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Demonetisation, Crime Perception and Welfare: Theory and Evidence from Kenya

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Keywords

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Demonetisation, Crime Perception and Welfare: Theory and Evidence from Kenya*

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1 Introduction

When governments forcibly withdraw physical currency to accelerate the shift toward digital finance, who absorbs the cost? The welfare consequences of policy-induced liquidity shocks are poorly understood in developing economies, where households and firms differ sharply in their access to digital financial infrastructure, and where aggregate output measures mask deep distributional heterogeneity. This paper provides causal empirical evidence and structural general equilibrium analysis demonstrating that the welfare penalty of aggressive monetary contraction operates as a regressive tax whose incidence is governed not by the severity of the aggregate shock, but by the depth and geographic reach of pre-existing digital institutions.

Kenya's 2019 demonetisation provides an ideal laboratory. On June 1, 2019, the Central Bank of Kenya (CBK) announced the withdrawal of the 1,000-shilling note, the highest denomination constituting approximately 80 percent of currency in circulation, granting citizens a strict four-month exchange window. The policy was executed during a period of macroeconomic stability and against a backdrop of a mature, world-leading mobile money ecosystem: by 2019, M-Pesa had achieved roughly 80 percent adult penetration and processed transactions equivalent to 48 percent of GDP (Central Bank of Kenya, 2019). Yet this digital infrastructure was geographically uneven, with agent networks concentrated in urban centres while rural areas remained heavily cash-dependent. This institutional configuration generates the central tension of our analysis: when a digital safety valve exists but is unevenly distributed, a liquidity shock does not affect all households equally, and aggregate indicators can actively mislead about where the true welfare burden falls. Unlike India's 2016 demonetisation (Chodorow-Reich et al., 2020), which unfolded in an environment of limited digital penetration, the Kenyan episode permits us to directly measure who uses the digital buffer and who is left behind.

We address this question through two complementary approaches. Empirically, we exploit repeated cross-sections from the Afrobarometer survey across Rounds 6 through 9 (2014–2021) in a difference-in-differences (DiD) framework, comparing Kenya against West African control countries (Ghana, Senegal, and Côte d'Ivoire) that shared similar macroeconomic trajectories but experienced no demonetisation shock. We document three outcome variables capturing the multidimensional impact of the policy: mobile money adoption, crime perception, and household income status. Theoretically, we develop a micro-founded Two-Agent New Keynesian (TANK) model tailored to a developing economy, incorporating a cash-in-advance (CIA) constraint for financially constrained households and a physical cash working capital constraint (WCC) for informal firms. We calibrate the model separately for national, urban, and rural Kenya, with the elasticity of substitution between cash and digital money as the key spatial parameter.

The empirical results reveal patterns that are simultaneously intuitive and paradoxical. At the aggregate level, demonetisation significantly increased mobile money adoption, improved safety perception, and reduced household income. Beneath these aggregates lie deep spatial and cohort heterogeneities. Urban areas experienced rising digital adoption and large perceived safety gains, but also suffered acute income disruptions. Rural areas experienced a decline in mobile money adoption alongside a mild improvement in safety perceptions and relatively contained income losses. Most strikingly, stratifying by pre-existing technological access reveals that rural cash-only households suffered income shocks more than twice as large as their rural peers with mobile money access, while urban mobile money users emerged as the singular cohort reporting deteriorating safety perceptions despite the aggregate improvement in crime perception. These patterns are precisely identified yet structurally unexplained: reduced-form estimates establish what happened, but cannot establish why.

Answering these questions requires the discipline of a structural general equilibrium framework. The TANK model identifies three mechanisms. The first is a liquidity vacuum. When demonetisation degrades the transaction efficiency of physical cash, informal firms facing a binding physical cash WCC respond by increasing precautionary cash hoarding. This reallocation drains liquidity from the household sector, tightening CIA constraints, depressing consumption, and generating an aggregate recession concentrated in high cash-dependent urban economies. The mechanism generates an endogenous financing premium on informal labour demand and reveals a perverse consequence of the policy: the firms most targeted by the formalisation agenda are precisely those whose defensive behaviour amplifies the aggregate contraction.

The second mechanism is a digital substitution trap. Computing welfare via consumption equivalent variation, which isolates consumption paths by neutralising the mechanical utility gains from involuntary leisure, reveals that rural cash-only households incur the most severe welfare losses (-0.539%), despite facing a shallower aggregate output contraction than urban areas. The mechanism is structural: in rural agricultural economies, physical cash and digital money function as complements rather than substitutes ($\sigma = 0.80$ versus $\sigma = 1.30$ in urban areas), because the local M-Pesa agent network depends on physical cash float that the demonetisation itself destroys. Rural households are therefore fully exposed to the liquidity vacuum with no digital buffer, while urban mobile money users substitute seamlessly to digital platforms and smooth consumption via bond markets. This result challenges a common assumption in the monetary policy literature: the region suffering the deepest aggregate output contraction does not necessarily bear the largest welfare loss.

The third mechanism is a crime perception paradox. We construct a household-specific crime index decomposing perceived safety into three channels: aggregate shadow economy activity, personal target vulnerability from holding physical cash, and localised labour market desperation from wage collapse. Urban mobile money users, already holding minimal physical currency, gain negligible target-reduction benefits from the withdrawal of cash. Their safety perception is instead dominated by the acute wage collapse accompanying the liquidity vacuum, driving perceived crime upward. Cash-only households, in contrast, are forced to rapidly liquidate physical holdings; the sharp reduction in theft exposure overrides the wage desperation effect, generating perceived safety improvements. This mechanism resolves a paradox that is empirically sharp but structurally invisible without a model: why the demographic cohort with the greatest access to digital finance reports the largest deterioration in perceived safety.

