Mobile Banking, Bank Branch Closures, and Self-Employment in the United States

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Abstract

This paper investigates whether mobile banking can substitute for traditional branch banking in supporting self-employment. Using data from the FDIC National Survey of Unbanked and Underbanked Households (2013–2023), I document that self-employment rates are significantly higher among branch banking users (9.95%) compared to mobile-only users (7.19%). I develop a dynamic structural model of joint banking mode and employment choice estimated via the Arcidiacono-Miller CCP approach with finite dependence and unobserved heterogeneity. Following recent econometric advances, I employ a three-pronged approach to select the number of latent types: Hao-Kasahara (2025) panel BIC, Bonhomme-Lamadon-Manresa (2022) counterfactual stability, and Budanova (2025) penalized MLE. All three methods support $K = 4$ types with heterogeneous responses to branch closures, including a substantial group (24%) highly dependent on branch-based relationship lending. Counterfactual simulations show that a 50% reduction in branch access reduces aggregate self-employment by approximately 11%, with meaningful sensitivity to unobserved heterogeneity assump-

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tions (effects range from 1% to 11% across specifications). The results demonstrate the importance of proper model selection in mixture models for policy evaluation.

JEL Codes: G21, J24, L26, O33, R12

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1 Introduction

The landscape of retail banking in the United States has undergone a dramatic transformation over the past decade. Between 2019 and 2023, U.S. bank branches declined by 5.6%, with over 4,000 branch closures nationwide (FDIC, 2023). Simultaneously, mobile banking adoption has surged: the share of banked households reporting mobile banking as their primary account access method rose from 15.1% in 2017 to 43.5% in 2021 (FDIC, 2021). These trends have left approximately 12.3 million Americans living in "banking deserts"—communities lacking physical bank branches within reasonable distance.

This paper investigates a critical question at the intersection of financial access and entrepreneurship: Does mobile banking serve as a substitute channel for credit access that supports self-employment in areas with declining branch presence? Self-employment represents a vital pathway to economic mobility, particularly for populations historically underserved by traditional financial institutions. If mobile banking can effectively replace branch-based banking relationships for entrepreneurial credit access, the ongoing digitization of financial services may partially offset the negative effects of branch closures on local economic dynamism. Conversely, if branch relationships remain essential for accessing the credit and financial services that enable entrepreneurship, the geographic concentration of branch closures in lower-income and minority communities may exacerbate existing disparities in entrepreneurship rates.

I study this question using microdata from the FDIC National Survey of Unbanked and Underbanked Households, which is administered biennially as a supplement to the Current Population Survey. The survey provides detailed information on banking behaviors, including the specific channels households use to access their accounts, combined with employment status from the CPS base survey. Importantly, the CPS identifies self-employment through its class-of-worker variable, allowing me to distinguish between wage employment and entrepreneurship.

The empirical analysis proceeds in two stages. First, I document descriptive patterns and estimate reduced-form relationships between mobile banking adoption and self-employment. The raw data reveal a striking pattern: households that primarily use branch banking have a self-employment rate of 12.6%, compared to just 8.7% among mobile-only banking users. However, this correlation likely reflects selection—the same characteristics that lead individuals to prefer branch banking (older age, higher wealth, established business relationships) may also be associated with higher rates of self-employment. After controlling for demographics, education, income, and CBSA fixed effects, the relationship between mobile banking and self-employment becomes small and statistically insignificant. Instrumental variable estimates using local broadband penetration as an instrument for mobile banking adoption yield positive but imprecise effects.

Second, I develop a structural model of joint banking mode and employment status choice. Individuals choose from three banking modes (unbanked, mobile/online only, branch user) and three employment statuses (wage employment, self-employment, not working), yielding nine discrete choice alternatives. The key structural parameters capture how banking mode affects access to credit, and how credit access in turn affects the returns to self-employment. This framework allows me to decompose the observed correlation between branch banking and self-employment into (i) selection effects (who chooses each banking mode), (ii) direct effects (how banking mode affects employment outcomes), and (iii) the role of local banking infrastructure in shaping both choices.

The structural model enables counterfactual policy analysis that reduced-form methods cannot provide. Specifically, I can simulate the effects of: (1) continued branch closures with no change in mobile banking access; (2) branch closures accompanied by improvements in broadband infrastructure that facilitate mobile banking adoption; and (3) targeted subsidies for mobile banking adoption in banking deserts.

This paper contributes to several literatures. First, it adds to the growing body of work on the real effects of bank branch closures (Nguyen, 2019; Granja et al., 2022; Celerier and Matray, 2019). While existing research has documented effects on small business lending and local economic activity, I provide the first evidence specifically on self-employment entry. Second, the paper contributes to the literature on technology and financial inclusion (Jack and Suri, 2014; Muralidharan et al., 2016; Breza et al., 2020), extending the analysis from developing country contexts to examine whether mobile technology can substitute for physical banking infrastructure in advanced economies. Third, I contribute methodologically by developing a structural framework for analyzing the joint determination of banking mode and employment status, which can be applied to study other aspects of financial access and labor market outcomes.

2 Background and Institutional Context

2.1 Bank Branch Closures in the United States

The consolidation of the U.S. banking sector has accelerated in recent years. Following the 2008 financial crisis, regulatory changes increased compliance costs for small banks, spurring mergers and branch network optimization. More recently, the COVID-19 pandemic accelerated the shift toward digital banking, leading banks to close branches deemed redundant.

Branch closures have not been geographically uniform. Rural areas, low-income urban neighborhoods, and communities with higher shares of minority residents have experienced disproportionate declines in branch presence (Morgan et al., 2016; Ergungor, 2010). This pattern raises concerns about equitable access to financial services, as branch relationships remain important for accessing certain products—particularly small business credit that relies on soft information and relationship lending (Petersen and Rajan, 2002; Berger et al., 2005).

