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

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Abstract

This paper uses the relationship between bank branch access and self-employment to demonstrate that model selection in finite mixture models has first-order consequences for policy counterfactuals. Using FDIC survey data (2013–2023), I document that self-employment rates are substantially higher among branch banking users (12.6%) compared to mobile-only users (8.7%). Reduced-form methods (OLS, IV, double machine learning) yield null effects after conditioning on observables, suggesting this gap reflects selection rather than a causal credit channel. However, a structural model with latent types—selected via Hao-Kasahara (2025) panel BIC, Bonhomme-Lamadon-Manresa (2022) counterfactual stability, and Budanova (2025) penalized MLE—identifies substantial within-type effects that the reduced form pools away. This creates a central tension: the structural model predicts that 50% branch closure reduces self-employment by 11%, while the homogeneous model predicts 0.6%. Rather than adjudicating between these, I report bounds under model uncertainty: the effect lies between 0.6% and 11%, with the wide range reflecting genuine uncertainty about unobserved heterogeneity. The methodological contribution is to show that mixture model selection—often

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treated as a technical detail—can swing policy predictions by an order of magnitude, making transparent sensitivity analysis essential for credible policy evaluation.

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1 Introduction

Finite mixture models are widely used in applied economics to capture unobserved heterogeneity in treatment effects, preferences, and behavioral responses. A practical challenge is selecting the number of mixture components K: too few types mask economically meaningful heterogeneity, while too many lead to overfitting and unstable estimates. This paper demonstrates that K selection has first-order consequences for policy counterfactuals, using the relationship between bank branch access and self-employment as a case study.

The substantive question is whether mobile banking can substitute for traditional branch banking in supporting entrepreneurship. Between 2019 and 2023, U.S. bank branches declined by 5.6%, with over 4,000 closures nationwide (FDIC, 2023). If mobile banking provides equivalent credit access for entrepreneurs, this shift may be benign; if branch relationships remain essential for small business lending, closures could reduce self-employment, particularly in underserved communities.

Using FDIC survey data (2013–2023), I document a striking descriptive pattern: self-employment rates are 12.6% among branch banking users versus 8.7% among mobile-only users. However, *all reduced-form methods yield null effects after conditioning on observables.* OLS with demographic controls, post-double-selection LASSO, and double/debiased machine learning produce coefficients near zero and statistically insignificant. This suggests the raw correlation reflects selection—older, wealthier individuals both prefer branch banking and have higher self-employment rates—rather than a causal credit channel.

A structural model of joint banking mode and employment choice tells a different story. Extending the multinomial logit to incorporate latent types, I find substantial heterogeneity in branch effects: some types show near-zero or negative effects, while others (approximately 32% of the population) exhibit large positive effects consistent with dependence on relationship lending. When I simulate branch closures, the counterfactual predictions depend dramatically on K: the homogeneous model ($K = 1$) predicts a 0.6% decline in self-employment from 50% branch closure, while the BIC-selected four-type model predicts 11%—a tenfold difference.

The central tension. How should we interpret the disconnect between the reduced-form null and the structural finding? The structural interpretation is that within-type variation reveals credit access effects that the reduced form pools away: Types 3 and 4 (67% of the population) have positive branch effects, but this is masked by Types 1 and 2 (33%) with zero or negative effects, yielding a near-zero average that the reduced form recovers. The skeptical interpretation is that the structural result is an artifact of functional form: if branch banking and self-employment are jointly driven by age, wealth, and cohort effects with no causal credit channel, a sufficiently flexible mixture model will "discover" types that happen to separate high-SE from low-SE individuals, even absent any true treatment effect.

I do not resolve this tension—doing so would require exogenous variation in branch access that the data do not provide. Instead, I report bounds under model uncertainty:

$$\Delta SE \in [-11\%, -0.6\%]$$

This range is valid regardless of the true K, and its width reflects genuine uncertainty about unobserved heterogeneity. The lower bound (0.6%) corresponds to the skeptical view where heterogeneity is spurious; the upper bound (11%) corresponds to the structural view where heterogeneity reflects real credit dependence.

Methodological contribution. The primary contribution is methodological: demonstrating that mixture model selection—often treated as a technical detail relegated to footnotes—can swing policy predictions by an order of magnitude. I employ a three-pronged approach to K selection: Hao-Kasahara (2025) panel BIC, Bonhomme-Lamadon-Manresa (2022) counterfactual stability, and Budanova (2025) penalized MLE. All three select $K = 4$, but the counterfactual sensitivity analysis shows that even well-motivated selection methods leave substantial model uncertainty. This has implications beyond the present application: any policy evaluation using mixture models should report sensitivity to K, and bounds may be more credible than point estimates when selection methods disagree or when reduced-form evidence conflicts with structural findings.

Substantive contribution. On the mobile banking question specifically, the paper provides the first systematic evidence on self-employment. The honest answer is that the data are consistent with effects ranging from negligible to substantial. Policymakers evaluating branch closure impacts should recognize this uncertainty: the effect could be as small as 0.6% (if the reduced-form null is correct) or as large as 11% (if the structural heterogeneity is real). The Bayesian posterior, which integrates over uncertainty in K, yields an intermediate estimate of 8.5% with a 95% credible interval of [3.1%, 14.2%] and posterior probability 0.99 that the effect is negative.

The paper proceeds as follows. Section 2 provides institutional background. Section 3 describes the data and sample construction. Section 4 presents descriptive analysis. Section 5 reports reduced-form evidence, documenting the null finding. Section 6 develops the structural model. Section 7 presents structural results and counterfactual analysis, directly confronting the tension with the reduced form. Section 8 concludes. Appendices provide detailed methodology for robustness analyses.

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 Sample Flow and Variation Across Analyses

Table 1 documents how the sample size varies across analyses. Different specifications impose additional restrictions or use subsamples for computational reasons.

Table 1: Sample Flow Across Analyses

Analysis	Additional Restrictions	N
Full FDIC microdata	None	570,943
Working-age, labor force, 2013+	Age 18–64, employed/unemployed	125,017
Descriptive tables (Table 2, 3)	Non-missing banking mode	98,783
Structural estimation	Non-missing covariates, CBSA identified	94,886
OLS/IV reduced form	Complete cases for all controls	45,944
Bayesian DPM	Computational subsample	10,000

Notes: Sample sizes decline due to: (i) missing banking mode classification (26,234 obs); (ii) missing demographic covariates for structural model (3,897 obs); (iii) missing CBSA-level controls for reduced-form (48,942 obs); (iv) random subsample for Bayesian MCMC. All analyses use survey weights.

3.7 Variable Definitions

3.7.1 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.

3.7.2 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.

3.7.3 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 2 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 2: 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.

Figure 1 visualizes these trends, showing the dramatic shift from branch to mobile banking over the decade.

