

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

Alina Malkova\*

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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. The model identifies three latent types: entrepreneurial (7%), risk-averse (29%), and credit-constrained (64%). The credit-constrained type—representing nearly two-thirds of the population—experiences the largest effects from branch closures, with self-employment declining by 25% under a 50% branch closure scenario. The weighted average effect across types is an 11% decline in self-employment. These findings suggest that branch closures disproportionately harm credit-constrained individuals who rely on relationship lending for entrepreneurial credit access.

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\*Florida Institute of Technology. Email: amalkova@fit.edu

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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:

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

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,  $\phi_j$  are CBSA fixed effects, and  $\lambda_t$  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***<br>(0.0037) | 0.0051<br>(0.0035)    | 0.0036<br>(0.0037)    | 0.0034<br>(0.0037)    |
| Age                 |                        | 0.0054***<br>(0.0012) | 0.0053***<br>(0.0012) | 0.0054***<br>(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:

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

where  $\mu_s$  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<br>(Mobile Banking) | Reduced Form<br>(Self-Employment) | IV<br>(Self-Employment) |
|-----------------------|---------------------------------|-----------------------------------|-------------------------|
| Broadband Penetration | 0.0051**<br>(0.0023)            | 0.0018*<br>(0.0010)               |                         |
| Mobile Banking        |                                 |                                   | 0.344<br>(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 Heterogeneity Analysis

Table 6 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 6: Heterogeneity in Mobile Banking Effects

|                | <i>Panel A: By Race/Ethnicity</i> |                  |                  |
|----------------|-----------------------------------|------------------|------------------|
|                | Black                             | Hispanic         | White            |
| Mobile Banking | −0.002<br>(0.009)                 | 0.007<br>(0.010) | 0.003<br>(0.004) |
| N              | 4,815                             | 5,785            | 31,682           |

  

|                | <i>Panel B: By Income</i> |                  |                   |                   |                  |
|----------------|---------------------------|------------------|-------------------|-------------------|------------------|
|                | <\$15K                    | \$15–30K         | \$30–50K          | \$50–75K          | >\$75K           |
| Mobile Banking | 0.009<br>(0.015)          | 0.004<br>(0.010) | −0.004<br>(0.008) | 0.014*<br>(0.007) | 0.002<br>(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. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

## 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:

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

where:

- $X_{it}$  = time-varying demographics (age category, potentially time-varying income)
- $E_{it} \in \{0, 1, 2, \dots\}$  = 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:**

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

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

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:**

$$b_t \rightarrow b_{t-1, \text{next period}} \quad (6)$$

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:

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

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:

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

where:

- $\alpha_{bd}$  = alternative-specific constants
- $\gamma_E$  = return to self-employment experience
- $\gamma_C$  = value of credit access for self-employment
- $\kappa$  = banking mode switching cost
- $\varepsilon_{ijt}^{bd}$  = 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:

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

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

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

The parameter  $\gamma_C$  captures how credit access affects self-employment returns. The  $\delta$  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  $\beta$ . The value function satisfies:

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

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:

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

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

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

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:

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

## 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:

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

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:

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

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 7 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  $\times$  Wage employment as the reference category.

Table 7: 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 ( $\text{RRR} = 3.51, p < 0.001$ ).
- **Education:** College education strongly reduces the probability of being unbanked ( $\text{RRR} = 0.03$ ) but has a modest negative effect on self-employment among branch users ( $\text{RRR} = 0.75$ ).
- **Broadband:** Higher broadband penetration increases mobile banking adoption ( $\text{RRR} = 1.13, p < 0.01$ ) and is associated with higher self-employment among mobile users ( $\text{RRR} = 1.18, p < 0.05$ ).

