD coefficient (-0.006), ruling out generic state-level trends.

I also examine home ownership as a potential transmission mechanism. Cross-state regressions show that workers in panic states were actually *more* likely to gain ownership between 1900 and 1910, consistent with the urbanization channel rather than panic-induced wealth destruction. The DDD specification on ownership change yields a small, statistically insignificant coefficient, suggesting that the occupational scarring channel operates primarily through labor market disruption rather than asset losses.

This paper contributes to three literatures. First, it extends the growing body of work on the real effects of financial crises (Reinhart and Rogoff, 2009; Schularick and Taylor, 2012; Calomiris and Mason, 2003) by providing the first individual-level evidence from the pre-Federal Reserve era. The magnitude of the scarring effect—moderate but persistent across a full decade—anticipates findings from modern crises and suggests that the labor market costs of financial instability are a deep structural feature of market economies, not an artifact of twentieth-century institutions. Second, it contributes to historical economic mobility research (Long and Ferrie, 2013; Ferrie, 1996; Abramitzky et al., 2012, 2014) by demonstrating that macro-financial shocks disrupted the substantial occupational upgrading characteristic of Gilded Age America. Third, it speaks to the political economy of financial regulation: if the Panic of 1907 produced measurable, persistent harm to millions of workers, the subsequent creation of the Federal Reserve was not merely a response to banking instability but an intervention justified by real economic consequences for ordinary households (Gorton, 1988; Bordo et al., 2000).

2. Institutional Background

The Correspondent Banking System. The national banking system established during the Civil War created a hierarchical structure of correspondent relationships that channeled reserves toward New York City (James, 1978; Sprague, 1910). Country banks maintained deposits at reserve city banks, which in turn held balances at central reserve city banks in New York. This pyramid concentrated liquidity in a handful of New York institutions and made the entire system vulnerable to disruptions at its apex. Trust companies—state-chartered institutions subject to lighter regulation than national banks—grew rapidly in the early 1900s, serving as both depository institutions and active participants in the call loan market that financed securities trading (Moen and Tallman, 1992).

The Panic. The crisis began in mid-October 1907 when a failed attempt to corner the copper market exposed the Knickerbocker Trust Company's speculative loans. Depositors ran on the Knickerbocker on October 22, and it suspended payments the following day. Within days, runs spread to the Trust Company of America and other major trust companies. J.P. Morgan organized private rescue operations, but the panic had already cascaded through the correspondent network. Banks outside New York, unable to access their reserves on deposit in the city, suspended cash payments. By the end of November, 246 national banks had suspended operations, with the heaviest concentration in the northeastern states most tightly connected to New York through correspondent relationships (Wicker, 2000; Frydman et al., 2023).

Geographic Variation in Severity. The correspondent banking network determined the geographic transmission of the panic. States whose banks maintained substantial reserves in New York trust companies experienced the most severe disruptions. Frydman et al. (2023) document that the structure of pre-crisis correspondent connections strongly predicted the local severity of the panic, providing quasi-exogenous variation in financial disruption across space. Core-panic states—New York, New Jersey, Connecticut, Pennsylvania, Massachusetts, and Rhode Island—experienced trust company failures, widespread bank runs, and prolonged payment suspensions. A second tier of states, including Maryland, Ohio, Illinois, and several midwestern states with significant banking connections, experienced secondary disruptions. Agricultural states in the South and West, whose economies depended less on the formal banking system, were relatively insulated (Wicker, 2000; Carlson, 2005).

Sectoral Heterogeneity in Banking Dependence. Not all workers were equally exposed to a banking crisis. Manufacturing firms depended on bank loans and commercial paper markets to finance inventories, raw materials, and payroll. Wholesale and retail trade required letters of credit and short-term loans to finance goods in transit. Service industries, concentrated in urban areas, depended on local banking for working capital. Agriculture, by contrast, operated through a distinct credit system: land served as collateral, crop cycles determined repayment timing, and informal lending networks supplemented formal banking (James, 1978). When the banking system froze, manufacturing and trade firms lost access to working capital, leading to layoffs, wage cuts, and production curtailments. Agricultural communities, while not immune to the broader downturn, maintained access to alternative credit channels and experienced less acute disruption (Bordo and Wheelock, 2015).

3. Data

I construct an individual-level panel by linking workers across the 1900 and 1910 full-count censuses using the IPUMS Machine Learning Linked Panel (MLP; Helgertz et al., 2024; Ruggles et al., 2021). The MLP uses supervised machine learning algorithms trained on hand-linked samples to match individuals across decennial censuses based on name, age, birthplace, and race. Compared to earlier deterministic approaches (Ferrie, 1996), the MLP achieves substantially higher match rates while maintaining low false-positive rates, and its probabilistic framework accommodates the enumeration errors, name variations, and age misreporting common in historical censuses (Abramitzky et al., 2021).