2.2 Mobile Banking Adoption

Mobile banking technology has evolved rapidly from simple balance checking to comprehensive financial management platforms. Modern mobile banking applications allow users to deposit checks, transfer funds, apply for loans, and manage investments. The Federal Reserve's survey of household financial technology use documents steady increases in mobile banking adoption across all demographic groups, though significant disparities remain by age, income, and education (Federal Reserve, 2022).

For entrepreneurs and self-employed individuals, mobile banking offers potential benefits including: reduced transaction costs for managing business finances, faster access to account information for cash flow management, and the ability to conduct banking outside traditional business hours. However, mobile banking may be less effective than branch relationships for establishing the trust and soft information transmission that facilitate access to credit.

2.3 Self-Employment and Credit Access

Self-employment requires access to capital for startup costs, working capital, and investment in growth. Traditional bank lending to small businesses relies heavily on relationship banking, where loan officers develop knowledge about borrowers through repeated interactions (Berger and Udell, 1995). This model inherently favors borrowers with physical access to branches.

Recent research has examined alternative financing channels for entrepreneurs, including online lending platforms (Morse, 2015; Tang, 2019), fintech credit scoring (Berg et al., 2020; Fuster et al., 2019), and mobile money in developing countries (Beck et al., 2018). However, evidence on whether mobile banking—as distinct from mobile lending—affects entrepreneurship in advanced economies remains limited.

3 Data

3.1 FDIC National Survey of Unbanked and Underbanked Households

The primary data source is the FDIC National Survey of Unbanked and Underbanked Households, conducted biennially since 2009 as a supplement to the June Current Population Survey. The survey collects detailed information on household banking status, account types, methods of accessing accounts, and use of alternative financial services.

For this analysis, I use the multi-year public use microdata file covering survey waves from 2009 to 2023, yielding approximately 570,000 household-level observations. The survey includes harmonized variables across waves, enabling consistent measurement of banking behaviors over time. Key variables from the FDIC supplement include:

- **Banking status:** Whether the household has a bank account (checking, savings, or both), and detailed underbanking measures based on use of alternative financial services.
- **Account access methods:** The specific channels used to access bank accounts, including branch visits, ATM, telephone, online banking, and mobile banking. Crucially, the survey asks which method is used most frequently.
- **Mobile banking activities:** For mobile banking users, detailed information on specific activities conducted (balance checking, bill payment, deposits, transfers, etc.).

3.2 Current Population Survey

Because the FDIC survey is administered as a CPS supplement, I observe the full set of CPS variables for each respondent. Key variables from the CPS base survey include:

- **Employment status:** Labor force participation, employment/unemployment, and class of worker (wage and salary vs. self-employed, with distinction between incorporated and unincorporated self-employment).

- **Demographics:** Age, sex, race/ethnicity, education, marital status, and household composition.
- **Geography:** State, Core-Based Statistical Area (CBSA), and metropolitan status. Geographic identifiers enable merging with area-level data on banking infrastructure and economic conditions.

3.3 FDIC Summary of Deposits

I supplement the survey data with information on local banking infrastructure from the FDIC Summary of Deposits (SOD), which provides an annual census of all FDIC-insured bank branches including their precise locations. From the SOD, I construct CBSA-year measures of:

- Total number of bank branches
- Branch density (branches per capita or per square mile)
- Net branch changes (openings minus closures)
- Banking desert indicators (absence of branches within specified distance)

3.4 American Community Survey

I merge CBSA-level control variables from the American Community Survey (ACS), including:

- **Broadband penetration:** Share of households with broadband internet subscription and/or smartphone data plans. This serves as both a control variable and instrumental variable for mobile banking adoption.

- **Demographic composition:** Population, racial/ethnic composition, age distribution, and educational attainment.
- **Economic conditions:** Median household income, unemployment rate, and industry employment shares.

3.5 Sample Construction

The analysis sample is constructed as follows:

1. Start with the FDIC multi-year microdata (N = 570,943 observations).
2. Restrict to working-age adults (18–64) in the labor force (employed or actively seeking work), reducing the sample to observations where self-employment is a feasible choice.
3. Keep survey waves from 2013 onward, when mobile banking questions were consistently available.
4. Retain observations with identifiable CBSA codes for geographic analysis.

The final analysis sample contains 125,017 individual observations across 293 CBSAs and 6 survey waves (2013, 2015, 2017, 2019, 2021, 2023).

3.6 Variable Definitions

3.6.1 Banking Mode

I classify households into three mutually exclusive banking modes:

1. **Unbanked:** Household does not have a checking or savings account at a bank or credit union.
2. **Mobile/Online Only:** Banked household that accesses accounts exclusively through mobile or online channels, without visiting bank tellers.

3. **Branch User:** Banked household that uses bank teller services, either exclusively or in combination with other access methods.

This classification captures the key distinction between households that maintain relationships with physical branches versus those relying entirely on digital channels.

3.6.2 Employment Status

Employment status is classified into three categories:

1. **Wage Worker:** Employed in a wage and salary position (private sector, government, or nonprofit).
2. **Self-Employed:** Employed in own business, either incorporated or unincorporated.
3. **Not Working:** Unemployed (actively seeking work) or temporarily not working.

3.6.3 Key Control Variables

- **Age:** Continuous measure in years, with quadratic term to capture nonlinear lifecycle patterns.
- **Education:** Four categories: less than high school, high school diploma, some college, and college degree or higher.
- **Race/Ethnicity:** Seven categories following Census definitions, with separate indicators for Black, Hispanic, Asian, and White non-Hispanic.
- **Family Income:** Five categories: below $15,000; $15,000–$30,000; $30,000–$50,000; $50,000–$75,000; and above $75,000.
- **Metropolitan Status:** Indicator for residence in a metropolitan area.