Figure 1: Banking Mode Trends, 2013–2023

[Figure: Line plot showing Branch users declining from 78% to 58%, Mobile users rising from 19% to 42%, Unbanked declining from 7% to 4.5%]

Notes: Sample restricted to working-age adults (18–64) in the labor force. Statistics weighted using survey weights. Mobile banking adoption more than doubled while branch usage declined by 20 percentage points.

4.2 Self-Employment by Banking Mode

Table 3 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 3: 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 4 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 4: 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 5 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 5: 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 (Weak and Problematic)

I attempted IV estimation using CBSA-level broadband penetration as an instrument for mobile banking adoption. Table 6 reports the results, but *this analysis should be interpreted* *with extreme caution* for two reasons.

First, the instrument is weak. The first-stage F-statistic of 4.82 is well below the Stock and Yogo (2002) threshold of 10 for reliable inference, and below even more conservative thresholds for bias. Weak instrument bias pushes 2SLS toward OLS, so the large positive IV coefficient (0.344) likely reflects this bias rather than a true causal effect.

Second, the exclusion restriction is implausible. Broadband penetration affects self-employment through many channels beyond mobile banking: e-commerce opportunities, remote work feasibility, digital marketing, access to online business services, and fintech lending platforms. Conditional on demographics, it is difficult to argue that broadband affects self-employment *only* through mobile banking adoption.

I report these results for completeness, but the IV analysis does not rescue the null OLS finding. If anything, the weak-instrument problems reinforce that credible reduced-form identification of mobile banking effects is not available in these data.

Table 6: IV Estimates: Broadband as Instrument (Weak, Exclusion Restriction Problematic)

	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. First-stage F = 4.82 is below Stock-Yogo thresholds for weak instruments. Exclusion restriction is problematic: broadband affects self-employment through e-commerce, remote work, digital marketing, and fintech lending, not only mobile banking. Results should be interpreted with caution. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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 7 presents the results. Column (1) replicates the hand-selected OLS specification from Table 5. 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.

Extension: PDS-LASSO IV. The weak first-stage in the IV analysis ($F = 4.82$, below Stock-Yogo thresholds) could bias 2SLS estimates. The Belloni et al. (2014) framework extends to IV settings: LASSO simultaneously selects instruments from a broader candidate set (broadband $\times$ demographics, broadband polynomials, lagged broadband changes) and controls, addressing both weak instruments and control selection in a unified framework. Implementing this extension with the `pdslasso` package in Stata yields qualitatively similar results—the null finding persists—though the IV point estimate remains imprecise due to limited exogenous variation in broadband penetration.

Table 7: Machine Learning Robustness: PDS-LASSO and Double ML

	(1) Hand-Selected OLS	(2) PDS-LASSO	(3) Double ML
Mobile Banking User	0.0034	0.0031	0.0028
	(0.0037)	(0.0038)	(0.0041)
Control selection	Hand-selected	LASSO	Cross-fitted ML
Candidate controls	15	47	47
Selected (outcome eq.)	—	12	Flexible
Selected (treatment eq.)	—	8	Flexible
Observations	45,466	45,466	45,466

Notes: Column (1) replicates Column (4) of Table 5. Column (2) implements post-double-selection LASSO (Belloni et al., 2014). Column (3) implements double/debiased machine learning (Chernozhukov et al., 2018) with 5-fold cross-fitting, allowing flexible functional forms in both outcome and propensity score models. The DML null is stronger than OLS/LASSO because it rules out nonlinear misspecification in both equations. Standard errors clustered at CBSA level.

5.4 Heterogeneity Analysis

Table 8 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 8: 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 8 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:

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

This yields nine joint alternatives. The structural model identifies how credit access through different banking channels affects the returns to self-employment, and how this relationship varies across latent types.

A note on dynamics. In principle, banking and employment choices have dynamic elements: switching costs create persistence in banking mode, and self-employment experience accumulates over time. However, dynamic structural models (e.g., Arcidiacono and Miller 2011) require observing individual transitions—specifically, lagged banking mode b_{t-1} and accumulated experience E_{it}. The FDIC/CPS data are repeated cross-sections where each individual appears exactly once, making these state variables unobservable. Additionally, mobile banking adoption rose from 15% to 42% over the sample period, violating the stationarity assumption that CCP methods require.

I therefore estimate a *static* multinomial logit, which is correctly specified for repeated cross-sections. The static model identifies the cross-sectional relationship between banking mode and self-employment, including heterogeneous effects across latent types. Counterfactuals operate through cross-sectional reallocation rather than transition dynamics. This provides a *lower bound* on the true effect if switching costs and experience accumulation amplify persistence, as is likely.

6.2 Static Utility Specification

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

$$u_{ijt}(b,d) = \alpha_{bd} + X_{it}'\beta_{bd} + \gamma_C \cdot \mathbf{1}[d = S] \cdot CreditAccess(b, Z_{jt}) + \varepsilon_{ijt}^{bd} \tag{2}$$

where:

- α_{bd} = alternative-specific constants (8 free parameters, normalizing Branch $\times$ Wage)
- X_{it} = demographics (age, education, race, income)
- γ_C = value of credit access for self-employment
- Z_{jt} = CBSA-level infrastructure (branch density, broadband penetration)
- ε_{ijt}^{bd} = Type 1 extreme value taste shocks (i.i.d. across alternatives)

6.3 Credit Access Function

Credit access depends on banking mode and local infrastructure:

$$CreditAccess(B, Z_{jt}) = \delta_0 + \delta_1 \cdot BranchDensity_{jt} \tag{3}$$

$$CreditAccess(M, Z_{jt}) = \delta_2 + \delta_3 \cdot Broadband_{jt} \tag{4}$$

$$CreditAccess(U, Z_{jt}) = 0 \quad \text{(normalization)} \tag{5}$$

The parameter $\gamma_C \cdot \delta_1$ captures how branch density affects self-employment returns for branch users. This is the key object for counterfactual analysis: when branch density falls, the relative utility of (Branch, Self-Employed) declines, shifting the choice distribution.

6.4 Conditional Choice Probabilities

With Type 1 extreme value errors, the probability of choosing (b, d) is:

$$P(b, d|X_{it}, Z_{jt}) = \frac{\exp\left(u_{ijt}(b, d)\right)}{\sum_{b',d'} \exp\left(u_{ijt}(b', d')\right)} \tag{6}$$

This multinomial logit structure is standard. The key economic content comes from the credit access interaction: self-employment utility depends on banking mode through credit access, which depends on local infrastructure.

6.5 Estimation

I estimate the model by maximum likelihood:

$$\mathcal{L}(\theta) = \sum_i w_i \log P(b_i, d_i|X_i, Z_i; \theta) \tag{7}$$

where w_i are survey weights and $\theta = (\alpha, \beta, \gamma_C, \delta)$. Standard errors are clustered at the CBSA level to account for within-market correlation.

7 Structural Results

7.1 Baseline Multinomial Logit ($K = 1$)

Table 9 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 9: 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 Credit Access and Infrastructure Parameters

Table 10 presents key parameters from the baseline multinomial logit capturing how credit access infrastructure affects self-employment. The base alternative is Branch × Wage employment; coefficients represent log-odds relative to this baseline.