This paper makes three contributions. First, it extends the empirical literature on demonetisation (Chodorow-Reich et al., 2020; Kurosaki, 2019) by providing, to our knowledge, the first DiD evidence on a Sub-Saharan African episode, establishing causal effects on mobile money adoption, crime perception, and household income across spatial and technological cohorts. Second, it contributes to the structural macroeconomic literature on financial frictions and informality (Christiano et al., 2005; Ulyssea, 2018; Meghir et al., 2015) by embedding a dual liquidity friction architecture in a TANK framework and showing that aggregate output severity and household welfare losses systematically decouple when digital institutional capacity is geographically uneven. Third, it connects to the criminological economics literature (Wright et al., 2017) by constructing a theory-grounded, household-specific crime perception index that resolves an empirical paradox unexplained by either aggregate crime models or reduced-form estimates alone.

The remainder of the paper proceeds as follows. Section 2 reviews the relevant empirical and theoretical literature. Section 3 provides institutional context and describes the data. Section 4 presents the DiD empirical strategy and results. Section 5 develops the structural TANK model. Section 6 presents calibration, theoretical equivalents, and welfare analysis. Section 7 concludes.

2 Related Literature

This study intersects with three distinct strands of economic literature: the empirical evaluation of demonetisation and digital financial services in developing economies, the theoretical macroeconomic modelling of financial frictions, money demand, and informality, and the criminological economics literature linking cash, income shocks, and crime.

2.1 Empirical Evidence on Demonetisation and Digital Finance

The literature on large-scale, sudden currency withdrawals has expanded significantly following India's 2016 demonetisation. Research on the Indian episode highlights severe, albeit temporary, contractions in economic output, significant disruptions to informal sector employment, and a pronounced shift towards digital payment platforms (Chodorow-Reich et al., 2020; Kurosaki, 2019). These studies consistently document that the immediate effects of demonetisation are contractionary and that the distributional impacts are highly uneven, with cash-dependent households and informal workers bearing disproportionate costs. However, the Indian context differs markedly from the Sub-Saharan African setting in terms of institutional capacity, pre-existing digital infrastructure, and the nature of the informal economy.

In the African context, the literature has historically focused on the organic diffusion of mobile money rather than policy-induced adoption. Foundational work by Jack and Suri (2011) and Suri and Jack (2016) demonstrates that access to M-Pesa in Kenya significantly improved household risk-sharing, consumption smoothing, and financial resilience, ultimately lifting a substantial portion of users out of extreme poverty. Mbiti and Weil (2013) further document the home economics of e-money, noting that the adoption of mobile money involves careful calculations regarding transaction velocity, cash management, and withdrawal fees. Our paper builds upon this literature by examining what occurs when adoption is no longer entirely voluntary but is instead forced by a macroeconomic liquidity shock. By stratifying our empirical sample into mobile money users and cash-only users, we provide direct evidence that the protective benefits of digital finance documented by Suri and Jack (2016) act as a critical buffer during acute monetary contractions.

2.2 Macroeconomic Modelling of Financial Frictions and Informality

To rationalise our empirical findings, we draw on the theoretical literature governing money demand, financial frictions, and the shadow economy. Our structural framework builds upon the classic cash-in-advance literature pioneered by Lucas Jr and Stokey (1987). We adapt this framework to a developing economy setting by allowing physical cash and digital money to serve as imperfect substitutes in satisfying the consumption constraint. This approach aligns with recent advancements in modelling the elasticity of substitution between physical currency and digital payment instruments (Bordo and Levin, 2017), allowing us to formally capture the technological constraints faced by rural populations.

Our model incorporates a working capital constraint on the production side, a mechanism extensively explored by Christiano et al. (2005) to explain the transmission of monetary shocks. We specifically apply this constraint to the informal sector. In developing economies, informal firms cannot access commercial bank overdrafts and are entirely reliant on physical cash to clear daily factor payments. Ulyssea (2018) and Meghir et al. (2015) document the severe frictions and unrecorded costs inherent in informal sector operations. By mandating that informal firms hold physical cash to satisfy their working capital requirements, our model generates an endogenous financing premium on informal labour demand.

We embed these micro-foundations in a TANK framework (Galí et al., 2007; Debortoli and Galí, 2024), which divides households into financially unconstrained savers and hand-to-mouth constrained agents. This structure preserves analytical tractability while capturing the primary axis of distributional heterogeneity during a liquidity shock. Debortoli and Galí (2024) demonstrate that a well-calibrated TANK model replicates the aggregate dynamics of a full heterogeneous agent framework, providing theoretical justification for our approach. The insight that firms engage in precautionary hoarding of monetary assets during liquidity crises echoes findings by Alvarez et al. (2009), who show that agents facing high transaction frictions optimally lower their money velocity and hold precautionary buffer stocks. Together, these micro-foundations allow us to identify the liquidity vacuum mechanism and connect aggregate macro-monetary theory to the highly heterogeneous, micro-level survey responses documented in our difference-in-differences analysis.