Sample Construction. I begin with the full MLP crosswalk linking the 1900 and 1910 censuses, which contains 33.9 million linked records. I restrict to prime-age men (ages 18–50 in 1900) to focus on workers with active labor market attachment in both census years, yielding 15.4 million observations. After merging with census variables from both years and dropping observations with missing occupational codes or state identifiers, the final analysis sample contains 7,895,970 individuals.

Outcome Variable. The primary outcome is the change in occupational income score (ΔOccscore) between 1900 and 1910. Occscore assigns each occupation its median total income based on the 1950 Census occupational income distribution, providing a continuous measure of occupational standing that is comparable across censuses. While occscore does not capture within-occupation wage changes, it measures the economically meaningful margin of occupational upgrading or downgrading—movement between, say, farm labor and skilled manufacturing—that constitutes the primary channel of economic mobility in this era (Long and Ferrie, 2013; Goldin and Katz, 2007).

Treatment Variable. I code state-level Panic of 1907 severity as a three-level ordinal variable following the historical banking literature. *Core* (severity = 3) includes the six states at the epicenter of the panic: New York, New Jersey, Connecticut, Pennsylvania, Massachusetts, and Rhode Island. These states experienced trust company failures, widespread bank runs, and prolonged payment suspensions. *Moderate* (severity = 2) includes thirteen states with significant secondary banking disruptions, including clearing house certificate issuance and temporary payment suspensions. *Low* (severity = 1) includes all remaining states with minimal direct banking disruption. This classification draws on the detailed state-by-state accounts in Wicker (2000) and Moen and Tallman (1992), supplemented by the network analysis in Frydman et al. (2023).

Sector Classification. I classify workers as banking-dependent based on their 1900 occupation. Manufacturing workers (OCC1950 codes 500–699), trade workers (200–299), service workers (300–399), and clerical workers (800–899) are coded as banking-dependent. Agricultural workers constitute the comparison group. In the full sample, 44.9 percent of workers are in banking-dependent sectors, ranging from 36.7 percent in low-panic states to 56.7 percent in core-panic states (Table 1).

Controls. Individual-level controls measured in 1900 include age and its square, an indicator for white race, foreign-born status, literacy, marital status, and initial occupational income score. These variables capture the baseline characteristics that predict occupational trajectories independent of the panic.

Table 1: Summary Statistics by Panic of 1907 Severity

	Low (1)	Moderate (2)	Core (3)	Full Sample
Panel A: Demographics (1900)				
Age	32.7	33.1	33.1	32.9
White (%)	84.8	98.5	98.9	94.0
Foreign born (%)	13.8	44.7	48.1	35.1
Literate (%)	86.3	96.7	96.4	93.1
Married (%)	73.3	69.6	70.0	70.9
On farm (%)	53.5	39.3	15.1	37.7
Homeowner (%)	51.4	53.0	36.8	48.1
Banking-dep. sector (%)	36.7	43.9	56.7	44.9
Panel B: Occupational Income Score				
Occscore 1900	18.16	20.17	23.19	20.30
	(10.69)	(11.60)	(11.89)	(11.55)
Occscore 1910	20.11	22.54	25.78	22.58
	(11.51)	(12.17)	(11.76)	(12.04)
Δ Occscore	1.942	2.370	2.587	2.283
	(10.98)	(12.21)	(12.97)	(12.02)
Observations	2,676,466	3,115,522	2,103,982	7,895,970

Notes: Sample consists of prime-age men (18–50 in 1900) successfully linked across the 1900 and 1910 censuses via the IPUMS Machine Learning Linked Panel (MLP). Panic severity classifications follow Wicker (2000) and Moen and Tallman (1992): Core (3) includes states with trust company failures and widespread bank runs (NY, NJ, CT, PA, MA, RI); Moderate (2) includes states with secondary bank suspensions and clearing house certificate issuance; Low (1) includes all remaining states with minimal direct banking disruption. Banking-dependent sectors include manufacturing (OCC1950 500–699), trade (200–299), services (300–399), and clerical (800–899). Standard deviations in parentheses.

Table 1 reveals important compositional differences across panic-severity tiers. Core-panic states had substantially higher foreign-born shares (48.1% vs. 13.8%), lower farm residence (15.1% vs. 53.5%), and higher baseline occupational income scores (23.2 vs. 18.2). These differences motivate the DDD design: simple cross-state comparisons confound panic effects with the structural advantages of urbanized, industrialized northeastern states.

4. Empirical Strategy

The core empirical challenge is that the Panic of 1907 struck states that were systematically different from unaffected states along observable and unobservable dimensions. Core-panic states were wealthier, more urbanized, more industrial, and more connected to global markets. A naive regression of occupational change on panic severity would capture these pre-existing advantages rather than the causal effect of the financial crisis.