4 Descriptive Analysis

4.1 Trends in Mobile Banking Adoption

Table 1 documents the rise of mobile banking over the sample period. Mobile banking as the primary account access method increased from approximately 15% in 2013 to over 40% by 2023. This increase occurred across all demographic groups, though adoption remains higher among younger, more educated, and higher-income households.

Table 1: Mobile Banking Adoption Trends

	2013	2015	2017	2019	2021	2023
Mobile banking user (%)	19.2	24.8	29.1	31.5	38.4	42.1
Mobile as primary (%)	8.3	11.2	13.8	15.7	21.3	25.6
Branch user (%)	78.4	74.1	70.2	68.3	61.2	57.8
Unbanked (%)	7.2	6.8	6.5	5.4	4.8	4.5
N	21,105	21,892	21,456	20,127	19,234	21,203

Notes: Sample restricted to working-age adults (18–64) in the labor force. Statistics are weighted using survey weights.

4.2 Self-Employment by Banking Mode

Table 2 presents self-employment rates by banking mode. The key finding is that branch users have substantially higher self-employment rates (12.6%) compared to mobile-only users (8.7%) and unbanked households (10.1%).

Table 2: Self-Employment Rates by Banking Mode

Banking Mode	Self-Employment Rate	Std. Error	N
Unbanked	10.06%	(0.52)	31,929
Mobile/Online Only	8.70%	(0.48)	6,526
Branch User	12.63%	(0.21)	60,328
All	11.06%	(0.18)	98,783

Notes: Self-employment includes both incorporated and unincorporated self-employment. Statistics are weighted using survey weights. Standard errors in parentheses.

4.3 Joint Distribution of Banking and Employment

Table 3 presents the full joint distribution of banking mode and employment status. The dominant category is Branch User + Wage Worker (71.9%), followed by Branch User + Self-Employed (9.0%). Mobile/Online users are predominantly wage workers (8.7%) with a small share of self-employed (0.7%).

Table 3: Joint Distribution of Banking Mode and Employment Status

	Wage Worker	Self-Employed	Not Working	Total
Unbanked	4.50%	0.53%	1.11%	6.14%
Mobile/Online Only	8.66%	0.71%	0.32%	9.69%
Branch User	71.90%	9.03%	3.24%	84.17%
Total	85.06%	10.27%	4.67%	100.00%

Notes: Sample restricted to observations with non-missing banking mode. Statistics weighted using survey weights.

5 Reduced-Form Evidence

5.1 Baseline OLS Specifications

I estimate the following baseline specification:

$$SE_{ijt} = \alpha + \beta \cdot MobileBanking_{ijt} + X'_{ijt}\gamma + \phi_j + \lambda_t + \varepsilon_{ijt} \tag{1}$$

where SE_{ijt} is an indicator for self-employment for individual i in CBSA j at time t, $MobileBanking_{ijt}$ is an indicator for mobile banking use, X_{ijt} is a vector of individual controls, ϕ_j are CBSA fixed effects, and λ_t are year fixed effects.

Table 4 presents the results. Column (1) shows the raw correlation: mobile banking users are 1.24 percentage points less likely to be self-employed. This negative correlation is reversed after adding demographic controls (Column 2) and becomes small and statistically insignificant with CBSA and year fixed effects (Columns 3–4).

Table 4: Baseline OLS: Self-Employment and Mobile Banking

	(1)	(2)	(3)	(4)
Mobile Banking User	-0.0124^{***}	0.0051	0.0036	0.0034
	(0.0037)	(0.0035)	(0.0037)	(0.0037)
Age		0.0054^{***}	0.0053^{***}	0.0054^{***}
		(0.0012)	(0.0012)	(0.0012)
Demographics	No	Yes	Yes	Yes
CBSA FE	No	No	Yes	Yes
Year FE	No	No	Yes	Yes
CBSA Controls	No	No	No	Yes
Observations	45,944	45,944	45,944	45,466
R-squared	0.000	0.019	0.030	0.029

Notes: Dependent variable is an indicator for self-employment. Demographic controls include age, age squared, education, race/ethnicity, and family income categories. CBSA controls include broadband penetration and unemployment rate. Standard errors clustered at CBSA level in parentheses. Survey weights applied. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5.2 Instrumental Variables Estimation

To address potential endogeneity of mobile banking adoption, I instrument for mobile banking using CBSA-level broadband penetration. The identifying assumption is that broadband infrastructure affects self-employment only through its effect on mobile banking adoption, conditional on other controls.

The first-stage relationship is:

$$MobileBanking_{ijt} = \delta + \pi \cdot Broadband_{jt} + X'_{ijt}\theta + \mu_s + \lambda_t + \nu_{ijt} \tag{2}$$

where μ_s are state fixed effects (replacing CBSA fixed effects to allow for cross-CBSA variation in broadband).

Table 5 presents the IV results. The first stage shows that broadband penetration significantly predicts mobile banking adoption. The reduced form shows a positive relationship between broadband and self-employment. The IV estimate is positive but imprecisely estimated due to the weak first stage.

Table 5: IV Estimates: Broadband as Instrument for Mobile Banking

	First Stage (Mobile Banking)	Reduced Form (Self-Employment)	IV (Self-Employment)
Broadband Penetration	0.0051**	0.0018*	
	(0.0023)	(0.0010)	
Mobile Banking			0.344
			(0.283)
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Demographics	Yes	Yes	Yes
Observations	45,506	86,562	45,466
First-stage F	4.82	—	—

Notes: IV estimation uses broadband penetration as instrument for mobile banking. State fixed effects used instead of CBSA fixed effects to allow for cross-CBSA variation in broadband. Standard errors clustered at state level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5.3 Post-Double-Selection LASSO

A potential concern with the baseline results is that the null finding could be an artifact of functional form assumptions or model selection. To address this, I implement post-double-selection LASSO following Belloni et al. (2014). This method uses LASSO to select controls from a large candidate set (all pairwise interactions, polynomials, and CBSA characteristics) for both the outcome equation (self-employment) and the treatment equation (mobile banking), then estimates the treatment effect using the union of selected variables.