2.3 Cash, Income Shocks, and Crime Perception

A growing criminological economics literature establishes that the circulation of physical cash and local labour market conditions are primary determinants of both criminal activity and perceived safety. The foundational framework of Becker (1968) models crime as a rational response to economic incentives, predicting that income shocks and changes in the returns to legitimate activity alter criminal behaviour. Empirical support for this channel is provided by Foley (2011), who documents that daily crime rates in US cities rise systematically as welfare payment cycles deplete household cash, directly linking income desperation to property crime. Watson et al. (2020) extend this analysis to universal cash transfers, finding asymmetric effects: property crime declines when cash holdings increase, but substance-related incidents rise, underscoring that the crime effects of cash depend critically on the direction of the liquidity shock and the type of criminal behaviour being measured.

On the supply side of cash-targeted crime, Wright et al. (2017) provide direct evidence that reducing the physical circulation of cash through the digitisation of social benefit transfers generates significant reductions in cash-targeted street crime. Dalinghaus (2017) further notes that while cash facilitates anonymity for illicit trade, its removal creates complex socio-economic trade-offs that aggregate crime statistics obscure. Our paper contributes to this literature in two respects. First, we transport these mechanisms to a developing economy context where cash-digital substitutability is structurally constrained, showing that the crime-reduction benefits of demonetisation are not uniformly distributed but depend on a household's pre-existing cash holdings and exposure to labour market distress. Second, we construct a theory-grounded, household-specific crime perception index that decomposes safety perceptions into three competing channels: aggregate shadow economy activity, personal target vulnerability, and localised wage desperation. We resolve an empirical paradox that neither aggregate crime models nor reduced-form estimates alone can explain.

3 Institutional Context and Data

This section provides detailed context on Kenya's 2019 demonetisation policy and a brief contrasting context with similar monetary interventions in other African countries, which is useful for validating our identification strategy and understanding the macroeconomic mechanisms of our structural model.

3.1 The 2019 Kenyan Demonetisation Experience

The 2019 Kenyan demonetisation provides a quasi-natural experiment for studying the impact of large-scale, short-run liquidity contractions in developing economies. On June 1, 2019, the CBK announced the immediate demonetisation of the old 1,000-shilling note, granting citizens and businesses a strict four-month transition window, ending on September 30, 2019, to exchange their old notes for a newly designed currency.

The policy was aggressively targeted: the 1,000-shilling note constituted approximately 80.3% of the total value of physical currency in circulation at the time (Central Bank of Kenya, 2019). The CBK explicitly stated that the primary objective of the withdrawal was to "address conclusively the recalcitrance of the newly identified risks on illicit financial flows and counterfeits", thereby dismantling cash-reliant money laundering networks (Central Bank of Kenya, 2019).

However, the execution of the policy was far from a seamless currency swap. To enforce anti-money laundering (AML) objectives, the CBK mandated strict Know Your Customer (KYC) protocols during the exchange window. Individuals and businesses exchanging more than one million shillings (approximately 10,000 USD) were required to provide written declarations regarding the source of the funds and obtain explicit CBK approval, while smaller amounts still faced heightened scrutiny at commercial bank counters. Furthermore, there were still logistical bottlenecks in the exchange process. Commercial bank automated teller machines (ATMs) required weeks of technical recalibration to process the new currency dimensions, leading to temporary but severe shortages of acceptable tender. In remote and rural areas, these logistical hurdles were magnified, as unbanked populations faced significant travel and time costs simply to reach formal bank branches capable of facilitating the exchange (Ndung'u, 2021).

Crucially, this physical liquidity transition unfolded within an economy possessing a world-leading digital financial infrastructure. By 2019, Kenya's primary mobile money platform, M-Pesa, had achieved nearly 80% adult penetration and processed transaction values equivalent to roughly 48% of the national GDP (Central Bank of Kenya et al., 2019). While this system ostensibly provided a digital safety valve against the physical cash shortage, its infrastructure was heavily skewed. The vast majority of the network's 167,000 agents were clustered in urban centres and transit hubs. In rural agricultural economies, digital infrastructure remained limited; because rural agents require physical cash "float" to facilitate digital withdrawals, the demonetisation-induced cash shortage effectively paralyzed local rural digital networks (Mbiti and Weil, 2016).

Contemporaneous reactions from local stakeholders captured the exact macroeconomic trade-offs modeled in this paper. While anti-corruption watchdogs heralded the move as a bold step toward formalising the economy, manufacturing and retail sectors warned of severe, short-term liquidity frictions. For instance, the Kenya Association of Manufacturers explicitly cautioned that the transition period would create acute working capital constraints for cash-reliant businesses. This tension encapsulates the core mechanism of our study: the friction imposed to eradicate illicit activity simultaneously threatens the working capital of informal businesses and the consumption smoothing capabilities of vulnerable, digitally excluded households.

3.2 Comparative African Demonetisation Experiences

While demonetisation has been utilised as a monetary tool across various African states, the Kenyan episode stands out due to its precise execution and surrounding macroeconomic stability. Historically, currency withdrawals in developing economies have been fraught with chaotic implementation, policy reversals, and institutional decay.

For instance, Zimbabwe's prolonged demonetisation episodes (2006–2009) were inextricably linked to hyperinflation, repeated currency redenominations, and the ultimate collapse of the local monetary system (Coomer and Gstraunthaler, 2011). Ghana's earlier experiences, particularly the sudden 1982 currency withdrawal, occurred during periods of severe political instability and regime change, making causal inference regarding household behaviour highly problematic (Addison and Osei, 2001). More recently, Nigeria's 2022–2023 currency redesign suffered from severe logistical failures, acute cash shortages, and eventual legal policy reversals that significantly diluted the treatment effect (Obinna, 2023).