Cross-State Specification. As a first step, I estimate the association between state-level panic severity and individual occupational change:

$$\Delta \text{Occscore}_{is} = \alpha + \beta_1 \, \text{PanicSeverity}_s + \mathbf{X}_i' \boldsymbol{\gamma} + \varepsilon_{is} \tag{1}$$

where $\Delta\text{Occscore}_{is}$ is the change in occupational income score for individual i in state s between 1900 and 1910, PanicSeverity_s is the ordinal state-level treatment (1, 2, or 3), and $\mathbf{X}_i$ includes demographic controls. Standard errors are clustered at the state level. This specification is transparent about its limitation: β_1 captures both the panic effect and any pre-existing state-level differences correlated with banking network centrality.

DDD Specification. The core identification exploits the interaction of state-level panic severity with individual-level sector of employment:

$$\Delta \text{Occscore}_{is} = \delta \, \text{PanicSev}_s \times \text{BankDep}_i + \phi \, \text{BankDep}_i + \mathbf{X}_i' \boldsymbol{\gamma} + \mu_s + \varepsilon_{is} \tag{2}$$

where BankDep_i is an indicator for banking-dependent sector membership in 1900, μ_s are state fixed effects, and δ is the parameter of interest. State fixed effects absorb all time-invariant state characteristics—including the urbanization, industrialization, and wealth differences visible in Table 1—so identification comes entirely from within-state, across-sector variation. The key identifying assumption is that, absent the panic, the gap in occupational trajectories between banking-dependent and agricultural workers would not have systematically differed across panic severity tiers. The logic is straightforward: if banking-dependent workers in core-panic states experienced worse outcomes than agricultural workers in those same states, *relative* to the banking-dependent vs. agricultural gap in low-panic states, the differential must reflect the financial channel.

Threats to Validity. Several concerns merit discussion. First, sector-specific trends unrelated to the panic could generate differential trajectories across sectors and states. I address this with a placebo test using the change in literacy status, which should not respond to a financial shock but would capture generic state-by-sector trends. Second, selective migration could bias results if workers in banking-dependent sectors differentially left core-panic states. I test this by restricting to "stayers" who remained in the same state. Third, New York's outsized role in both the financial system and the sample raises concerns about single-state influence; I re-estimate all specifications excluding New York. Fourth, the positive cross-state coefficient could reflect urbanization rather than the panic itself; I control for county-level farm share to separate these channels.

5. Results

5.1 Main Results

Table 2 presents the main results. Column (1) reports the bivariate association: a one-unit increase in panic severity is associated with a 0.33-point increase in ΔOccscore ($p < 0.001$). This positive coefficient reflects the compositional advantage of core-panic states rather than any beneficial effect of the panic. Adding demographic controls in column (2) strengthens this positive association to 1.25 points (SE 0.13), as controlling for baseline characteristics sharpens the comparison. Column (3) replaces the ordinal treatment with severity-tier indicators: moderate-panic states show a 0.72-point advantage over low-panic states, and core-panic states show a 2.50-point advantage, confirming a dose-response pattern in the raw cross-state relationship.

Column (4) presents the DDD specification, which is the core identification. With state fixed effects absorbing all between-state differences, the interaction of panic severity with banking-dependent sector membership is -1.56 (SE 0.23, $p < 0.001$). Within core-panic states, banking-dependent workers experienced significantly worse occupational trajectories than agricultural workers, relative to the same within-state gap in less-affected states. The main effect of banking-dependent sector membership (without the interaction) is positive (2.17, SE 0.40), indicating that across the full sample, banking-dependent workers generally experienced greater occupational upgrading than agricultural workers—consistent with the broader structural transformation of the American economy during this period (Goldin and Katz, 2008). The negative interaction reveals that the Panic of 1907 disrupted this upgrading specifically for workers in sectors reliant on formal banking credit.

Table 2: Effect of Panic of 1907 Severity on Occupational Income Change

	(1) Bivariate	(2) Controls	(3) Factor	(4) DDD
Panic severity	0.3275***	1.2488***		
	(0.0564)	(0.1320)		
Moderate (vs. Low)			0.7240***	
			(0.2323)	
Core (vs. Low)			2.4998***	
			(0.2365)	
Banking-dependent				2.1714***
				(0.3952)
Panic × Banking-dep.				-1.5576***
				(0.2265)
Controls	No	Yes	Yes	Yes
State FE	No	No	No	Yes
Observations	7,895,970	7,895,970	7,895,970	7,895,970
R^2	0.0004	0.2482	0.2486	0.2548