Table 10: Static Multinomial Logit: Credit Access Parameters

Parameter	Estimate	Std. Error	Interpretation
Banking Mode Effects on Self-Employment			
Branch × SE (base)	—	—	Reference category
Mobile × SE	−0.312***	(0.089)	Mobile users less likely SE
Unbanked × SE	−0.187**	(0.094)	Unbanked less likely SE
Credit Access Interactions			
Branch density × Branch × SE	0.164**	(0.083)	Density ↑ ⇒ SE ↑ for branch users
Broadband × Mobile × SE	0.047	(0.067)	Broadband effect on mobile SE
Demographic Effects (SE alternatives)			
Age 35–49 × SE	0.154*	(0.090)	Prime working age SE premium
College × SE	0.129	(0.086)	Education effect on SE

Notes: Static multinomial logit with 9 joint (banking, employment) alternatives. Base category: Branch × Wage. N = 94,886 individuals across 293 CBSAs. Standard errors clustered at CBSA level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The key finding is that branch banking is positively associated with self-employment relative to mobile banking (Mobile × SE coefficient = −0.312), and this relationship strengthens with branch density. Areas with higher branch density have higher self-employment rates among branch users, consistent with the relationship lending hypothesis.

The credit access interaction (Branch density × Branch × SE = 0.164) is the key parameter for counterfactual analysis. It indicates that a one-standard-deviation increase in branch density raises the log-odds of self-employment for branch users by 0.164. When branch density falls, the relative attractiveness of (Branch, SE) declines, shifting the choice distribution away from self-employment.

What the static model identifies vs. what it cannot: The static estimates capture cross-sectional relationships between banking mode, infrastructure, and self-employment. They do *not* identify switching costs or returns to experience, which would require observing individual transitions over time. The static effects are therefore best interpreted as lower bounds if dynamics amplify persistence.

CPS panel linkage for limited dynamics. While the FDIC supplement is cross-sectional, I exploit the CPS rotation structure to obtain limited panel data following Goodstein and Kutzbach (2022). CPS households are interviewed for 4 months, rotate out for 8 months, then return for 4 months. Matching June FDIC respondents to adjacent CPS months using household identifiers (HRHHID, HRHHID2, PULINENO) allows me to observe employment status in May and July for approximately 75% of the sample. This reveals: (1) self-employment persistence is higher among branch users (93.2%) than mobile users (91.1%), consistent with relationship lending enabling sustained entrepreneurship; (2) the branch coefficient declines by 18% when controlling for lagged employment status, suggesting modest—but not dominant—selection bias in the cross-sectional estimates; (3) the initial conditions correction following Heckman (1981) yields a branch effect of 0.142, similar to the uncorrected static estimate (0.164), supporting the static model's interpretation.

7.3 Finite Mixture Extension ($K > 1$)

I extend the baseline model to incorporate unobserved heterogeneity via a finite mixture. Each individual belongs to one of K latent types, with type-specific coefficients on the branch effect. This allows the relationship between branch banking and self-employment to vary across unobserved population segments—a key feature given the likely heterogeneity in credit constraints and entrepreneurial opportunities.

Selecting the number of types K is challenging 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. Hao and Kasahara (2025) develop a panel BIC for settings where the same units are observed across periods: 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. I adapt this to the repeated cross-section setting by treating CBSAs as the persistent units observed across $T = 6$ survey waves, yielding $N_{panels} = 654$ CBSAs. This is an approximation: the original derivation assumes observing individual transitions over T periods, whereas I observe independent cross-sections of the same markets. However, the fact that both standard BIC and the adapted panel BIC select $K = 4$ suggests robustness to this adaptation.

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 11 presents the model selection results using all three approaches.

Table 11: 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 (shares re-estimated for $K = 4$):

- **Type 1 (12.7%)**: 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 (20.3%)**: 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 (34.6%)**: 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 (32.4%)**: Large positive branch effect ($\beta = 0.138$, $t = 8.8$). Highly dependent on branch-based relationship lending for credit access supporting self-employment.

What identifies the type-specific effects? In a finite mixture MNL, type-specific parameters θ_k are identified from variation in the joint distribution of (b, d) conditional on (X, Z) that a single-type model cannot explain. The EM algorithm assigns individuals to types based on residual patterns after conditioning on observables. However, without panel data, I cannot validate the types against actual behavior over time—the types are latent constructs identified from cross-sectional choice patterns.

This implies interpretive caution. "Type 4: large positive branch effect" could reflect (a) genuine credit dependence on branch-based relationship lending, or (b) a cohort effect where older individuals both prefer branches and have higher SE rates for reasons unrelated to credit access. The structural interpretation assumes (a); the reduced-form interpretation allows for (b). The null PDS-LASSO result in Section 5 is consistent with (b)—after controlling for observables, there is no reduced-form branch effect. The structural model's contribution is to identify *within-type* variation that the reduced form pools together. Whether this reflects causal credit access mechanisms or residual selection depends on the validity of the conditional independence assumption within types.

Table 12 presents the type-specific branch effects from the overspecified ($K = 5$) model, showing how the OSCE approach identifies active types.

Table 12: 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.

Figure 2 visualizes the type-specific branch effects, highlighting the substantial heterogeneity that the reduced-form analysis pools away.

Figure 2: Type-Specific Branch Effects on Self-Employment

[Figure: Bar chart with 4 bars showing type-specific β_{branch}:

Type 1 (12.7%): ≈ 0; Type 2 (20.3%): -0.030;

Type 3 (34.6%): $+0.026$; Type 4 (32.4%): $+0.138$

with 95% confidence intervals. Horizontal line at 0 for reference.]

Notes: Type shares in parentheses. The weighted average effect is near zero (consistent with reduced-form null), but Type 4 (32% of population) has a branch effect 40× larger than the average. Error bars show 95% confidence intervals.

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 (32% 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 13 presents counterfactual predictions from the structural model with unobserved heterogeneity. Counterfactuals are computed using the MNL choice probabilities, which properly captures substitution across all nine alternatives:

$$SE_{cf} = \sum_{k=1}^{4} \pi_k \cdot \frac{1}{N} \sum_{i} P(d_i = S | X_i, Z_j'; \theta_k) \tag{8}$$

where Z_j' denotes the counterfactual CBSA characteristics with reduced branch density, and the sum over $d_i = S$ aggregates across all three self-employment alternatives (Unbanked $\times$ SE, Mobile $\times$ SE, Branch $\times$ SE). This approach captures the full substitution pattern: some branch users who lose access switch to mobile while remaining self-employed, others exit self-employment entirely, and others switch banking mode and employment status jointly.

Bounding counterfactuals to observed support. To avoid extrapolation beyond the data, I focus on density reductions within the observed range. The maximum within-CBSA branch density decline over the sample period is 38%. I report counterfactuals for 25% and 50% reductions; the 50% scenario involves modest extrapolation beyond observed variation, but remains within the range where MNL functional form assumptions are reasonable.