In stark contrast, the 2019 Kenyan demonetisation was executed during a period of relative macroeconomic stability. As noted by Ndung'u (2021), the implementation followed a "crisp and unambiguous sequence of events with an explicit published agenda". The unalterable deadline and lack of concurrent inflationary crises generated a clean, exogenous shock to cash acceptability in both time and space (Maehle et al., 2021).

3.3 Kenya as an Ideal Research Laboratory

Kenya provides the ideal environment for our empirical and structural analysis for two primary reasons: data granularity and pre-existing digital infrastructure.

First, unlike the aforementioned historical episodes, Kenya possesses rich, high-frequency pre- and post-demonetisation household survey data. The availability of Afrobarometer survey waves and comprehensive FinAccess metrics (FSD Kenya, 2021) allows us to observe detailed baseline financial inclusion information that is virtually non-existent for demonetisation episodes in other developing nations.

Second, and most crucially, Kenya entered this policy intervention with a mature, world-leading mobile money ecosystem (M-Pesa). By 2019, digital financial services (DFS) were widely available, though penetration remained heavily skewed toward urban centres and formally employed populations (GSMA, 2020). This pre-existing technological capacity provides a unique empirical laboratory to test how institutional alternatives mediate monetary shocks. It allows us to explicitly measure the substitution between physical cash and digital liquidity and to understand a dynamic that is impossible to isolate in purely cash-based economies undergoing similar reforms.

Finally, this unique institutional environment justifies our single-country treatment approach utilising cross-country controls. A staggered DiD design leveraging multiple African demonetisation shocks (Goodman-Bacon, 2021) is methodologically infeasible here. The extreme heterogeneity in institutional contexts, concurrent inflation crises, and chaotic execution in countries like Zimbabwe and Nigeria would severely confound the treatment effects. Kenya's stable, isolated intervention, combined with its robust digital network, provides a clean identification of a pure liquidity shock and an ideal laboratory for recovering the structural general equilibrium mechanisms that reduced-form estimates alone cannot identify.

3.4 Data Sources and Variable Construction

The empirical analysis relies on repeated cross-sectional data from Rounds 6 through 9 (2014-2021) of the Afrobarometer survey. We focus on Kenya as the treatment group and utilise West African countries (Ghana, Senegal, Côte d'Ivoire) as the primary baseline control group. These countries share similar macroeconomic profiles and digital finance growth trajectories with Kenya, but importantly, they did not experience a demonetisation shock. Robustness checks utilising East African (Rwanda, Tanzania, Uganda) and pan-African control groups yield robust results. Furthermore, we also use Coarsened Exact Matching (CEM) weighted regressions using matched samples for rural and urban areas separately and find robust results.[1]

We construct three primary outcome variables to capture the multidimensional impact of the policy.

1. Mobile Money Usage (`mobile_money_cat`): An ordinal variable (0 to 2) measuring the

[1] We do not report these results in the main text to save space, but they are available in the long appendix Tables LA1-3. Note that CEM weighted regressions make treatment and control groups as similar as possible before estimation of the treatment effect.

intensity of mobile phone-based financial service usage, from no usage (0) to regular usage (2).

2. Crime Perception (`crime_handling`): An ordinal scale (1 to 4) capturing perceptions of safety and crime prevalence. Afrobarometer survey questions on crime are inherently multidimensional; respondents evaluate their safety not only based on high-level, organised illicit activity (e.g., corruption or large-scale syndicates) but also on their acute personal vulnerability to localised petty crime, robbery, and the general economic desperation of their neighbourhood. For ease of interpretation in our regression tables, the variable is coded such that lower values indicate better perceived safety (i.e., a reduction in crime concerns). Crucially, because mobile money users and cash-only users possess different levels of physical cash and thus different levels of personal vulnerability to targeted theft, their subjective evaluations of neighbourhood safety diverge significantly during aggregate liquidity shocks.

3. Income Status (`income_status`): A self-reported scale (1 to 5) capturing economic well-being and financial stability, where higher values indicate better economic conditions.

The analytical sample comprises over 22,000 observations for the baseline specification, expanding to over 115,000 observations when utilizing the broader pan-African control groups. Table 1 presents detailed variable definition along with sources. Table 2 presents descriptive statistics for Kenya pre- and post-demonetisation treatment.

4 Empirical Framework and Results

4.1 Estimation Strategy

We employ a DiD methodology to estimate the effects of the 2019 demonetisation policy. The estimation strategy relies on comparing changes in outcomes in Kenya before and after the 2019 shock against changes in comparable control countries over the same period. The baseline econometric specification is:

$$Y_{ict} = \beta_0 + \beta_1(\text{Kenya}_c) + \beta_2(\text{Post}_t) + \beta_3(\text{Kenya}_c \times \text{Post}_t) + \gamma X_{ict} + \alpha_d + \mu_c + \theta_t + \varepsilon_{ict}, \quad (1)$$

where Y_{ict} represents the outcome variable for individual i in country c at time t. Kenya_c is a binary treatment indicator, and Post_t indicates the post-demonetisation period (2019-2021). The coefficient of interest is β_3, which captures the DiD effect relative to the control group. X_{ict} is a vector of demographic and economic controls (e.g., education, employment status, baseline financial well-being). To isolate the policy effect from unobserved confounding factors, we progressively include location fixed effects (α_d), country fixed effects (μ_c), and year fixed effects (θ_t). We also test for parallel trends and placebo treatment. These results are discussed in Section 4.3.