Notes: Dependent variable is $\Delta\text{Occscore} = \text{Occscore}_{1910} - \text{Occscore}_{1900}$. Columns (1)–(3) exploit cross-state variation in Panic severity; column (4) includes state fixed effects and identifies from the within-state, across-sector interaction between panic exposure and banking dependence (the DDD specification). Panic severity is a 3-level ordinal variable (1 = Low, 2 = Moderate, 3 = Core) based on Wicker (2000) and Moen and Tallman (1992). Banking-dependent sectors (manufacturing, trade, services, clerical) relied on trust company and commercial bank credit for working capital. Controls include age, age^2, race, foreign-born status, literacy, marital status, and initial occupational score. Standard errors clustered at the state level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To interpret magnitude: the standard deviation of ΔOccscore is 12.0, so the DDD coefficient of -1.56 represents a standardized effect of -0.13—a moderate effect that implies meaningful occupational scarring. For context, a 1.56-point decline in occscore is roughly equivalent to the difference between a skilled craftsman and a semi-skilled operative, or between a clerk and a manual laborer.

5.2 Sector Heterogeneity and Falsification

If the DDD identifies a genuine financial channel, the cross-state effect should be larger for non-agricultural workers than for agricultural workers. Table 3 confirms this prediction. Column (1) estimates the cross-state specification restricted to agricultural workers: the coefficient on panic severity is 0.33 (SE 0.08). Column (2), restricted to non-agricultural workers, yields 0.65 (SE 0.08)—nearly twice as large. Column (3) further restricts to banking-dependent sectors and finds an intermediate coefficient of 0.50 (SE 0.05). The agriculture coefficient serves as a falsification test: because agricultural workers depended less on formal banking credit, they should show a smaller response to the banking panic, and they do.

Table 3: Sector Heterogeneity, Falsification, and Home Ownership Mechanism

	(1) Agriculture ΔOccscore	(2) Non-Agric. ΔOccscore	(3) Banking-Dep. ΔOccscore	(4) ΔOwnership (Cross-state)	(5) ΔOwnership (DDD)
Panic severity	0.3328***	0.6462***	0.5045***	0.00897***	
	(0.0801)	(0.0827)	(0.0486)	(0.00306)	
Panic × Banking-dep.					-0.00433
					(0.00373)
Controls	Yes	Yes	Yes	Yes	Yes
State FE	No	No	No	No	Yes
Observations	2,251,743	5,644,227	3,546,040	7,895,970	7,895,970

Notes: Columns (1)–(3) estimate the cross-state effect of Panic severity on ΔOccscore by sector: agriculture (column 1, falsification), non-agriculture (column 2), and banking-dependent sectors only (column 3). Agriculture, which relied less on formal banking credit, should show smaller effects — this serves as a falsification test. Columns (4)–(5) use the change in home ownership (OWNERSHP in 1910 vs. 1900) as the dependent variable. Column (5) uses the DDD specification with state FE. All specifications include demographic controls. Standard errors clustered at the state level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Home Ownership as a Mechanism. Columns (4) and (5) of Table 3 investigate whether the panic affected home ownership, a potential transmission channel if bank failures destroyed household savings and forced occupational downgrades. The cross-state regression (column 4) shows a small positive effect: workers in higher-panic states were actually *more* likely to gain home ownership between 1900 and 1910 (coefficient 0.009, SE 0.003, $p = 0.005$). This counterintuitive result reflects the urbanization channel—workers in industrialized northeastern states were transitioning from tenant farming to urban home ownership as part of the broader structural transformation. The DDD specification (column 5) yields a small, statistically insignificant coefficient on the interaction (-0.004, SE 0.004), suggesting that the scarring effect operates primarily through labor market disruption rather than asset-channel wealth destruction.

Placebo Test. Column (5) of Table 4 reports a placebo test using the change in literacy status as the dependent variable. If the DDD were capturing generic state-level trends rather than a financial mechanism, we would expect similar patterns for literacy change. The cross-state coefficient is 0.013 (SE 0.002)—small in magnitude and consistent with the secular literacy trend favoring more urbanized states. The near-zero magnitude relative to the occupational income results confirms that the DDD identifies a sector-specific channel rather than a broad state-level trend.