## 7.2 Phase 2: Dynamic CCP Estimation

Table 8 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 8: Dynamic Structural Parameters: CCP Estimation

| Parameter                                 | Estimate  | Std. Error | Interpretation                          |
|---|-----------|------------|---|
| <i>Dynamic Parameters</i>                 |           |            |   |
| $\gamma_{dynamic}$ (SE experience return) | 0.559***  | (0.082)    | Returns to SE experience                |
| $\kappa$ (switching cost)                 | -6.179*** | (0.095)    | Banking mode persistence                |
| <i>Credit Access Parameters</i>           |           |            |   |
| $\gamma_{broadband \times mobile}$        | 0.164**   | (0.083)    | Broadband $\rightarrow$ mobile adoption |
| $\gamma_{broadband \times SE}$            | -0.120*   | (0.067)    | Broadband effect on SE                  |
| <i>Demographic Interactions</i>           |           |            |   |
| $\gamma_{age30-44 \times SE}$             | 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  $\times$  Wage employment. Discount factor  $\beta = 0.90$ . 436 CBSA  $\times$  year  $\times$  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 with three latent types. This addresses the concern that individuals may differ in unobservable ways that affect both their banking choices and employment decisions. The three types are characterized as:

- **Type 1 (Entrepreneurial):** High baseline self-employment preference, older, college-educated
- **Type 2 (Risk-Averse):** Low self-employment preference, younger, lower education
- **Type 3 (Credit-Constrained):** High sensitivity to banking mode and credit access

Table 9 presents the estimated type shares and type-specific parameters.

Table 9: Unobserved Heterogeneity: Type-Specific Parameters

|   | Type 1<br>(Entrepreneurial) | Type 2<br>(Risk-Averse) | Type 3<br>(Credit-Constrained) | Weighted<br>Average |
|---|-----------------------------|-------------------------|--------------------------------|---------------------|
| Population share                          | 7.2%                        | 28.9%                   | 63.9%                          | —                   |
| $\gamma_{dynamic}$ (SE experience)        | 0.285                       | 0.472                   | 0.825                          | 0.684               |
| $\gamma_{bb \times SE}$ (credit access)   | 0.515                       | -0.111                  | -0.175                         | -0.097              |
| <i>Counterfactual: 50% Branch Closure</i> |                             |                         |                                |                     |
| SE rate after closure                     | 27.5%                       | 9.5%                    | 8.5%                           | 10.2%               |
| % change from baseline                    | +141%                       | -16.9%                  | <b>-25.2%</b>                  | -10.8%              |

Notes: Type assignment based on observable characteristics (age, education, current employment, banking mode). Parameters estimated via weighted regression with type-probability weights. The credit-constrained type (63.9% of population) experiences the largest decline in self-employment from branch closures.

The results reveal substantial heterogeneity in how branch closures affect different population segments. The credit-constrained type—representing nearly two-thirds of the population—experiences a 25.2% decline in self-employment from 50% branch closure. This group has the highest return to self-employment experience ( $\gamma_{dynamic} = 0.825$ ) but also the strongest negative sensitivity to losing branch access ( $\gamma_{bb \times SE} = -0.175$ ). These are precisely the individuals for whom branch relationships are most valuable for accessing entrepreneurial credit.

In contrast, the entrepreneurial type (7.2% of population) shows resilience to branch closures, likely because they have already accumulated sufficient experience and credit relationships to sustain self-employment through alternative channels. The risk-averse type experiences moderate effects.

The weighted average effect across types (-10.8%) differs from the homogeneous model

estimate ( $-19.3\%$ ), illustrating the importance of accounting for population heterogeneity. The homogeneous model overstates the aggregate effect because it does not account for the entrepreneurial type's ability to adapt to branch closures.

## 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 10 presents counterfactual predictions from the dynamic structural model. The dynamic framework captures three channels through which branch closures affect self-employment:

1. **Static credit access:** Immediate loss of branch-based relationship lending
2. **Dynamic experience effects:** Reduced self-employment entry leads to less experience accumulation
3. **Compounding over time:** Lower experience reduces future self-employment returns, creating a downward spiral

Under 50% branch closure, I assume 80% of displaced branch users switch to mobile banking and 20% become unbanked. The self-employment adjustment incorporates both static credit access differentials and dynamic experience effects.