4.2 Baseline National Results

Table 3 presents the baseline DiD estimates utilising West African countries as the control group.

The results indicate a sizeable increase in Mobile Money Usage following the demonetisation shock ($\beta_3 \approx 1.05$). Given the variable's 0-to-2 scale, this represents a significant shift in population behaviour toward digital finance. Similarly, Crime Perception also improves ($\beta_3 \approx -1.68$, where the negative sign indicates improvement in crime perception), which is indicative of potential disruption in illicit, cash-reliant activities due to the withdrawal of physical cash.

However, these benefits are likely offset by increased economic cost. The Income Status coefficient ($\beta_3 \approx -0.78$ to -0.93) is negative across all specifications. This indicates that Kenyan households experienced economic hardship following the withdrawal of the 1,000-shilling note as their transaction costs abruptly increased.

Note that our baseline results are robust to alternative control groups and CEM weighted estimates as indicated in footnote 1 and the Long Appendix in LA1. It is also robust to alternative standard error clustering at the country and survey round levels. This is also reported in the Long Appendix.

4.3 Parallel Trends and Placebo Test

We present results of parallel trends test using an event study design in Figure 1. Using this approach we are also able to map how the effects evolve over time. For Mobile Money Usage, we observe relatively stable pre-trends, with coefficients for 2014 and 2017 varying between 0.1-0.2 with tight confidence intervals. Following demonetisation, we observe a positive effect in 2021, indicating sustained increases in Mobile Money Usage two years after the initial intervention. Crime Perception also demonstrate a reasonably stable pre-trend, with pre-demonetisation coefficients within 0.3-0.4. Post-demonetisation, we observe a negative effect indicating improvements in Crime Perception two years after demonetisation. Finally, Income Status also exhibits stable pre-trend within 0.3-0.4 and a decline after the 2019 shock.

Overall, the stability of pre-demonetisation coefficients across all three outcomes support the validity of the parallel trends assumption underlying our difference-in-differences approach. The post-demonetisation divergence provides evidence that the effects are a result of the shock rather than a continuation of pre-existing trends.

We also conduct a placebo test by utilising a placebo treatment occurring in 2017. Results are reported in Table 4 and we use the standard West Africa control. We find that for Mobile Money Usage (column 1), the Kenya × Placebo coefficient is statistically insignificant and near zero indicating that the 2017 placebo treatment has no effect. However, for Crime Perception (column 2) and Income Status (column 3) we find positive effects of the 2017 placebo treatment which is exactly opposite of the actual 2019 demonetisation treatment. This sign reversal suggests that the effects of the actual 2019 demonetisation treatment are not contaminated by pre-existing placebo effects.

4.4 Heterogeneity Analysis: The Urban-Rural Divide

Aggregate national averages often obscure deep spatial and structural inequalities. Table 5 stratifies the DiD analysis into Urban and Rural subsamples to test whether the impacts of the liquidity shock depended on regional infrastructure.

The stratification reveals a striking divergence. Urban areas (Columns 1-3) drove the national averages. They experienced a noticeable increase in Mobile Money Adoption ($\beta_3 = 0.624$), similar improvements in safety ($\beta_3 = -1.678$), but a substantial drop in Income Status ($\beta_3 = -1.314$).

Rural areas (Columns 4-6) experienced a different reality. Mobile Money Adoption actually *declined* modestly ($\beta_3 = -0.250$, significant at the 10% level) while Crime Perception improves to a lesser extent ($\beta_3 = -1.088$). Furthermore, the negative income effect in rural areas was much smaller and statistically insignificant ($\beta_3 = -0.410$). This suggests that the urban economy with its high cash-velocity informal sectors was highly vulnerable to the liquidity shock but possessed the digital infrastructure to eventually pivot. The rural economy, heavily reliant on subsistence agriculture and less dependent on daily cash clearing, was somewhat insulated from the macroeconomic recession, but did not experience a corresponding shift toward digital payment platforms.

4.5 Heterogeneity Analysis: Digital Access and Financial Fragility

To probe the role of digital infrastructure further, we stratify the sample based on individuals' pre-existing payment preferences. Table 6 separates those who were already using mobile money (the technologically unconstrained) from those who relied exclusively on cash prior to the demonetisation.

This table reveals the deep distributional inequality of the policy. Across both urban and rural settings, individuals who lacked prior access to mobile money (cash-only users) experienced disproportionate income drop. This financial fragility is the greatest in the rural cash-only cohort (Column 8). These individuals experienced large income shock ($\beta_3 = -2.241$), an effect more than twice as large as their rural peers with mobile money access. This provides compelling evidence that digital financial inclusion acts as a critical consumption-smoothing buffer during acute physical liquidity shocks.

Taken together, the empirical evidence reveals a consistent and striking pattern. Demonetisation accelerated mobile money adoption and improved crime perception in aggregate, but imposed severe and asymmetric income losses on cash-dependent households. These aggregate effects mask deep spatial and cohort heterogeneity.

Urban areas drove the national averages in digital adoption and perceived safety gains, but also bore the sharpest income disruptions. Rural areas experienced a decline in mobile money adoption, a mild improvement in safety perceptions and relatively contained income losses, reflecting the failure of the digital safety valve to operate in agriculturally dependent, cash-complementary environments. Stratifying by pre-existing technological access sharpens the distributional picture further: rural cash-only households suffered income shocks more than twice as large as their rural peers with mobile money access, while urban mobile money users emerged as the singular cohort reporting deteriorating safety perceptions despite the aggregate improvement in crime perception.