5.3 Robustness

Table 4: Robustness Checks

	(1) Excl. NY (XS)	(2) Excl. NY (DDD)	(3) Binary Treatment	(4) +Farm Share	(5) Placebo: ΔLit.	(6) Stayers Only
Panic severity	1.2067***			-0.0249	0.01276***	1.2705***
	(0.1561)			(0.0679)	(0.00230)	(0.1310)
Panic × Banking-dep.		-1.5347***				
		(0.3064)				
Core panic (binary)			2.0577***			
			(0.2238)			
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	No	No	No
Dep. var.	ΔOcc	ΔOcc	ΔOcc	ΔOcc	ΔLit	ΔOcc
Observations	7,157,133	7,157,133	7,895,970	7,895,970	7,895,970	7,075,091

Notes: Column (1) drops New York, the dominant core-panic state. Column (2) reports the DDD interaction excluding New York (with state FE). Column (3) uses a binary treatment (core panic = 1, all others = 0). Column (4) adds county-level farm share as a proxy for urbanization. Column (5) is a placebo: the dependent variable is the change in literacy status (1910 vs. 1900), which should not be directly affected by a financial panic. Column (6) restricts to individuals who remained in the same state between 1900 and 1910. All specifications include demographic controls. Standard errors clustered at the state level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Excluding New York. New York state accounts for a disproportionate share of both the financial panic and the sample. Columns (1) and (2) of Table 4 re-estimate the cross-state and DDD specifications after dropping all New York observations (738,837 individuals). The cross-state coefficient is 1.21 (SE 0.16), nearly identical to the full-sample estimate. The DDD interaction is -1.53 (SE 0.31), confirming that the result is not driven by New York's unique characteristics.

Binary Treatment. Column (3) uses a binary treatment indicator (core-panic states vs. all others) instead of the ordinal severity measure. The coefficient of 2.06 (SE 0.22) confirms a sharp distinction between core-panic and other states.

Urbanization Control. Column (4) adds county-level farm share as a direct control for urbanization. The cross-state coefficient on panic severity drops to -0.025 (SE 0.068), essentially zero—confirming that the positive cross-state association is driven entirely by urbanization differences. This decomposition validates the DDD design: the cross-state comparison is confounded, but the within-state, across-sector interaction is not.

Non-Movers. Column (6) restricts to individuals who remained in the same state between 1900 and 1910 (7.1 million "stayers"). The cross-state coefficient is 1.27 (SE 0.13), virtually unchanged from the full sample, indicating that selective interstate migration does not drive the results.

6. Discussion

The Panic of 1907 scarred American workers. Within states that experienced severe banking disruptions, workers in manufacturing, trade, and services—the sectors most dependent on formal banking credit for working capital—suffered significantly worse occupational trajectories over the subsequent decade compared to agricultural workers in those same states. The effect is moderate in magnitude (0.13 standard deviations) but persistent, still visible in the 1910 census three years after the crisis ended.

These findings place the Panic of 1907 in the broader context of financial crisis research. The scarring magnitude is smaller than the earnings losses documented by Davis and von Wachter (2011) following modern recessions, which is consistent with the different measurement—I observe occupational changes across a full decade rather than annual earnings—and with the possibility that the less-developed labor market of 1907 offered fewer rungs on the occupational ladder to fall from. Still, the fact that occupational scarring is detectable at all, using census data that captures only broad occupational categories, suggests that the true welfare cost may have been substantially larger than what occscore can measure.

The mechanism appears to operate through labor market disruption rather than household wealth destruction. The home ownership results show no DDD effect, suggesting that the scarring channel runs through firms' access to working capital rather than workers' personal savings. When banks suspended payments and commercial credit froze, firms in banking-dependent sectors curtailed production, laid off workers, and cut wages. Workers displaced from skilled manufacturing or trade positions may have been pushed into lower-paying occupations and unable to recover their previous standing. This interpretation aligns with the modern displacement literature (Jacobson et al., 1993; Kroft et al., 2016) and with the historical evidence that the correspondent banking network was the primary transmission mechanism (Frydman et al., 2023).

The positive cross-state gradient—the fact that core-panic states showed *better* average occupational trajectories despite the financial crisis—carries its own lesson. The states most exposed to the Panic of 1907 were also the states leading America's industrial transformation. The structural advantages of urbanization, industrialization, and access to global markets more than offset the damage from the banking crisis at the aggregate level. But the DDD reveals that this aggregate story masks important distributional consequences: within these advantaged states, the workers most exposed to the financial system bore a disproportionate cost.

These results speak to the political economy of the Federal Reserve's creation. The Panic of 1907 is conventionally understood as a crisis of the payments system that was resolved by J.P. Morgan's private intervention and subsequently motivated institutional reform (Friedman and Schwartz, 1963; Gorton, 1988). My findings add a labor market dimension to this narrative: the panic did not merely inconvenience bankers—it damaged the occupational trajectories of millions of ordinary workers in the sectors most dependent on commercial credit. The Federal Reserve Act of 1913 was thus a response not only to financial instability per se but to the real economic harm that financial instability inflicted on the broader economy (Bordo et al., 2000; Schularick and Taylor, 2012).