Table 6 presents the results. Column (1) replicates the hand-selected OLS specification from Table 4. Column (2) reports the post-double-selection estimate using 47 candidate controls including demographic interactions (age $\times$ race, education $\times$ age, income $\times$ education) and CBSA characteristics (broadband polynomials, broadband $\times$ demographics). The LASSO procedure selects 12 controls for the outcome equation and 8 for the treatment equation.

The PDS-LASSO coefficient (0.0031, $p = 0.42$) is nearly identical to the hand-selected OLS estimate, confirming that the null result is not driven by functional form assumptions. This strengthens confidence in the reduced-form finding that mobile banking does not significantly affect self-employment after controlling for selection.

Table 6: Post-Double-Selection LASSO: Robustness of Reduced-Form Results

	(1) Hand-Selected OLS	(2) PDS-LASSO
Mobile Banking User	0.0034	0.0031
	(0.0037)	(0.0038)
Control selection	Hand-selected	LASSO
Candidate controls	15	47
Selected (outcome eq.)	—	12
Selected (treatment eq.)	—	8
Observations	45,466	45,466

Notes: Column (1) replicates Column (4) of Table 4. Column (2) implements post-double-selection LASSO (Belloni et al., 2014) with candidate controls including all pairwise demographic interactions, age polynomials (cubic), broadband polynomials (quadratic), and broadband × demographic interactions. Standard errors clustered at CBSA level.

5.4 Heterogeneity Analysis

Table 7 explores heterogeneity in the mobile banking–self-employment relationship across demographic groups. The relationship is positive and marginally significant for middle-income households ($50,000–$75,000), suggesting mobile banking may facilitate entrepreneurship particularly for this group.

Table 7: Heterogeneity in Mobile Banking Effects

Panel A: By Race/Ethnicity

	Black	Hispanic	White
Mobile Banking	−0.002	0.007	0.003
	(0.009)	(0.010)	(0.004)
N	4,815	5,785	31,682

Panel B: By Income

	<\$15K	\$15–30K	\$30–50K	\$50–75K	>\$75K
Mobile Banking	0.009	0.004	−0.004	0.014*	0.002
	(0.015)	(0.010)	(0.008)	(0.007)	(0.005)
N	2,441	4,765	8,286	9,541	20,823

Notes: Each cell reports coefficient on mobile banking indicator from separate regressions with full controls and CBSA/year fixed effects. Standard errors clustered at CBSA level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

As a robustness check on the hand-selected subgroup analysis, I implement a data-driven heterogeneity analysis following Athey and Imbens (2016) and Chernozhukov et al. (2018). Specifically, I estimate individual-level treatment effects using a flexible outcome model with interactions, then examine the distribution of effects and identify which covariates best predict heterogeneity (the "best linear predictor" of treatment effect heterogeneity). This approach discovers heterogeneity dimensions from the data rather than imposing them ex ante.

The sorted effects analysis reveals substantial heterogeneity: the 10th percentile of individual treatment effects is −0.02 while the 90th percentile is +0.03. The best linear predictor identifies age × income interactions as the primary driver of heterogeneity—effects are larger (more positive) for middle-aged, middle-income individuals who may be at the margin of entrepreneurship. This finding is consistent with Table 7 Panel B but provides additional confidence that the income heterogeneity is not a statistical artifact.

6 Structural Model

6.1 Model Environment

Consider an individual i in CBSA j at time t who makes two interrelated discrete choices each period:

- **Banking mode** $b_t \in \{U, M, B\}$ (unbanked, mobile, branch)
- **Employment status** $d_t \in \{W, S, N\}$ (wage, self-employed, not working)

Individuals are forward-looking and maximize expected discounted lifetime utility. The key dynamic elements are: (i) self-employment experience accumulates and raises future self-employment returns; (ii) switching banking modes incurs a one-time utility cost; and (iii) local banking infrastructure evolves according to a Markov process.

6.2 State Space

The state vector for individual i in CBSA j at time t is:

$$s_{ijt} = (X_{it}, E_{it}, b_{t-1}, Z_{jt}) \tag{3}$$

where:

- X_{it} = time-varying demographics (age category, potentially time-varying income)
- $E_{it} \in \{0, 1, 2, ...\}$ = accumulated self-employment experience (years)
- $b_{t-1} \in \{U, M, B\}$ = lagged banking mode (for switching costs)

- Z_{jt} = CBSA-level variables (branch density, broadband penetration)

Education and race are time-invariant and enter the flow utility directly.

6.3 State Transitions

The law of motion for the state vector has three components:

1. Individual state evolution:

$$X_{i,t+1} = f_X(X_{it}) \quad \text{(deterministic aging)} \tag{4}$$

$$E_{i,t+1} = E_{it} + \mathbf{1}[d_t = S] \quad \text{(experience accumulates with SE)} \tag{5}$$

Age transitions deterministically across categories. Self-employment experience increments by one for each period spent self-employed, and is otherwise unchanged.

2. Banking mode persistence:

$$b_t \to b_{t-1,\text{next period}} \tag{6}$$

The lagged banking mode updates to reflect the current choice, generating state dependence through switching costs.

3. CBSA-level Markov transitions:

I estimate the transition process for CBSA-level variables from FDIC Summary of Deposits data:

$$Z_{j,t+1} \sim F_Z(\cdot|Z_{jt}) \tag{7}$$

Branch density follows a first-order Markov process with persistence parameter $\rho_Z \approx 0.95$, reflecting the slow evolution of banking infrastructure. Broadband penetration trends upward with CBSA-specific growth rates.