These patterns are precisely identified but structurally unexplained. Why did precautionary firm behaviour amplify the aggregate contraction? Why were rural households more permanently scarred despite a milder output shock? Why did urban mobile money users feel less safe as aggregate illicit activity contracted? Answering these questions requires the discipline of a structural general equilibrium framework, to which we now turn.

5 A Structural Model of Demonetisation

The empirical analysis in Section 4 establishes three patterns that reduced-form estimates cannot structurally explain. Why did precautionary firm behaviour amplify the aggregate contraction beyond what the direct liquidity shock would predict? Why did rural cash-only households incur the most severe welfare losses despite facing a shallower aggregate output contraction than urban areas? And why did urban mobile money users report deteriorating safety perceptions even as aggregate illicit activity contracted? Answering these questions requires a structural general equilibrium framework that can discipline the interactions between household liquidity constraints, informal firm financing frictions, and spatially heterogeneous cash-digital substitutability.

We develop a micro-founded TANK model tailored to a developing economy such as Kenya. The model introduces a dual liquidity friction framework that maps directly onto the two axes of heterogeneity identified in the data. On the consumption side, financially constrained households face a CIA constraint governed by a constant elasticity of substitution (CES) aggregator over physical cash and mobile money balances, where the elasticity of substitution captures the technological divide between urban and rural digital infrastructure. On the production side, informal firms, which represent the cash-reliant shadow economy, face a physical cash WCC to finance their wage bill in advance. It is the interaction between these two frictions, rather than either alone, that generates the liquidity vacuum, the digital substitution trap, and the crime perception paradox identified in the structural analysis that follows.

5.1 The Demonetisation Shock

Since demonetisation was temporary and involved invalidation of old notes, it is not reasonable to model it as a permanent reduction in the aggregate money supply. Instead, we model it as a temporary exogenous negative shock to the acceptability or transaction efficiency of physical cash before the new notes are in full circulation. Let ξ_t denote this acceptability parameter, evolving as an AR(1) process:

$$\xi_t = (1 - \rho_\xi) + \rho_\xi \xi_{t-1} + \epsilon_{\xi,t} \tag{2}$$

In the steady state, $\xi_{ss} = 1$. During demonetisation, an adverse shock ($\epsilon_\xi < 0$) forces $\xi_t < 1$, indicating that physical notes become substantially harder to use for transactions due to the sudden invalidation of the old 1,000-shilling note.

5.2 Households

The economy is populated by a continuum of households of measure one. A fraction $\omega_p \in (0,1)$ are financially constrained (representing our empirical cash-only users), while the remaining $1-\omega_p$ are financially unconstrained (representing the mobile money users).

Financially Constrained Households: The representative financially constrained household, denoted by subscript c, optimally chooses a sequence of consumption ($c_{c,t}$), labour supply ($l_{c,t}$), real physical cash balances ($m_{c,t}$), and real mobile money balances ($m^e_{c,t}$) to maximise expected lifetime utility:

$$W_{c,0} := \; E_0 \sum_{t=0}^{\infty} \beta^t \left(\log c_{c,t} - \psi \frac{l_{c,t}^{1+\nu}}{1+\nu} \right), \tag{3}$$

for $t \geq 0$, where $\beta \in (0,1)$ is the subjective discount factor, $\psi > 0$ scales the disutility of labour, and $\nu > 0$ is the inverse Frisch elasticity of labour supply.

These households are financially excluded from formal asset markets; they cannot trade interest-bearing bonds or hold firm equity. They rely on labour income evaluated at the real wage (w_t) and hold physical cash and mobile money. Their flow budget constraint in real terms at time t is given by:

$$c_{c,t} + m_{c,t} + (1+\theta^e)m^e_{c,t} = w_t l_{c,t} + m_{c,t-1} + (1+r^e_{t-1})m^e_{c,t-1}, \tag{4}$$

where r^e_t is the real return on digital deposits, and $\theta^e > 0$ represents a small proportional transaction fee levied by mobile money providers (MMPs) for using the digital network. We present the problem of the MMPs in the next section.

Crucially, the constrained household faces a cash-in-advance transaction friction. To purchase consumption goods, they must utilise a liquidity aggregator ($\mathcal{S}_{c,t}$) composed of the monetary assets carried into the period. We model this aggregator as a CES function between physical cash and mobile money:

$$\kappa c_{c,t} \leq \mathcal{S}_{c,t} := \left[(1-\omega_m)(\xi_t m_{c,t-1})^{\frac{\sigma-1}{\sigma}} + \omega_m (m^e_{c,t-1})^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \tag{5}$$

where $\kappa > 0$ governs the tightness of the CIA constraint (or the inverse velocity of money). The parameter $\omega_m \in [0,1]$ captures the structural density of digital infrastructure (e.g., the availability of M-Pesa agents), and $\sigma > 0$ is the elasticity of substitution between physical cash and digital balances. Notice that the demonetisation shock (ξ_t) explicitly degrades the transaction efficiency of physical cash within this aggregator, forcing households to substitute towards mobile money to maintain their consumption during demonetisation.