Table 10: Dynamic Counterfactual Policy Simulations

| Scenario                               | SE Rate | Change   | % Change | Dynamic Multiplier |
|--|---------|----------|----------|--------------------|
| <b>Baseline</b>                        | 11.40%  | —        | —        | —                  |
| <i>Branch Closures (Dynamic Model)</i> |         |          |          |                    |
| 50% closure                            | 9.20%   | −2.20 pp | −19.3%   | 2.45×              |
| <i>Comparison: Static Model</i>        |         |          |          |                    |
| 50% closure (static)                   | 10.27%  | −0.88 pp | −7.9%    | 1.00×              |

Notes: Dynamic counterfactual predictions based on Arcidiacono-Miller CCP estimates with  $\beta = 0.90$ . Branch closure assumes 80% switch to mobile, 20% become unbanked. Static adjustment factor:  $\exp(\gamma_{bb,SE} - \gamma_{bb,mobile}) = 0.74$ . Dynamic adjustment factor: static  $\times \exp(\gamma_{dynamic} \times (-0.5)) = 0.56$ . Dynamic multiplier shows the ratio of dynamic to static effects.

## 8.2 Key Findings

1. **Dynamic effects substantially amplify branch closure impacts:** The dynamic model predicts a 19.3% decline in self-employment from 50% branch closure, compared to only 7.9% in the static model—a **dynamic multiplier of 2.45**. This amplification occurs because branch closures not only reduce current self-employment but also reduce experience accumulation, which lowers future self-employment returns through the  $\gamma_{dynamic}$  channel.
2. **Path dependence creates persistent effects:** The large switching cost ( $\kappa = -6.18$ ) means that individuals displaced from branch banking are unlikely to return even if branches reopen. Combined with reduced experience accumulation, this creates hysteresis: temporary branch closures can have permanent effects on local entrepreneurship rates.

**3. Mobile banking cannot substitute for branches:** The credit access differential ( $\gamma_{bb,SE} - \gamma_{bb,mobile} = -0.28$ ) means that even perfect mobile banking access cannot replicate the relationship lending that supports small business formation. The dynamic framework reveals that this gap compounds over time as entrepreneurs accumulate less experience.

### 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, the model with unobserved heterogeneity identifies three distinct population types with very different responses to branch closures. The credit-constrained type—representing 64% of the population—experiences a 25% decline in self-employment from 50% branch closure. These individuals have the highest returns to self-employment experience but are most dependent on branch relationships for credit access. In contrast, the entrepreneurial

type (7% of population) shows resilience, likely because they have already accumulated sufficient experience and alternative credit relationships. The weighted average effect across types is an 11% decline in self-employment, with substantial heterogeneity around this mean.

These findings have important policy implications. As bank branches continue to close—particularly in lower-income and minority communities—policymakers should recognize that the effects are highly heterogeneous. Credit-constrained individuals, who are disproportionately represented in underserved communities, bear the largest burden of branch closures. Mobile banking and broadband investment cannot offset these effects because they cannot replicate the relationship lending that supports small business formation for credit-constrained entrepreneurs. Policies that preserve branch access in underserved communities, or that develop alternative channels for relationship-based small business lending, may be essential to maintaining pathways to self-employment for populations most dependent on traditional banking relationships.

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## A Additional Tables and Figures

Table 11: 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 12: Variable Definitions

| Variable             | Definition  |
|----------------------|---|
| <i>Outcomes</i>      |   |
| 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 |
| <i>Banking Mode</i>  |   |
| Unbanked             | No checking or savings account                        |
| Mobile/Online only   | Banked, uses only off-site channels                   |
| Branch user          | Banked, uses bank teller                              |
| <i>Demographics</i>  |   |
| 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          |
| <i>CBSA Controls</i> |   |
| Broadband            | % households with broadband (ACS S2801)               |
| Unemployment         | Unemployment rate (ACS S2301)                         |