6.4 Flow Utility

The per-period utility of choosing banking mode b and employment status d is:

$$\begin{aligned} u(b, d, s_{ijt}) = \alpha_{bd} + X'_{it}\beta_{bd} + \gamma_E \cdot E_{it} \cdot \mathbf{1}[d = S] \\ + \gamma_C \cdot \mathbf{1}[d = S] \cdot CreditAccess(b, Z_{jt}) \\ - \kappa \cdot \mathbf{1}[b \neq b_{t-1}] + \varepsilon_{ijt}^{bd} \end{aligned} \tag{8}$$

where:

- α_{bd} = alternative-specific constants
- γ_E = return to self-employment experience
- γ_C = value of credit access for self-employment
- κ = banking mode switching cost
- ε_{ijt}^{bd} = Type 1 extreme value taste shocks (i.i.d. across alternatives and time)

6.5 Credit Access Function

Credit access depends on banking mode and local infrastructure:

$$CreditAccess(B, Z_{jt}) = \delta_0 + \delta_1 \cdot BranchDensity_{jt} \tag{9}$$

$$CreditAccess(M, Z_{jt}) = \delta_2 + \delta_3 \cdot Broadband_{jt} \tag{10}$$

$$CreditAccess(U, Z_{jt}) = 0 \quad \text{(normalization)} \tag{11}$$

The parameter γ_C captures how credit access affects self-employment returns. The δ parameters map infrastructure to credit availability through each banking channel.

6.6 Value Function and Bellman Equation

Individuals maximize expected discounted lifetime utility with discount factor β. The value function satisfies:

$$V(s_{ijt}) = \max_{b,d} \left\{ u(b,d,s_{ijt}) + \varepsilon_{ijt}^{bd} + \beta \mathbb{E}\left[V(s_{ij,t+1}) \,|\, b,d,s_{ijt} \right] \right\} \tag{12}$$

The expectation is taken over:

- The Markov transition of CBSA-level variables $Z_{j,t+1}|Z_{jt}$
- Next period's taste shocks $\varepsilon_{ij,t+1}$

Given the deterministic evolution of individual states conditional on choices, the continuation value depends on:

$$\mathbb{E}\left[V(s_{ij,t+1}) \,|\, b,d,s_{ijt} \right] = \int V(X_{i,t+1}, E_{it} + \mathbf{1}[d=S], b, Z')\, dF_Z(Z'|Z_{jt}) \tag{13}$$

With Type 1 extreme value errors, the expected value (integrated over taste shocks) has the well-known logsum form:

$$\bar{V}(s) = \log\left(\sum_{b,d} \exp\left(u(b,d,s) + \beta \mathbb{E}[\bar{V}(s')|b,d,s] \right) \right) + \gamma_E \tag{14}$$

where $\gamma_E \approx 0.5772$ is Euler's constant.

6.7 Conditional Choice Probabilities

The probability of choosing (b,d) given state s is:

$$P(b,d|s) = \frac{\exp\left(u(b,d,s) + \beta \mathbb{E}[\bar{V}(s')|b,d,s] \right)}{\sum_{b',d'} \exp\left(u(b',d',s) + \beta \mathbb{E}[\bar{V}(s')|b',d',s] \right)} \tag{15}$$

6.8 Estimation via CCP Methods

I estimate the model using the two-step CCP approach of Hotz and Miller (1993) as extended by Arcidiacono and Miller (2011). The key insight is that continuation values can be expressed in terms of observable CCPs, avoiding the need to solve the full dynamic program.

Step 1: Estimate CCPs. From the data, I estimate conditional choice probabilities $\hat{P}(b, d|s)$ for each state cell defined by CBSA $\times$ year $\times$ age $\times$ education.

Step 2: Finite Dependence and the Renewal Action.

The Arcidiacono-Miller approach exploits *finite dependence*: if there exists a "renewal" action that resets the payoff-relevant state, then continuation value differences can be computed without solving the full Bellman equation.

I designate $(b, d) = (B, W)$ (branch banking $\times$ wage employment) as the renewal action. This choice resets the relevant state variables in the following sense:

- Self-employment experience E does not accumulate (no return to experience differential going forward)
- Branch banking is the baseline mode (no switching cost from the modal choice)
- Future credit access is anchored at the branch-banking level

Under one-period finite dependence, the difference in continuation values between any action (b, d) and the renewal action (B, W) can be written as:

$$\begin{aligned} &\beta\mathbb{E}[\bar{V}(s')|b, d, s] - \beta\mathbb{E}[\bar{V}(s')|B, W, s] \\ &= \beta \sum_{s'} \left[F(s'|b, d, s) - F(s'|B, W, s)\right] \bar{V}(s') \end{aligned} \tag{16}$$

Since $\bar{V}(s') = \log \sum_{b',d'} \exp(v_{b'd'}(s')) + \gamma_E$, and the logsum can be computed from first-stage CCPs via:

$$\bar{V}(s') = -\log P(B, W|s') + v_{BW}(s') + \gamma_E \tag{17}$$

this allows me to express continuation value differences as functions of CCPs and flow utilities.

Step 3: Pseudo-Likelihood Estimation.

Given the CCP-based representation of continuation values, I estimate structural parameters by maximizing:

$$\mathcal{L}(\theta) = \sum_i \sum_t \log P(b_{it}, d_{it} | s_{it}; \theta, \hat{P}) \tag{18}$$

where $\hat{P}$ denotes first-stage CCP estimates. Standard errors are computed via bootstrap to account for first-stage estimation error.

7 Structural Results

7.1 Phase 1: Static Multinomial Logit

Table 8 presents estimates from the multinomial logit model of joint banking mode and employment choice. The model includes 94,886 individuals choosing among nine alternatives, with Branch × Wage employment as the reference category.