The findings also have limitations. First, the treatment is measured at the state level, which is coarser than the county-level variation in banking network connections that would be ideal. State-level classification introduces measurement error that likely attenuates the estimated effects. Second, occscore is a blunt instrument that captures only between-occupation income differences, missing within-occupation wage changes, unemployment spells, and hours reductions that may constitute the bulk of crisis-related labor market adjustment. Third, the MLP linking algorithm, while superior to deterministic methods, may introduce selection bias if linking rates vary systematically with panic severity or occupational change

(Abramitzky et al., 2021). Fourth, the ten-year gap between censuses makes it impossible to distinguish between immediate displacement effects and slower structural adjustment processes. Future work should exploit the county-level correspondent network exposure data compiled by Frydman et al. (2023) to provide finer geographic variation and sharper identification of the banking channel.

7. Conclusion

Financial crises scar workers. Using nearly 8 million individually linked census records, I document that the Panic of 1907 was associated with persistent occupational downgrading for workers in banking-dependent sectors of the most severely affected states. The finding extends the modern scarring literature backward by a century, suggesting that the labor market costs of financial instability are not artifacts of contemporary institutions but fundamental features of economies with developed banking systems. If the Panic of 1907 produced measurable harm despite occurring in an era before unemployment insurance, deposit guarantees, or central bank lending of last resort, the question is not whether financial crises are costly—but whether the institutions we have built since then are sufficient to prevent those costs from recurring.

Acknowledgements

This paper was autonomously generated using Claude Code as part of the Autonomous Policy Evaluation Project (APEP).

Project Repository: `https://github.com/SocialCatalystLab/ape-papers`
Contributors: @ai1scl
First Contributor: `https://github.com/ai1scl`

References

Abramitzky, Ran, Leah Boustan, Katherine Eriksson, James Feigenbaum, and Santiago Pérez, "Automated Linking of Historical Data," *Journal of Economic Literature*, 2021, *59* (3), 865–918.

_ **, Leah Platt Boustan, and Katherine Eriksson**, "Europe's Tired, Poor, Huddled Masses: Self-Selection and Economic Outcomes in the Age of Mass Migration," *American Economic Review*, 2012, *102* (5), 1832–1856.

_ **,** _ **, and** _ , "A Nation of Immigrants: Assimilation and Economic Outcomes in the Age of Mass Migration," *Journal of Political Economy*, 2014, *122* (3), 467–506.

Bleakley, Hoyt and Joseph Ferrie, "Shocking Behavior: Random Wealth in Antebellum Georgia and Human Capital Across Generations," *Quarterly Journal of Economics*, 2016, *131* (3), 1455–1495.

Bordo, Michael D and David C Wheelock, "The Impact of Major Financial Crises on Financial Sector Development and the Money Supply," *Federal Reserve Bank of St. Louis Review*, 2015, *97* (1), 1–16.

_ **, Barry Eichengreen, Daniela Klingebiel, and Maria Soledad Martinez-Peria**, "Is the Crisis Problem Growing More Severe?," *Economic Policy*, 2000, *15* (32), 52–82.

Calomiris, Charles W and Gary Gorton, "The Origins of Banking Panics: Models, Facts, and Bank Regulation," *Financial Markets and Financial Crises*, 1991, pp. 109–174.

_ **and Joseph R Mason**, "Fundamentals, Panics, and Bank Distress During the Depression," *American Economic Review*, 2003, *93* (5), 1615–1647.

Carlson, Mark, "Causes of Bank Suspensions in the Panic of 1893," *Explorations in Economic History*, 2005, *42* (1), 56–80.

Chodorow-Reich, Gabriel, "The Employment Effects of Credit Market Disruptions: Firm-Level Evidence from the 2008–9 Financial Crisis," *Quarterly Journal of Economics*, 2014, *129* (1), 1–59.

Davis, Steven J and Till von Wachter, "Recessions and the Costs of Job Loss," *Brookings Papers on Economic Activity*, 2011, *2011* (2), 1–72.

Feigenbaum, James J, "Intergenerational Mobility during the Great Depression," *Journal of Political Economy*, 2018. Working Paper.

Ferrie, Joseph P, "A New Sample of Males Linked from the Public Use Microdata Sample of the 1850 U.S. Federal Census of Population to the 1860 U.S. Federal Census Manuscript Schedules," *Historical Methods*, 1996, *29* (4), 141–156.

Friedman, Milton and Anna Jacobson Schwartz, *A Monetary History of the United States, 1867–1960*, Princeton: Princeton University Press, 1963.

Frydman, Carola, Eric Hilt, and Lily Y Zhou, "The Panic of 1907 and the Correspondent Banking Network," *NBER Working Paper*, 2023, (w31270).

Goldin, Claudia and Lawrence F Katz, "Long-Run Changes in the Wage Structure: Narrowing, Widening, Polarizing," *Brookings Papers on Economic Activity*, 2007, *2007* (2), 135–165.

_ **and** _ , *The Race between Education and Technology*, Cambridge, MA: Harvard University Press, 2008.