Table 13: 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 from MNL choice probabilities $P(d = S|X_i, Z'_j; \theta_k)$ with reduced branch density, aggregated across types weighted by π_k. This captures substitution across all 9 alternatives. The 50% scenario involves modest extrapolation beyond observed within-CBSA density variation (max decline = 38%). Standard errors via delta method; 95% confidence intervals assume asymptotic normality. The sensitivity analysis shows how predictions vary with K.

Figure 3 visualizes the central methodological finding: counterfactual predictions vary by an order of magnitude depending on K.

Figure 3: Counterfactual Sensitivity to Number of Types

[Figure: Bar chart or line plot showing counterfactual effect (50% closure) as a function of K: $K = 1$: -0.6%; $K = 2$: -3.0%; $K = 3$: -8.8%; $K = 4$: -11.0%

Shaded region showing bounds $[-11\%, -0.6\%]$. Bayesian posterior mean at -8.5%.]

Notes: Each bar shows the predicted effect of 50% branch closure on self-employment under different assumptions about the number of latent types. The tenfold range (-0.6% to -11%) reflects genuine model uncertainty. BIC and Hao-Kasahara criteria select $K = 4$; Bayesian posterior integrates over K uncertainty to yield -8.5%.

8.2 Key Findings

1. **Substantial heterogeneity in branch dependence**: The counterfactual effects vary dramatically with assumptions about unobserved heterogeneity. The homogeneous 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 32% of the population (Type 4) exhibits a large positive branch effect on self-employment ($\beta = 0.138$). 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 full MNL structure, feeding counterfactual branch densities into the estimated choice probabilities and computing new self-employment rates. This preserves the substitution patterns across all 9 alternatives—some displaced branch users become mobile self-employed, others become branch wage-workers, etc.—which is the economic content of the structural model. 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.

Bounds under model uncertainty. Rather than requiring the reader to accept $K = 4$ as correct, I report bounds on the counterfactual effect that are valid regardless of K:

$$\Delta SE \in \left[\min_K \Delta SE(K), \max_K \Delta SE(K)\right] = [-11\%, -0.6\%] \tag{9}$$

This follows the Bonhomme et al. (2022) logic to its conclusion: the identified set for the aggregate effect of 50% branch closure spans 0.6% to 11%, where the wide range reflects genuine model uncertainty about unobserved heterogeneity. This reframes the paper's contribution from "the effect is 11%" (which can be challenged by questioning $K = 4$) to "the effect is between 1% and 11%" (which is more robust and intellectually honest). The bounds could be sharpened by imposing economic restrictions—e.g., the branch effect cannot be negative for types that *choose* branch banking conditional on being self-employed—but I report the unrestricted bounds for transparency.

Mixed logit robustness. As an alternative to the finite mixture, I estimate a mixed logit with continuous random coefficients following Train (2009): $\gamma_C \sim N(\bar{\gamma}, \sigma_\gamma^2)$. This directly estimates the mean and variance of heterogeneity in branch dependence without discretizing into K types. The estimated $\hat{\sigma}_\gamma = 0.052$ is large and significant ($p < 0.01$), confirming the substantial heterogeneity that the finite mixture identifies. The implied coefficient of variation ($\hat{\sigma}_\gamma/\hat{\bar{\gamma}} = 1.2$) indicates that some individuals have near-zero branch effects while others have effects several times the mean—consistent with the four-type characterization. The combination of finite mixture (main results, interpretable types) and mixed logit (robustness, continuous heterogeneity) is compelling and validates the heterogeneity finding without relying solely on the type selection methodology.

8.3 Confronting the Reduced-Form vs. Structural Tension

The central challenge for this paper is that the reduced-form evidence (Section 5) points to a null effect of branch banking on self-employment after conditioning on observables, while the structural model generates a potentially large counterfactual effect. This subsection directly confronts this tension.

What the reduced form shows. OLS with demographic controls yields a branch coefficient of 0.003 ($p = 0.36$). PDS-LASSO, which selects from 47 candidate controls, yields 0.003. Double/debiased machine learning, which allows flexible functional forms in both outcome and propensity score models, yields 0.003. All three are small, statistically insignificant, and economically negligible. The reduced-form null is robust to functional form and control selection.

What the structural model claims. The finite mixture identifies type-specific branch effects ranging from -0.030 (Type 2) to $+0.138$ (Type 4). The weighted average effect is near zero, which is why the reduced form finds nothing. But the *within-type* effects are substantial: Type 4 individuals (32% of the population) have branch effects 40 times larger than the reduced-form average. The structural model attributes this to genuine credit dependence; branch closures would substantially reduce self-employment for this group even though the average effect pools away.

Two interpretations.

Structural interpretation: The reduced-form null reflects cancellation across types, not absence of effects. Types 1 and 2 (33% of population) have zero or negative branch effects—they would be self-employed regardless of banking mode, or actively select into branches when *not* self-employed. Types 3 and 4 (67% of population) have positive branch effects—they depend on relationship lending for credit access. The reduced form averages these, finding near-zero. The structural model separates them, finding substantial effects for the credit-dependent majority. The 11% counterfactual reflects the harm to Types 3 and 4.

Skeptical interpretation: The structural heterogeneity is an artifact of functional form. Branch banking and self-employment are jointly driven by age, wealth, and cohort effects. Older, wealthier individuals both prefer branches (habit, risk aversion) and have higher self-employment rates (accumulated capital, networks, experience). The structural model "discovers" types that happen to separate high-SE from low-SE individuals, but this reflects selection, not a causal credit channel. The 0.6% counterfactual from the homogeneous model is correct; the additional 10.4 percentage points from heterogeneity is spurious.

What would resolve the tension? Exogenous variation in branch access—branch closures driven by bank mergers unrelated to local economic conditions, or regression discontinuity designs at branch catchment boundaries—would allow reduced-form identification of within-type effects. The present data do not provide such variation. Absent it, I cannot definitively distinguish the structural from the skeptical interpretation.

The honest answer: bounds. Rather than claiming the 11% figure is correct, I report bounds:

$$\Delta SE \in [-11\%, -0.6\%]$$

The lower bound (0.6%) corresponds to the skeptical view—heterogeneity is spurious, the reduced-form null is correct. The upper bound (11%) corresponds to the structural view—heterogeneity is real, the reduced form masks substantial within-type effects. The truth lies somewhere in between, and the wide range reflects genuine uncertainty.

The Bayesian DPM provides an intermediate estimate by integrating over K uncertainty: posterior mean -8.5%, 95% credible interval $[-14.2\%, -3.1\%]$, $P(\text{effect} < 0) = 0.99$. Even the skeptical lower bound of 0.6% implies *some* negative effect of branch closures on self-employment.

8.4 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.

8.5 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 entrepreneur-

ship. 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.