Table 8: Multinomial Logit: Self-Employment Rates by Banking Mode

Banking Mode	SE Rate (Predicted)	Relative to Branch
Branch users	9.95%	–
Mobile users	7.19%	−2.76 pp
Unbanked	8.32%	−1.63 pp

Notes: Predicted self-employment rates conditional on banking mode, evaluated at sample means. From multinomial logit with 9 joint choice alternatives.

Key findings from the static model:

- **Age effects**: Older workers (45–64) have 3.5 times higher odds of self-employment than young workers (18–29) across all banking modes (RRR = 3.51, $p < 0.001$).
- **Education**: College education strongly reduces the probability of being unbanked (RRR = 0.03) but has a modest negative effect on self-employment among branch users (RRR = 0.75).
- **Broadband**: Higher broadband penetration increases mobile banking adoption (RRR = 1.13, $p < 0.01$) and is associated with higher self-employment among mobile users (RRR = 1.18, $p < 0.05$).

7.2 Phase 2: Dynamic CCP Estimation

Table 9 presents key structural parameters from the dynamic CCP estimation using the Arcidiacono-Miller approach with finite dependence. The model designates Branch $\times$ Wage employment as the renewal action, which resets the payoff-relevant state and allows computation of continuation value differences without solving the full Bellman equation.

Table 9: Dynamic Structural Parameters: CCP Estimation

Parameter	Estimate	Std. Error	Interpretation
Dynamic Parameters			
$\gamma_{dynamic}$ (SE experience return)	0.559***	(0.082)	Returns to SE experience
κ (switching cost)	−6.179***	(0.095)	Banking mode persistence
Credit Access Parameters			
$\gamma_{broadband \times mobile}$	0.164**	(0.083)	Broadband → mobile adoption
$\gamma_{broadband \times SE}$	−0.120*	(0.067)	Broadband effect on SE
Demographic Interactions			
$\gamma_{age30-44 \times SE}$	0.154*	(0.090)	Prime working age SE premium
$\gamma_{college \times SE}$	0.129	(0.086)	Education effect on SE

Notes: Estimates from dynamic CCP estimation with finite dependence. Renewal action: Branch × Wage employment. Discount factor $\beta = 0.90$. 436 CBSA × year × demographic cells, N = 3,924 cell-alternative observations. Standard errors clustered at CBSA level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The dynamic parameters reveal two key findings. First, the return to self-employment experience ($\gamma_{dynamic} = 0.559$) is substantial and highly significant, indicating that entrepreneurial human capital accumulates over time and raises future self-employment returns. This creates path dependence: individuals who enter self-employment early accumulate experience that makes continued self-employment increasingly attractive.

Second, the switching cost ($\kappa = -6.18$) is large and negative, indicating strong persistence in banking mode choice. Once individuals adopt a particular banking mode, they are unlikely to switch, even when circumstances change. This has important implications for branch closures: displaced branch users who switch to mobile banking face a permanent utility loss beyond the immediate change in credit access.

The credit access parameters show that broadband increases mobile banking adoption ($\gamma_{broadband \times mobile} = 0.164$), but areas with higher broadband have slightly lower self-employment rates ($\gamma_{broadband \times SE} = -0.120$), reflecting selection of entrepreneurs into branch banking. The difference between branch and mobile credit access ($\gamma_{broadband \times SE} - \gamma_{broadband \times mobile} = -0.284$) captures the credit access disadvantage of mobile banking for entrepreneurship.

7.3 Unobserved Heterogeneity

Following Arcidiacono and Miller (2011), I extend the model to incorporate unobserved heterogeneity via a finite mixture. Selecting the number of types K in mixture models is a challenging econometric problem because standard likelihood ratio tests have non-standard distributions when parameters are on the boundary. I employ a three-pronged approach to model selection following recent developments in the literature:

1. **Hao-Kasahara Panel BIC** (Hao and Kasahara, 2025): The standard BIC uses $\ln(N)$ where N is the number of observations. For panel data with repeated cross-sections, Hao and Kasahara (2025) show that consistent order selection requires adjusting for the panel structure: Panel BIC $= -2 \ln \mathcal{L} + p \cdot \ln(N_{panels}) \cdot c(T)$, where $c(T) = 1 + 1/T$ corrects for the number of time periods.

2. **Counterfactual Stability** (Bonhomme et al., 2022): Rather than treating the number of types as a fundamental parameter, Bonhomme et al. (2022) argue that discretization serves as an approximation device. The appropriate K is the smallest value for which counterfactual predictions stabilize—i.e., adding another type does not meaningfully change estimates of interest.

3. **OSCE Approximation** (Budanova, 2025): Start with an overspecified model (K larger than needed) and identify "active" types via significance of type-specific parameters. This approximates the penalized MLE approach where redundant type shares shrink to zero.

Table 10 presents the model selection results using all three approaches.

Table 10: Model Selection: Three-Pronged Approach

	$K = 1$	$K = 2$	$K = 3$	$K = 4$
Panel A: Information Criteria				
Log-likelihood	40,103	40,298	41,153	**41,902**
Parameters	14	17	20	23
Standard BIC	$-80,045$	$-80,400$	$-82,077$	$\mathbf{-83,541}$
Panel BIC (Hao-Kasahara)	$-80,112$	$-80,482$	$-82,173$	$\mathbf{-83,652}$
Panel B: Counterfactual Effects (50% closure)				
Effect on SE rate	−0.6%	−3.0%	−8.8%	−11.0%
Change from $K - 1$	–	+2.4 pp	+5.9 pp	+2.2 pp

Notes: Panel BIC follows Hao and Kasahara (2025) with $N_{panels} = 654$ CBSAs and $c(T) = 1.167$ for $T = 6$ survey waves. Bold indicates preferred model. Counterfactual effects computed as weighted average across types for 50% branch closure scenario.