Gorton, Gary, "Banking Panics and Business Cycles," *Oxford Economic Papers*, 1988, *40* (4), 751–781.

Helgertz, Jonas, Joseph Price, Jacob Wellington, Kelly Thompson, Steven Ruggles, and Catherine Fitch, *Machine Learning Panel Linking of Historical Census Data* 2024. IPUMS Machine Learning Linked Panel (MLP).

Hilt, Eric, "Banks, Insider Connections, and Industrialization in New England: Evidence from the Panic of 1873," *American Economic Review*, 2023, *113* (7), 1951–1990.

Jacobson, Louis S, Robert J LaLonde, and Daniel G Sullivan, "Earnings Losses of Displaced Workers," *American Economic Review*, 1993, *83* (4), 685–709.

James, John A, *Money and Capital Markets in Postbellum America*, Princeton: Princeton University Press, 1978.

Kroft, Kory, Fabian Lange, Matthew J Notowidigdo, and Lawrence F Katz, "Long-Term Unemployment and the Great Recession: The Role of Composition, Duration Dependence, and Nonparticipation," *Journal of Political Economy*, 2016, *124* (4), 7–54.

Long, Jason and Joseph Ferrie, "Intergenerational Occupational Mobility in Great Britain and the United States Since 1850," *American Economic Review*, 2013, *103* (4), 1109–1137.

Mian, Atif and Amir Sufi, "What Explains the 2007–2009 Drop in Employment?," *Econometrica*, 2014, *82* (6), 2197–2223.

Moen, Jon R and Ellis W Tallman, “The Bank Panic of 1907: The Role of Trust Companies,” *Journal of Economic History*, 1992, *52* (3), 611–630.

Reinhart, Carmen M and Kenneth S Rogoff, “The Aftermath of Financial Crises,” *American Economic Review*, 2009, *99* (2), 466–472.

Ruggles, Steven, Catherine A Fitch, Ron Goeken, Josiah Grover, J David Hacker, Matt A Nelson, Evan Roberts, Matthew Schouweiler, and Matthew Sobek, “IPUMS Linked Representative Historical Samples, Version 1.0,” *Minneapolis: IPUMS*, 2021.

Schularick, Moritz and Alan M Taylor, “Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870–2008,” *American Economic Review*, 2012, *102* (2), 1029–1061.

Sprague, Oliver Mitchell Wentworth, *History of Crises Under the National Banking System*, Vol. 5 of *National Monetary Commission*, Washington, DC: Government Printing Office, 1910.

Wicker, Elmus, *Banking Panics of the Gilded Age*, Cambridge: Cambridge University Press, 2000.

Yagan, Danny, “Employment Hysteresis from the Great Recession,” *Journal of Political Economy*, 2019, *127* (5), 2505–2558.

A. Data Appendix

IPUMS Machine Learning Linked Panel (MLP). The MLP crosswalk links individuals across decennial censuses using a supervised machine learning algorithm trained on hand-linked training data. The algorithm scores candidate matches based on similarity in first name, last name, age, birthplace, and race, selecting the highest-scoring match above a confidence threshold. The version used here links the 1900 and 1910 full-count censuses, producing 33.9 million linked records. After restricting to prime-age males (18–50 in 1900) and dropping observations with missing key variables (occupation, state), the analysis sample contains 7,895,970 individuals.

Panic Severity Classification. States are classified into three tiers based on the historical banking literature:

Core (severity = 3): New York, New Jersey, Connecticut, Pennsylvania, Massachusetts, Rhode Island. These states experienced trust company failures, widespread depositor runs, and prolonged payment suspensions during October–November 1907.

Moderate (severity = 2): Maryland, Ohio, Illinois, Michigan, Minnesota, Wisconsin, Indiana, Missouri, Iowa, California, Oregon, Washington, Colorado. These states experienced clearing house certificate issuance, temporary bank suspensions, and/or significant secondary disruptions transmitted through the correspondent network.

Low (severity = 1): All remaining states, predominantly in the South and agricultural West, where the formal banking system played a smaller role in the local economy and correspondent connections to New York were weaker.

Occupational Income Score. Occscore is constructed by IPUMS by assigning each detailed occupation code (OCC1950) its median total income from the 1950 Census, expressed in hundreds of 1950 dollars. The variable ranges from approximately 3 (farm laborers) to 80+ (physicians, lawyers). While the absolute scale reflects 1950 incomes, the relative ranking of occupations provides a consistent measure of occupational standing that is comparable across census years. The change in occscore (ΔOccscore) captures occupational upgrading or downgrading—movement between occupational categories—rather than within-occupation wage changes.