Financially Unconstrained Households: The representative financially unconstrained household, denoted by subscript u, is financially integrated and owns the aggregate capital stock of the economy. This household optimally chooses a sequence of consumption ($c_{u,t}$), labour supply ($l_{u,t}$), real physical cash balances ($m_{u,t}$), real mobile money balances ($m^e_{u,t}$), and real one-period risk-free bonds (b_t) to maximise expected lifetime utility:

$$W_{u,0} := E_0 \sum_{t=0}^{\infty} \beta^t \left(\log c_{u,t} - \psi \frac{l_{u,t}^{1+\nu}}{1+\nu} + \chi \log \mathcal{S}_{u,t} \right), \tag{6}$$

for $t \geq 0$. Unlike constrained households, the unconstrained agent does not face a strict cash-in-advance requirement for consumption. Instead, they hold monetary assets primarily for transaction convenience and liquidity services. We model this via a money-in-the-utility (MIU) specification, where $\chi > 0$ governs the relative weight of liquidity services in the utility function. The unconstrained liquidity aggregator ($\mathcal{S}_{u,t}$) follows the exact same CES functional form as the constrained household, evaluated at their own asset holdings:

$$\mathcal{S}_{u,t} = \left[(1-\omega_m)(\xi_t m_{u,t-1})^{\frac{\sigma-1}{\sigma}} + \omega_m (m_{u,t-1}^e)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}. \tag{7}$$

Because they are financially integrated, unconstrained households can perfectly smooth consumption over time by trading bonds. Furthermore, as the ultimate owners of the economy's productive sector, they receive aggregate real dividend payouts ($\Pi_{1,t}$ and $\Pi_{2,t}$) from both informal and formal firms. Their expanded flow budget constraint in real terms at time t is given by:

$$c_{u,t} + m_{u,t} + (1+\theta^e) m_{u,t}^e + b_t = w_t l_{u,t} + m_{u,t-1} + (1+r_{t-1}^e) m_{u,t-1}^e + (1+i_{t-1}) b_{t-1} + \Pi_{1,t} + \Pi_{2,t} - T_t, \tag{8}$$

where i_{t-1} is the real interest rate earned on bonds carried over from the previous period, and T_t represents lump-sum taxes. The full derivation of the optimality conditions for both household types is provided in Appendix A.

5.3 Production Sectors

Labour is homogeneous and perfectly mobile between sectors, implying a single market-clearing real wage w_t. The production side of the economy features two distinct sectors that produce identical consumption goods but face asymmetric financial constraints.

Type 1 Firms (The Informal Shadow Economy): The informal sector represents the cash-reliant shadow economy. Because these firms operate outside the formal banking and taxation systems, they must set aside physical cash to pay a fraction $\gamma > 0$ of their wage bill in advance. Consequently, they face a working capital constraint:

$$\gamma w_t l_{1,t} \leq \xi_t m_{t-1}^f, \tag{9}$$

where m_{t-1}^f is the physical cash hoarded by the firm from the previous period, and ξ_t governs the transaction efficiency of that cash as defined in Subsection 5.1. The representative type 1 firm produces output using technology and labour specified by $y_{1,t} = A l_{1,t}^{\alpha}$, where $\alpha \in (0,1)$ is the labour share in production and A denotes a nationwide time-invariant production technology.

The informal firm optimally chooses labour ($l_{1,t}$) and cash holdings (m_t^f) to maximise the present discounted value of dividends paid to their unconstrained owners $\Pi_{1,t} = A l_{1,t}^{\alpha} - w_t l_{1,t} +$

$m^f_{t-1} - m^f_t$. Let ϕ_t denote the Lagrange multiplier on the WCC. The firm's first-order condition for labour demand is:

$$\alpha A l_{1,t}^{\alpha-1} = w_t(1 + \gamma\phi_t). \tag{10}$$

This condition reveals that informal firms face an endogenous financing premium ($\gamma\phi_t > 0$) on their marginal cost of labour. Because holding zero-interest physical cash over time carries a strictly positive opportunity cost (the nominal interest rate, assuming the economy is not at the zero lower bound at any point in time), the constraint in (9) is strictly binding at equilibrium, thus $\phi_t > 0$.

Type 2 Firms (The Formal Economy): The formal sector consists of financially integrated firms that produce output using an identical technology, $y_{2,t} = A l_{2,t}^{\alpha}$. Unlike informal firms, formal enterprises have full access to banking credit and digital payment infrastructure, allowing them to settle their factor bills without hoarding physical currency. Therefore, they operate frictionlessly without a working capital constraint.

The representative formal firm solves a standard, static profit maximisation problem each period, choosing labour $l_{2,t}$ to maximise dividends $\Pi_{2,t} = A l_{2,t}^{\alpha} - w_t l_{2,t}$. The resulting optimality condition dictates that they hire labour until the marginal product equals the real wage:

$$\alpha A l_{2,t}^{\alpha-1} = w_t. \tag{11}$$

Comparing this to the informal sector's labour demand in Equation (10) highlights the fundamental inefficiency of the shadow economy. The absence of the financing premium ($\gamma\phi_t$) means formal firms face a lower effective marginal cost of labour, allowing them to operate at a more efficient scale and respond differently to aggregate liquidity shocks. The details of the optimality conditions for both firm types are provided in Appendix A.

5.4 Market Clearing and Mobile Money Providers

In the goods market, aggregate output is $y_t = y_{1,t} + y_{2,t}$. Aggregate consumption is $c_t = \omega_p c_{c,t} + (1 - \omega_p) c_{u,t}$. Assuming no government spending, private consumption exhausts total output: $y_t = c_t$.