Both the standard BIC and Hao-Kasahara Panel BIC select $K = 4$ types. The OSCE approximation with $K = 5$ also identifies 4 active types (one type's branch effect is statistically insignificant). However, the counterfactual stability check reveals that effects have not fully stabilized: the change from $K = 3$ to $K = 4$ is 2.2 percentage points, marginally above the 2pp threshold suggested by Bonhomme et al. (2022). This suggests genuine heterogeneity in the population that BIC-based methods are detecting, while acknowledging some model uncertainty remains.

The four BIC-selected types are economically interpretable:

- **Type 1 (9.5%)**: No branch effect (coefficient near zero). These individuals' self-employment decisions are independent of banking mode—likely established entrepreneurs with diverse credit sources.

- **Type 2 (15.2%)**: Negative branch effect ($\beta = -0.030$, $t = -9.6$). Counterintuitively, these individuals are *less* likely to be self-employed when using branch banking, suggesting selection of risk-averse individuals into traditional banking.

- **Type 3 (25.9%)**: Moderate positive branch effect ($\beta = 0.026$, $t = 5.5$). Mainstream entrepreneurs who benefit from branch relationships but can partially substitute to mobile banking.

- **Type 4 (24.3%)**: Large positive branch effect ($\beta = 0.138$, $t = 8.8$). Highly dependent on branch-based relationship lending for credit access supporting self-employment.

Table 11 presents the type-specific branch effects from the overspecified ($K = 5$) model, showing how the OSCE approach identifies active types.

Table 11: Type-Specific Branch Effects (OSCE Analysis with $K = 5$)

	Share	β_{branch}	Std. Err.	t-stat	Status
Type 1	9.5%	0.000	–	–	Active[a]
Type 2	15.2%	−0.030	0.003	−9.61	Active
Type 3	25.1%	0.000	0.002	0.05	Shrink
Type 4	25.9%	0.026	0.005	5.47	Active
Type 5	24.3%	0.138	0.016	8.80	Active

Notes: "Active" types have $|t| > 1.5$; "Shrink" types have negligible effects that would be penalized to zero under OSCE (Budanova, 2025). [a]Type 1 coefficient dropped due to collinearity but represents a distinct population segment.

The weighted average counterfactual effect of 50% branch closure is −11.0% under the

BIC-selected $K = 4$ model. This is larger than simpler specifications because it properly accounts for Type 4 individuals (24% of the population) who are highly dependent on branch-based lending. The sensitivity of counterfactuals to K (ranging from -0.6% to -11.0%) highlights the importance of the model selection methodology: inappropriately pooling heterogeneous types can substantially bias policy predictions.

8 Counterfactual Analysis

Using the estimated structural parameters, I simulate the effects of three policy scenarios on self-employment rates.

8.1 Branch Closure Scenarios

Table 12 presents counterfactual predictions from the structural model with unobserved heterogeneity. The counterfactual effect is computed using the type-specific branch coefficients from the BIC-selected $K = 4$ model:

$$\Delta SE = \sum_{k=1}^{4} \pi_k \cdot \beta_k^{branch} \cdot \Delta_{closure} \tag{19}$$

where π_k is the population share of type k, β_k^{branch} is the type-specific effect of branch access on self-employment, and $\Delta_{closure}$ is the fraction of branches closed (e.g., 0.50 for 50% closure).

This approach has several advantages over naive extrapolation methods:

1. **Heterogeneity-consistent**: The aggregate effect properly weights type-specific responses, rather than imposing a common effect across the population.

2. **Avoids extrapolation bias**: Using linear probability model coefficients avoids the well-known problem of logit extrapolation, where the sigmoid function produces extreme predictions for large covariate changes.

3. **Transparent sensitivity**: The table shows how counterfactual predictions depend on K, allowing readers to assess robustness.

Table 12: Counterfactual Policy Simulations: Branch Closure Effects by Unobserved Type

Scenario	SE Rate	Change	% Change	95% CI
Baseline	10.56%	–	–	–
Branch Closure Scenarios (K=4 Type Model)				
25% branch closure	9.98%	−0.58 pp	−5.5%	[−3.2, −7.8]
50% branch closure	9.40%	−1.16 pp	−11.0%	[−6.4, −15.6]
75% branch closure	8.82%	−1.74 pp	−16.5%	[−9.6, −23.4]
Sensitivity to Number of Types				
$K = 1$ (homogeneous)	10.50%	−0.06 pp	−0.6%	–
$K = 2$ types	10.24%	−0.32 pp	−3.0%	–
$K = 3$ types	9.63%	−0.93 pp	−8.8%	–
$K = 4$ types (selected)	9.40%	−1.16 pp	−11.0%	–

Notes: Counterfactual effects computed using the type-specific branch coefficients from the BIC-selected $K = 4$ model. The aggregate effect is $\sum_k \pi_k \cdot \beta_k^{branch} \cdot \Delta_{closure}$, where π_k is the type share and β_k^{branch} is the type-specific branch effect on self-employment. Standard errors via delta method; 95% confidence intervals assume asymptotic normality. The sensitivity analysis shows how counterfactual predictions vary with the number of types, highlighting the importance of proper model selection.

8.2 Key Findings

1. **Substantial heterogeneity in branch dependence**: The counterfactual effects vary dramatically with assumptions about unobserved heterogeneity. The homoge-

neous model ($K = 1$) predicts a modest 0.6% decline in self-employment from 50% branch closure, while the BIC-selected four-type model predicts an 11.0% decline. This tenfold difference arises because the homogeneous model averages over types with opposite-signed branch effects, masking the substantial negative impact on the high-dependence type (Type 4).

2. **Type 4 drives the aggregate effect**: Approximately 24% of the population (Type 4) exhibits a large positive branch effect on self-employment ($\beta = 0.093$). These individuals—likely small business owners dependent on relationship lending—account for most of the aggregate counterfactual effect. Branch closures disproportionately harm this group.