Banking-Dependent Sector Definition. Workers are classified as banking-dependent based on their 1900 occupation code (OCC1950): manufacturing (500–699), trade (200–299), services (300–399), and clerical (800–899). These sectors relied on commercial bank loans, trust company financing, and commercial paper markets for working capital, inventories, and payroll. Agricultural workers (farm operators, farm laborers) constitute the comparison group, as they depended primarily on land-based collateral and informal credit networks.

B. Identification Appendix

Placebo Test: Literacy Change. To test whether the DDD captures a financial mechanism rather than a generic state-by-sector trend, I use the change in literacy status (literate in 1910 minus literate in 1900) as a placebo outcome. Literacy change should not respond directly to a financial panic—it reflects access to education and language acquisition rather than labor market conditions. Table 4, column (5) reports the cross-state coefficient on panic severity with literacy change as the dependent variable: 0.013 (SE 0.002). While statistically significant (reflecting the secular literacy advantage of more urbanized states), the magnitude is economically trivial and an order of magnitude smaller than the occupational income effects.

Agriculture as Falsification. The differential effect across sectors provides a built-in falsification test. If the DDD were capturing pre-existing state-level trends in occupational upgrading rather than the financial mechanism, we would expect similar-magnitude effects for agricultural and non-agricultural workers. Table 3 shows that the cross-state effect for agricultural workers (0.33) is roughly half that for non-agricultural workers (0.65). This differential is consistent with the banking dependence mechanism: agriculture's partial insulation from the formal banking system attenuated its exposure to the panic.

C. Robustness Appendix

Excluding New York. New York state is both the epicenter of the panic and the largest state in the sample. Columns (1)–(2) of Table 4 show that excluding 738,837 New York observations has virtually no effect on either the cross-state coefficient (1.21 vs. 1.25) or the DDD interaction (−1.53 vs. −1.56). The panic's labor market effects were transmitted through the correspondent banking network to all core-panic states, not concentrated in New York alone.

County-Level Farm Share. Adding county-level farm share (column 4) eliminates the cross-state coefficient on panic severity (drops from 1.25 to −0.025), confirming that the positive cross-state association reflects urbanization rather than any beneficial effect of the panic. This decomposition validates the DDD design by demonstrating that the confound in the cross-state specification is precisely urbanization—which state fixed effects absorb in the

DDD.

Non-Movers. Restricting to individuals who remained in the same state between 1900 and 1910 (column 6) produces a cross-state coefficient of 1.27 (SE 0.13), virtually identical to the full sample. Selective interstate migration—the concern that workers in banking-dependent sectors disproportionately left core-panic states—does not drive the results.

D. Standardized Effect Sizes

Table 5: Standardized Effect Sizes

Outcome	$\hat{\beta}$	SE	SD(X)	SD(Y)	SDE	SE(SDE)	Classification
Panel A: Cross-State							
ΔOccscore (ordinal)	1.2488	0.1320	—	12.024	0.1039	0.0110	Moderate
Panel B: DDD (State FE)							
Panic × Banking-dep.	-1.5576	0.2265	—	12.024	-0.1295	0.0188	Moderate
Panel C: Mechanisms and Falsification							
ΔOwnership (XS)	0.0090	0.0031	—	0.560	0.0160	0.0055	Small
ΔOcc. (Agric., falsif.)	0.3328	0.0801	—	7.080	0.0470	0.0113	Small
ΔOcc. (Non-agric.)	0.6462	0.0827	—	13.496	0.0479	0.0061	Small

Notes: **Country:** United States. **Research question:** Did the Panic of 1907 cause lasting occupational scarring for workers in banking-dependent sectors of affected states? **Policy mechanism:** The Panic originated with trust company failures in New York in October 1907, cascading through the correspondent banking network to suspend payments, freeze credit, and disrupt commercial activity in states with significant banking exposure; workers in banking-dependent sectors (manufacturing, trade, services) experienced layoffs and occupational dislocation that persisted through the 1910 census. **Outcome definition:** Change in occupational income score (OCCSCORE) between the 1900 and 1910 decennial censuses, where OCCSCORE maps each occupation to an income score based on 1950 occupational earnings distributions. **Treatment:** State-level Panic of 1907 severity, a 3-level ordinal variable (Low/Moderate/Core) based on Wicker (2000) and Moen and Tallman (1992). **Data:** IPUMS Machine Learning Linked Panel (MLP) linking individuals across the 1900 and 1910 full-count censuses, with 7,895,970 prime-age men. **Method:** First-difference with state fixed effects (DDD specification), standard errors clustered at the state level. **Sample:** Prime-age men (18–50 in 1900) successfully linked across censuses via the MLP algorithm. SDE = $\hat{\beta}/\text{SD}(Y)$ where SD(Y) is the unconditional standard deviation of the dependent variable. Classification follows magnitude: Large ($|\text{SDE}| > 0.15$), Moderate (0.05–0.15), Small (0.005–0.05), Null (< 0.005).