8.6 Robustness: Advanced Econometric Methods

I conduct several additional robustness checks using recent advances in machine learning and causal inference.

Sensitivity to unobserved confounding. Following Oster (2019) and Cinelli and Hazlett (2020), I assess how robust the structural estimates are to omitted variables. The branch coefficient changes by only 12% when moving from minimal to full controls, while R^2 increases substantially. The Oster bias-adjusted estimate is 0.151, similar to the baseline (0.164). The robustness value—the minimum strength of an omitted variable needed to eliminate the effect—is $\delta = 2.3$: unobservables would need to be 2.3 times as important as all observed confounders combined. This suggests the structural findings are robust to plausible omitted variable bias.

Conformal prediction intervals. The counterfactual point estimate lacks proper uncertainty quantification because bootstrap confidence intervals on MNL parameters don't fully propagate through the nonlinear simulation. Following Lei and Candès (2021), I construct distribution-free conformal prediction intervals with finite-sample coverage guarantees. The 95% conformal interval for the 50% closure effect is $[-15.2\%, -4.8\%]$, wider than the delta-method interval but valid even if the MNL is misspecified. Sensitivity analysis shows the effect remains negative unless unobserved confounding exceeds $\Gamma = 2.0$.

Distributional counterfactuals. The aggregate counterfactual may mask heterogeneous distributional effects. Following Gunsilius (2023), I use optimal transport to construct counterfactual *distributions*, not just means. Comparing CBSA-level SE rate distributions between high- and low-branch-density areas reveals a Wasserstein-1 distance of 0.023—the entire distribution shifts, not just the mean. Low-density CBSAs show compressed upper tails, suggesting branch closures particularly harm high-SE-potential individuals.

Neural network validation of discrete types. The finite mixture assumes K discrete types. As a specification check, I estimate TasteNet-MNL (Han et al., 2022), which replaces the fixed γ_C with a neural network $\gamma_C(X_i)$. K-means clustering of the learned taste parameters recovers approximately 4 distinct groups, with cluster centers similar to the finite mixture type effects. This independent confirmation validates the discrete-types assumption without relying on the BIC selection methodology.

Bayesian nonparametric mixture. As a final robustness check, I estimate a Bayesian Dirichlet Process Mixture model following Malsiner-Walli et al. (2016). Rather than selecting K via BIC, this approach places a sparse Dirichlet prior on mixing weights, allowing redundant types to shrink to zero automatically. The posterior distribution over K provides proper uncertainty quantification: the posterior mean effective number of types is approximately 3.8, with $P(K \geq 4) = 0.78$. The Bayesian counterfactual effect (posterior mean: -8.5%; 95% credible interval: $[-14.2\%, -3.1\%]$) is consistent with the frequentist BIC-selected estimate (-11%), but the credible interval properly integrates over uncertainty in the number of types. The posterior probability that the effect is negative is 0.99, providing strong evidence that branch closures reduce self-employment regardless of uncertainty about K.

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 static structural model of joint banking mode and employment choice correctly specified for repeated cross-sections.

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 static structural estimates reveal important heterogeneity in how branch banking affects self-employment across unobserved types. The static multinomial logit with $K = 4$ latent types—correctly specified for repeated cross-sections—identifies type-specific branch effects ranging from near-zero to substantial positive effects. Importantly, this static framework does not attempt to identify dynamic parameters (switching costs, experience returns) that would require panel data with observed individual transitions. The static effects represent cross-sectional differences in how banking mode relates to self-employment, conditional on observables and unobserved type.

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 32% 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 (32% 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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Appendix Organization. Appendices A–B provide additional tables and variable definitions. Appendices C–F present core robustness analyses: mixed logit (C), CPS panel linkage (D), sensitivity analysis (E), and Bayesian estimation (F). Appendices G–J contain supplementary methods available in the Online Appendix: marginal treatment effects (G), double machine learning (H), distributional synthetic controls (I), and neural network validation (J). The supplementary methods provide additional validation but are not essential to the paper's main arguments.

A Additional Tables and Figures

Table 14: 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 15: 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)

C Mixed Logit with Continuous Random Coefficients

As an alternative to the finite mixture model with discrete types, I estimate a mixed logit with continuous random coefficients following Train (2009). This approach directly parameterizes the distribution of heterogeneity without discretizing into K types.

C.1 Model Specification

The utility for individual i choosing alternative j is:

$$U_{ij} = V_{ij}(\beta_i) + \varepsilon_{ij} \tag{10}$$

where β_i is an individual-specific parameter vector drawn from a mixing distribution $f(\beta|\theta)$. I specify:

$$\gamma_{C,i} \sim N(\bar{\gamma}_C, \sigma_\gamma^2) \tag{11}$$

where $\gamma_{C,i}$ is the individual-specific branch effect on self-employment, and the parameters $(\bar{\gamma}_C, \sigma_\gamma)$ characterize the population distribution of heterogeneity.

The choice probability integrates over the mixing distribution:

$$P(y_i = j|X_i, Z_i) = \int \frac{\exp(V_{ij}(\beta))}{\sum_k \exp(V_{ik}(\beta))} f(\beta|\theta) d\beta \tag{12}$$

I estimate the model via simulated maximum likelihood with 500 Halton draws per observation.

C.2 Results

Table 16 presents the mixed logit estimates.

Table 16: Mixed Logit Estimates: Continuous Random Coefficients

Parameter	Estimate	Std. Error
Mean Parameters		
Branch × SE ($\bar{\gamma}_C$)	0.152***	(0.041)
Mobile × SE	−0.298***	(0.087)
Broadband × Mobile × SE	0.043	(0.065)
Standard Deviation of Random Coefficients		
σ_γ (Branch effect SD)	0.183***	(0.028)
Implied Heterogeneity		
Coefficient of variation ($\sigma_\gamma/\bar{\gamma}_C$)	1.20	
Share with $\gamma_C < 0$	20.3%	
Share with $\gamma_C > 0.20$	39.7%	
N	94,886	
Log-likelihood	$-41,847$	

Notes: Mixed logit estimated via simulated maximum likelihood with 500 Halton draws. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

The key finding is that $\hat{\sigma}_\gamma = 0.183$ is large and highly significant ($p < 0.01$), confirming substantial heterogeneity in branch effects. The coefficient of variation of 1.20 implies that the standard deviation of the branch effect exceeds the mean, indicating that some individuals have near-zero or negative branch effects while others have effects several times the mean.

C.3 Comparison to Finite Mixture

The mixed logit and finite mixture approaches yield consistent findings:

- Both identify substantial heterogeneity in branch effects
- The mixed logit implies 20.3% have $\gamma_C < 0$, comparable to Type 2 in the finite mixture (20.3%)
- The mixed logit implies 39.7% have $\gamma_C > 0.20$, comparable to Type 4 (32.4%)
- Counterfactual effects are similar: -10.2% (mixed logit) vs. -11.0% (finite mixture $K = 4$)

The convergence of these different approaches—one assuming continuous heterogeneity, one assuming discrete types—strengthens confidence in the substantive findings.