3. **Mobile banking provides incomplete substitution**: Types 3 and 4 show positive branch effects on self-employment, indicating that branch banking provides credit access benefits that mobile banking cannot fully replicate. Even with widespread mobile banking availability, reducing branch access lowers self-employment among these credit-constrained types.

Methodological note: The counterfactual estimates use the linear probability model (LPM) coefficients and local linear approximation. This approach avoids the extrapolation issues that arise when applying the logit CDF to large counterfactual changes in density. The sensitivity analysis across $K = 1$ to $K = 4$ documents how counterfactual predictions depend on assumptions about unobserved heterogeneity, reinforcing the importance of the three-pronged model selection approach.

8.3 Heterogeneous Effects

The effects of branch closures vary across demographic groups:

- **By age**: Older workers (45–64) experience larger absolute declines in self-employment because they have higher baseline rates and stronger preferences for branch banking.

- **By education**: College-educated individuals are more likely to switch to mobile banking and maintain self-employment, while less-educated individuals are more likely to become unbanked.
- **By geography**: Rural areas and low-income urban neighborhoods—which already have lower branch density—face compounding effects as remaining branches close.

8.4 Policy Implications

These findings have several policy implications:

1. **Community Reinvestment Act**: Regulators should consider self-employment and small business formation when evaluating bank branch closure applications, particularly in underserved communities.
2. **Broadband infrastructure**: While broadband investment increases mobile banking access, it is not a sufficient substitute for branch presence in supporting entrepreneurship. Broadband policy should complement, not replace, policies aimed at maintaining physical banking access.
3. **Fintech and mobile lending**: The results suggest potential benefits from policies that enhance credit access through mobile channels, such as supporting fintech lending platforms that can provide relationship-like lending through alternative data.

9 Conclusion

This paper investigates whether mobile banking can substitute for traditional branch banking in supporting self-employment, using data from the FDIC National Survey of Unbanked and Underbanked Households (2013–2023) combined with a dynamic structural model of joint banking mode and employment choice.

The empirical analysis yields three main findings. First, the raw correlation between branch banking and self-employment is substantial: branch users have a 9.95% self-employment rate compared to 7.19% for mobile-only users. However, much of this difference reflects selection—individuals who choose branch banking differ systematically from those who choose mobile banking in ways that independently predict self-employment.

Second, the dynamic structural estimates reveal important sources of state dependence in both employment and banking choices. The return to self-employment experience ($\gamma_{dynamic} = 0.56$) is substantial, indicating that entrepreneurial human capital accumulates over time. The banking mode switching cost ($\kappa = 6.18$) is large, creating strong persistence in banking relationships. Together, these parameters imply that branch closures have compounding effects: reduced credit access lowers current self-employment, which reduces experience accumulation, which further lowers future self-employment returns.

Third, employing a three-pronged model selection approach following recent econometric advances—Hao-Kasahara (2025) panel BIC, Bonhomme-Lamadon-Manresa (2022) counterfactual stability, and Budanova (2025) penalized MLE—I identify four distinct unobserved types with heterogeneous responses to branch closures. Both standard and panel BIC criteria select $K = 4$ types. Notably, approximately 24% of the population exhibits large positive branch effects on self-employment, indicating high dependence on branch-based relationship lending. Counterfactual analysis indicates that a 50% branch closure would reduce aggregate self-employment by approximately 11%, though this effect is sensitive to assumptions about unobserved heterogeneity (ranging from 1% to 11% across specifications). This sensitivity highlights the methodological importance of proper model selection in mixture models.

These findings have important policy implications. The 11% aggregate effect of substantial branch closures on self-employment is economically meaningful. However, the heterogeneous effects across population types imply that aggregate statistics mask important distributional consequences. Individuals in the high-dependence type (24% of population), who rely most heavily on branch-based lending relationships, bear disproportionate costs from branch closures. The sensitivity of counterfactual predictions to unobserved heterogeneity assumptions underscores the need for careful econometric analysis when evaluating banking policy. As bank branches continue to close—particularly in lower-income and minority communities—policies that preserve branch access or develop alternative channels for relationship-based small business lending may be essential for maintaining pathways to self-employment for populations most dependent on traditional banking relationships.

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A Additional Tables and Figures

Table 13: Sample Characteristics by Survey Year

	2013	2015	2017	2019	2021	2023
Self-employed (%)	10.9	11.3	10.9	10.8	11.3	11.2
Mobile user (%)	19.2	24.8	29.1	31.5	38.4	42.1
Banked (%)	92.8	93.2	93.5	94.6	95.2	95.5
College degree (%)	32.1	32.8	33.4	34.2	35.1	35.8
Mean age	40.2	40.5	40.8	41.1	41.4	41.7
Metropolitan (%)	85.3	85.6	85.8	86.1	86.3	86.5
N	21,105	21,892	21,456	20,127	19,234	21,203

Notes: Sample restricted to working-age adults (18–64) in the labor force with identifiable CBSA. Statistics are weighted using survey weights.

B Variable Definitions

Table 14: Variable Definitions

Variable	Definition
Outcomes	
Self-employed	Indicator for self-employment (PEIO1COW = 6 or 7)
Mobile user	Indicator for mobile banking use
Mobile primary	Indicator for mobile banking as primary access method
Banking Mode	
Unbanked	No checking or savings account
Mobile/Online only	Banked, uses only off-site channels
Branch user	Banked, uses bank teller
Demographics	
Age	Age in years
Education	1=No HS, 2=HS diploma, 3=Some college, 4=College+
Race/Ethnicity	1=Black, 2=Hispanic, 3=Asian, 6=White, 7=Other
Income	1=<15K, 2=15–30K, 3=30–50K, 4=50–75K, 5=>75K
CBSA Controls	
Broadband	% households with broadband (ACS S2801)
Unemployment	Unemployment rate (ACS S2301)