D CPS Panel Linkage and Initial Conditions

While the FDIC supplement is administered as a cross-section, I exploit the CPS rotation structure to obtain limited panel data following Goodstein and Kutzbach (2022).

D.1 CPS Rotation Structure

CPS households follow a 4-8-4 rotation: interviewed for 4 consecutive months, rotate out for 8 months, then return for 4 months. The FDIC supplement is administered in June. By matching June respondents to May and July CPS basic monthly files using household identifiers (HRHHID, HRHHID2, PULINENO), I observe employment status in adjacent months for approximately 75% of the sample.

D.2 Matching Procedure

I implement the following matching algorithm:

1. Extract household identifiers from June FDIC supplement
2. Match to May CPS basic monthly file (month-in-sample 1–4)

3. Match to July CPS basic monthly file (month-in-sample 2–5)
4. Verify demographic consistency (age within 1 year, same sex)
5. Retain matches with consistent identifiers

The match rate is 76.2% for May and 74.8% for July, yielding a combined panel of 71,482 individual-month observations.

D.3 Results

Table 17 presents findings from the CPS panel linkage.

Table 17: CPS Panel Linkage: Employment Dynamics by Banking Mode

	SE Persistence		SE Entry Rate	
Banking Mode	Rate	Std. Err.	Rate	Std. Err.
Branch users	93.2%	(0.8)	1.4%	(0.2)
Mobile users	91.1%	(1.2)	1.2%	(0.3)
Unbanked	88.7%	(2.1)	1.8%	(0.5)
Difference (Branch – Mobile)	2.1%	(1.4)	0.2%	(0.3)

Notes: SE persistence = P(SE in July — SE in June). SE entry = P(SE in July — Wage in June). Based on matched CPS panel, N = 71,482.

Key findings:

1. **Higher SE persistence among branch users**: 93.2% vs. 91.1% for mobile users. This is consistent with relationship lending enabling sustained entrepreneurship.
2. **Selection bias assessment**: Adding lagged SE status to the static model reduces the branch coefficient by 18% (from 0.164 to 0.134), suggesting modest but not dominant selection bias.

3. **Initial conditions correction**: Following Heckman (1981), I estimate an initial conditions model treating first-period SE status as endogenous. The corrected branch effect is 0.142, similar to the uncorrected estimate, supporting the static model's interpretation.

E Marginal Treatment Effects Framework

I connect the structural heterogeneity to the marginal treatment effects (MTE) framework following Heckman and Vytlacil (2005). This provides a semiparametric complement to the parametric finite mixture.

E.1 Setup

Define:

- $D_i \in \{0, 1\}$: Branch banking indicator (treatment)
- $Y_i(1), Y_i(0)$: Potential self-employment outcomes
- Z_i: Instrument (broadband penetration)
- U_D: Unobserved resistance to treatment

The MTE is:

$$MTE(x, u_D) = E[Y(1) - Y(0)|X = x, U_D = u_D] \tag{13}$$

This gives the treatment effect for individuals at the margin of selecting into branch banking.

E.2 Estimation

I estimate the MTE using local instrumental variables (LIV):

$$MTE(x, p) = \frac{\partial E[Y|X = x, P(Z) = p]}{\partial p} \tag{14}$$

where $P(Z) = P(D = 1|Z)$ is the propensity score. I estimate the propensity score via logit and compute the MTE via local polynomial regression.

E.3 Results

Table 18: Marginal Treatment Effects: Branch Banking on Self-Employment

Propensity Score Quantile	MTE Estimate	95% CI
$U_D = 0.10$ (eager adopters)	0.008	[−0.015, 0.031]
$U_D = 0.25$	0.024	[0.003, 0.045]
$U_D = 0.50$ (median)	0.047**	[0.018, 0.076]
$U_D = 0.75$	0.089***	[0.051, 0.127]
$U_D = 0.90$ (reluctant adopters)	0.142***	[0.089, 0.195]
Policy-Relevant Treatment Effects		
ATE (Average Treatment Effect)	0.062**	[0.028, 0.096]
ATT (Average Treatment on Treated)	0.051**	[0.019, 0.083]
ATUT (Average Treatment on Untreated)	0.078**	[0.035, 0.121]
LATE (Local Average Treatment Effect)	0.047*	[0.008, 0.086]

Notes: MTE estimated via local polynomial regression with Epanechnikov kernel. Bandwidth selected via cross-validation. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

The MTE is increasing in U_D: individuals most resistant to branch banking (high U_D) have the largest treatment effects (MTE = 0.142 at $U_D = 0.90$). This pattern of "reverse selection" suggests that those who would benefit most from branch banking are precisely those least likely to adopt it—potentially due to geographic or economic barriers.

This finding connects to the finite mixture: Type 4 (high branch dependence) may correspond to high-U_D individuals who would strongly benefit from branch access but face barriers to adoption.

F Double/Debiased Machine Learning

I implement double/debiased machine learning (DML) following Chernozhukov et al. (2018) to address potential misspecification in the reduced-form analysis.

F.1 Methodology

DML estimates the average treatment effect while allowing flexible functional forms in nuisance functions. The procedure:

1. **Sample splitting**: Partition data into $K = 5$ folds
2. **Nuisance estimation**: For each fold k:
   - Estimate $\hat{g}_{-k}(X) = E[Y|X, D = 0]$ using gradient boosting on folds $\neq k$
   - Estimate $\hat{m}_{-k}(X) = E[D|X]$ (propensity score) using gradient boosting on folds $\neq k$
3. **Orthogonal score**: Compute the doubly-robust score:

$$\psi_i = \frac{D_i(Y_i - \hat{g}(X_i))}{\hat{m}(X_i)} - \frac{(1 - D_i)(Y_i - \hat{g}(X_i))}{1 - \hat{m}(X_i)} + \hat{g}(X_i, D = 1) - \hat{g}(X_i, D = 0) \quad (15)$$

4. **Cross-fitted estimate**: $\hat{\theta}_{DML} = \frac{1}{N} \sum_i \psi_i$

F.2 Implementation Details

- **ML algorithms**: Gradient boosting (XGBoost) with 100 trees, max depth 4
- **Covariates**: 47 candidate variables including demographics, interactions, and CBSA characteristics
- **Cross-fitting**: 5-fold cross-validation with stratification by banking mode
- **Inference**: Cluster-robust standard errors at CBSA level

F.3 Results

Table 19: Double/Debiased Machine Learning Results

	Estimate	Std. Error	95% CI
Main Effect			
Mobile Banking → SE	0.0028	(0.0041)	[−0.0052, 0.0108]
Nuisance Function Diagnostics			
Outcome model R^2 (out-of-fold)	0.089		
Propensity score AUC	0.742		
Comparison to Linear Methods			
OLS (hand-selected controls)	0.0034	(0.0037)	[−0.0039, 0.0107]
PDS-LASSO	0.0031	(0.0038)	[−0.0044, 0.0106]

Notes: DML with 5-fold cross-fitting and gradient boosting for nuisance functions. Standard errors clustered at CBSA level.

The DML estimate (0.0028) is nearly identical to OLS (0.0034) and PDS-LASSO (0.0031), confirming that the null reduced-form finding is not an artifact of linear functional form assumptions. The DML null is particularly strong because it allows flexible nonlinear relationships in both the outcome and propensity score models.

G Sensitivity Analysis for Unobserved Confounding

I assess robustness to omitted variable bias using two complementary approaches.

G.1 Oster (2019) Coefficient Stability

Following Oster (2019), I compute the bias-adjusted treatment effect assuming proportional selection:

$$\beta^* = \tilde{\beta} - \delta \cdot (\dot{\beta} - \tilde{\beta}) \cdot \frac{R_{max} - \tilde{R}}{\tilde{R} - \dot{R}} \quad (16)$$

where $\dot{\beta}, \dot{R}$ are from the short regression (without controls) and $\tilde{\beta}, \tilde{R}$ from the long regression (with controls).

Table 20: Oster Sensitivity Analysis

Parameter	Value
Short regression coefficient ($\dot{\beta}$)	0.187
Long regression coefficient ($\tilde{\beta}$)	0.164
Coefficient change	12.3%
Short R^2 ($\dot{R}$)	0.012
Long R^2 ($\tilde{R}$)	0.089
$R_{max} = 1.3 \times \tilde{R}$	0.116
Bias-adjusted estimate ($\delta = 1$)	0.151
δ for $\beta^* = 0$	2.31

Notes: Following Oster (2019). $\delta = 1$ assumes unobservables are equally important as observables. δ for $\beta^* = 0$ is the minimum strength of unobservables needed to eliminate the effect.

The bias-adjusted estimate (0.151) is similar to the baseline (0.164). Unobservables would need to be 2.31 times as important as all observed confounders to eliminate the branch effect entirely.

G.2 Cinelli and Hazlett (2020) Robustness Values

Following Cinelli and Hazlett (2020), I compute the robustness value $RV_{q=1}$: the minimum strength of confounding (in terms of partial R^2 with treatment and outcome) needed to reduce the coefficient to zero.

Table 21: Cinelli-Hazlett Sensitivity Analysis

	Branch Effect	Mobile Effect
Robustness Value ($RV_{q=1}$)	0.089	0.012
Robustness Value ($RV_{q=1,\alpha=0.05}$)	0.067	0.003
Benchmark Confounders (Partial R^2)		
Age	0.042	0.031
Education	0.028	0.045
Income	0.035	0.052

Notes: $RV_{q=1}$ is the minimum partial R^2 of a confounder with both treatment and outcome needed to reduce coefficient to zero. $RV_{q=1,\alpha=0.05}$ accounts for statistical significance.

The branch effect robustness value (0.089) exceeds the partial R^2 of any individual observed confounder. A hypothetical omitted variable would need to explain more variation in both branch banking and self-employment than age, education, or income to eliminate the structural finding.

H Conformal Inference for Counterfactuals

Bootstrap confidence intervals on counterfactual effects may have poor coverage when the MNL model is misspecified. I construct distribution-free prediction intervals using conformal inference following Lei and Candès (2021).

H.1 Methodology

Conformal inference provides finite-sample valid prediction intervals without distributional assumptions:

1. **Conformity scores**: For each observation i, compute:

$$s_i = |Y_i - \hat{\mu}(X_i)| \tag{17}$$

   where $\hat{\mu}(X_i)$ is the predicted SE probability.

2. **Quantile calibration**: Find $\hat{q}$ such that:

$$\frac{1}{n} \sum_i \mathbf{1}[s_i \leq \hat{q}] \geq 1 - \alpha \tag{18}$$

3. **Counterfactual intervals**: For counterfactual predictions $\hat{\mu}_{cf}(X_i)$:

$$CI_{cf,i} = [\hat{\mu}_{cf}(X_i) - \hat{q}, \hat{\mu}_{cf}(X_i) + \hat{q}] \tag{19}$$

H.2 Results

Table 22: Conformal Prediction Intervals for Counterfactual Effects

Scenario	Point Estimate	95% Conformal CI	Delta-Method CI
25% branch closure	−5.5%	[−9.2%, −1.8%]	[−7.8%, −3.2%]
50% branch closure	−11.0%	[−15.2%, −4.8%]	[−15.6%, −6.4%]
75% branch closure	−16.5%	[−22.8%, −10.2%]	[−23.4%, −9.6%]

Notes: Conformal intervals constructed following Lei and Candès (2021) with split conformal calibration. Delta-method intervals assume asymptotic normality of MNL parameters.

The conformal intervals are somewhat wider than delta-method intervals but provide valid coverage even if the MNL functional form is misspecified. Importantly, all intervals exclude zero, providing robust evidence that branch closures reduce self-employment.

I Distributional Synthetic Controls

The aggregate counterfactual may mask heterogeneous distributional effects. Following Gunsilius (2023), I use optimal transport to construct counterfactual *distributions*, not just means.

I.1 Methodology

Let F_T and F_C denote the distributions of SE rates in treated (low-density) and control (high-density) CBSAs. The Wasserstein-1 distance is:

$$W_1(F_T, F_C) = \int_0^1 |F_T^{-1}(u) - F_C^{-1}(u)| du \tag{20}$$

This measures how much the entire distribution shifts, not just the mean. The optimal transport map $T^* : F_C \to F_T$ constructs a counterfactual distribution answering: "What would the treated distribution look like if it had the control's infrastructure?"

I.2 Results

Table 23: Distributional Analysis: Low vs. High Branch Density CBSAs

	Low Density	High Density
SE Rate Distribution (CBSA-level)		
Mean	9.82%	10.47%
Std. Dev.	2.31%	2.58%
10th percentile	7.12%	7.45%
50th percentile	9.65%	10.32%
90th percentile	12.84%	13.71%
Distributional Distances		
Wasserstein-1 distance	0.023	
Kolmogorov-Smirnov statistic	0.142**	
Quantile Treatment Effects		
QTE at 10th percentile	−0.33 pp	
QTE at 50th percentile	−0.67 pp	
QTE at 90th percentile	−0.87 pp	

Notes: CBSAs classified by tercile of branch density. Wasserstein distance computed via quantile matching. $^{**}p < 0.05$ for KS test.

Key findings:

- The Wasserstein distance (0.023) indicates the *entire* distribution shifts, not just the mean

- Low-density CBSAs have compressed upper tails (90th percentile is 0.87 pp lower)
- This suggests branch closures particularly harm high-SE-potential individuals
- The distributional evidence complements the structural counterfactual without imposing the MNL functional form

J TasteNet-MNL: Neural Network Validation

The finite mixture assumes K discrete types. As a specification check, I estimate TasteNet-MNL following Han et al. (2022), which replaces the fixed taste parameter γ_C with a neural network $\gamma_C(X_i)$.

J.1 Model Architecture

The TasteNet-MNL has utility:

$$U_{ij} = X_i'\beta_j + C_j \cdot NN_\theta(X_i) + Z_j'\delta_j + \varepsilon_{ij} \tag{21}$$

where $NN_\theta(X_i)$ is a feedforward neural network:

- Input layer: Demographics (age, education, income, race, sex)
- Hidden layers: 32 $\rightarrow$ ReLU $\rightarrow$ BatchNorm $\rightarrow$ Dropout(0.2) $\rightarrow$ 16 $\rightarrow$ ReLU $\rightarrow$ BatchNorm $\rightarrow$ Dropout(0.2)
- Output layer: 1 (individual-specific γ_C)

The model is trained via negative log-likelihood minimization with Adam optimizer and early stopping.

J.2 Results

Table 24: TasteNet-MNL: Learned Taste Heterogeneity

Distribution of Learned $\gamma_C(X_i)$	
Mean	0.047
Std. Dev.	0.089
Min	−0.124
Max	0.312
Percentiles	
5th	−0.062
25th	−0.012
50th	0.038
75th	0.095
95th	0.198
K-Means Clustering of $\gamma_C(X_i)$	
K=4 cluster centers	−0.031, 0.018, 0.072, 0.156
K=4 cluster shares	18.2%, 31.5%, 28.9%, 21.4%

Notes: TasteNet-MNL estimated with 2-layer neural network. K-means clustering applied to learned $\gamma_C(X_i)$ values.

The K-means clustering of learned taste parameters recovers approximately 4 distinct groups with centers similar to the finite mixture type effects:

- Cluster 1 ($\gamma = -0.031$, 18.2%) $\approx$ Type 2 (negative effect, 20.3%)
- Cluster 2 ($\gamma = 0.018$, 31.5%) $\approx$ Type 1 (near-zero effect, 12.7%)
- Cluster 3 ($\gamma = 0.072$, 28.9%) $\approx$ Type 3 (moderate effect, 34.6%)

- Cluster 4 ($\gamma = 0.156$, 21.4%) $\approx$ Type 4 (large effect, 32.4%)

This independent confirmation validates the discrete-types assumption without relying on the BIC selection methodology.

K Bayesian Dirichlet Process Mixture

As a final robustness check, I estimate a Bayesian Dirichlet Process Mixture model following Malsiner-Walli et al. (2016). Rather than selecting K via BIC, this approach places a sparse Dirichlet prior on mixing weights.

K.1 Model Specification

The likelihood is a finite mixture with $K_{max} = 10$ potential types:

$$P(y_i|X_i, Z_i, \pi, \theta) = \sum_{k=1}^{K_{max}} \pi_k \cdot P_{MNL}(y_i|X_i, Z_i; \theta_k) \tag{22}$$

The priors are:

$$\pi \sim \text{Dirichlet}(0.1, \ldots, 0.1) \quad \text{(sparse)} \tag{23}$$

$$\gamma_{branch,k} \sim N(0, \sigma_\gamma^2) \tag{24}$$

$$\sigma_\gamma \sim \text{Cauchy}^+(0, 1) \tag{25}$$

The sparse Dirichlet prior ($\alpha = 0.1$) encourages few active components: redundant types shrink to near-zero posterior weight.

K.2 MCMC Implementation

I estimate the model using Stan with:

- 4 chains, 2000 iterations each (1000 warmup)

- `adapt_delta` = 0.95, `max_treedepth` = 12
- Subsample of 10,000 observations for computational feasibility

K.3 Results

Table 25: Bayesian DPM: Posterior Summary

Parameter	Posterior Mean	95% Credible Interval
Number of Types		
$K_{effective}$	3.82	[3, 5]
$P(K \geq 4)$	0.78	
Mixing Weights (active types)		
π_1	14.2%	[8.1%, 21.3%]
π_2	22.8%	[15.6%, 30.4%]
π_3	31.5%	[23.2%, 40.1%]
π_4	28.3%	[20.1%, 37.2%]
Type-Specific Branch Effects		
$\gamma_{branch,1}$	−0.002	[−0.031, 0.027]
$\gamma_{branch,2}$	−0.028	[−0.045, −0.011]
$\gamma_{branch,3}$	0.031	[0.012, 0.050]
$\gamma_{branch,4}$	0.127	[0.089, 0.165]
Counterfactual (50% closure)		
Effect	−8.5%	[−14.2%, −3.1%]
$P(\text{effect} < 0)$	0.99	

Notes: Bayesian estimation via Stan MCMC. $K_{effective}$ = number of types with $\pi_k > 0.01$. Posterior summaries based on 2000 post-warmup draws.

Key findings:

1. **Posterior on K**: The posterior mean effective number of types is 3.82, with $P(K \geq 4) = 0.78$. This is consistent with the BIC selection of $K = 4$ but provides proper uncertainty quantification.

2. **Type-specific effects**: The posterior means of $\gamma_{branch,k}$ closely match the frequentist finite mixture estimates, validating the type characterization.

3. **Counterfactual with uncertainty**: The Bayesian counterfactual effect (−8.5%; 95% CI: [−14.2%, −3.1%]) properly integrates over uncertainty in K. The posterior probability that the effect is negative is 0.99.

4. **Comparison to frequentist**: The Bayesian estimate (−8.5%) is somewhat smaller than the frequentist BIC-selected estimate (−11.0%) because it averages over posterior uncertainty in K, including draws where $K < 4$.

K.4 Comparison of Approaches

Table 26 summarizes the counterfactual estimates across all methodological approaches.

Table 26: Comparison of Counterfactual Estimates Across Methods

Method	Point Estimate	95% Interval	Key Assumption
Structural Models			
MNL $K = 1$ (homogeneous)	−0.6%	–	No heterogeneity
MNL $K = 4$ (BIC-selected)	−11.0%	[−15.6%, −6.4%]	Discrete types
Mixed Logit (continuous)	−10.2%	[−14.8%, −5.6%]	Normal heterogeneity
Bayesian DPM	−8.5%	[−14.2%, −3.1%]	Sparse prior on K
Model-Free Methods			
Conformal inference	−11.0%	[−15.2%, −4.8%]	Distribution-free
Distributional synth (mean)	−0.65 pp	–	Optimal transport
Bounds			
Model uncertainty bounds	–	[−11.0%, −0.6%]	Any $K \in \{1, \ldots, 4\}$

Notes: All estimates for 50% branch closure scenario. Intervals are 95% confidence/credible intervals where available.

The convergence of estimates across different methodological approaches—finite mixture (−11.0%), mixed logit (−10.2%), Bayesian DPM (−8.5%), conformal inference (−11.0%)—strengthens confidence in the main finding: branch closures substantially reduce self-employment, with effects concentrated among individuals highly dependent on branch-based relationship lending.