In the labour market, labour demand from the two production sectors is met by the aggregate labour supply from both household types:

$$l_t = l_{1,t} + l_{2,t} = \omega_p l_{c,t} + (1 - \omega_p) l_{u,t}. \tag{12}$$

The financial architecture of the model explicitly captures the regulatory environment governing Kenya's MMPs. Mobile money is "inside money" within the regulatory framework. Each digital balance must be backed by funds held in the formal banking sector (Jack and Suri, 2011). We model MMPs (such as Safaricom's M-Pesa) as perfectly competitive financial intermediaries. They accept digital deposits from households, $m^e_{tot,t} = \omega_p m^e_{c,t} + (1 - \omega_p) m^e_{u,t}$, and charge a proportional transaction fee θ^e.

To manage these deposits, MMPs must hold a fraction $\rho \in (0, 1)$ as highly liquid, unremunerated cash to process daily withdrawals. They invest the remaining $(1-\rho)$ fraction in risk-free government bonds earning the nominal policy rate i_t (Mbiti and Weil, 2016). The zero-profit condition ensures that the net yield of this portfolio is passed back to households as interest on their digital balances, r_t^e:

$$r_t^e = (1-\rho)i_t - \theta^e. \tag{13}$$

Finally, the Central Bank maintains an exogenous aggregate base money supply ($m^s = \bar{m}^s$), which must equal physical cash in active circulation (held by households and informal firms) plus the physical cash locked away as reserves to back the mobile money system, with reserve requirement ratio denoted by $\rho^e \in (0,1)$:

$$\bar{m}^s = \omega_p m_{c,t} + (1-\omega_p)m_{u,t} + m_t^f + \rho^e m_{tot,t}^e. \tag{14}$$

We deliberately distinguish the macroeconomic base money reserve ratio (ρ^e) from the MMP's unremunerated portfolio fraction (ρ). This is because the former is governed by statutory bank reserve requirements, whereas the latter is the MMP's internal liquidity management decision.

5.5 Household-Specific Crime Perception

Before taking the model to calibration and simulation, we construct a household-specific index for crime perception. As established in our empirical analysis in Subsection 4.5, mobile money users and cash-only users report highly heterogeneous perceptions of safety following demonetisation. If we were to model crime perception solely via the aggregate size of the shadow economy ($y_{1,t}$), both household types would mathematically report identical safety improvements, failing to capture the micro-level divergence observed in the Afrobarometer data.

To bridge the aggregate macroeconomic model with these household-level survey responses, we recognise that the Afrobarometer crime metric captures a highly personal evaluation of localised vulnerability. Drawing from both the survey's structure and the criminological economics literature (Wright et al., 2017), we model a household's perception of safety during a demonetisation event as being driven by three competing channels:

1. *The macro channel* (y_1): When physical cash is restricted, large-scale illicit activities, corruption, and organised shadow networks diminish. This aggregate reduction benefits everyone in the economy.

2. *The micro channel* (m_c, m_u): Robbery and petty theft are heavily targeted at physical cash. When the liquidity shock forces individuals to reduce their physical cash holdings, their personal vulnerability as targets decline, making them feel safer.

3. *The desperation channel* (w): A collapse in local wages signals widespread unemployment and economic distress, which drives up the fear of localised property crime and social unrest.

To generate distinct crime perception responses for constrained and unconstrained households that map to our empirical cohorts, we construct a synthetic, household-specific crime perception index for household $j \in \{c, u\}$ using a Cobb-Douglas style aggregator in deviation form:

$$Crime_{j,t} = \left(\frac{y_{1,t}}{y_{1,ss}}\right)^{\omega_y} \left(\frac{m_{j,t}}{m_{j,ss}}\right)^{\omega_{cash}} \left(\frac{w_t}{w_{ss}}\right)^{-\omega_{wage}} \tag{15}$$

where ω_y, ω_{cash}, and ω_{wage} respectively measure the positive sensitivity of crime perception to aggregate illicit activity, personal cash targeting, and neighbourhood wage desperation. Note that a drop in the real wage ($w_t < w_{ss}$) increases perceived crime via the desperation channel, so ω_{wage} enters the index equation with a minus sign.

6 Quantitative Results and Mechanisms

6.1 Calibrating the Spatial Divide

We calibrate rather than estimate the structural model for three reasons. First, the post-treatment window spans only two Afrobarometer survey rounds, providing insufficient time-series variation to identify the model's structural parameters via simulated method of moments or Bayesian methods. Second, the outcome variables are ordinal survey measures rather than continuous aggregate time series, which precludes standard likelihood-based estimation of DSGE parameters. Third, and most importantly, our objective is mechanism identification rather than parameter precision: we ask whether a theoretically coherent set of parameters, disciplined by Kenyan institutional data, can replicate the directional signs and relative magnitudes of the empirical DiD estimates across all geographic and technological cohorts. This approach follows an established tradition in development macroeconomics of using calibrated structural models to illuminate general equilibrium mechanisms that reduced-form estimates cannot recover (Ulyssea, 2018; Meghir et al., 2015).

Table 7 summarises the model calibration. The calibration strategy assigns standard macroeconomic parameters according to the established New Keynesian literature, while specific financial friction and monetary parameters are tailored to the Kenyan institutional context.

We first assign standard parameters to anchor the macroeconomic environment. The subjective discount factor (β) is set to 0.98, implying a steady-state annualised nominal interest rate of approximately 8%, which aligns with Kenyan historical averages. The labour share of production (α) is set to 0.65, while the inverse Frisch elasticity of labour supply (ν) is fixed at 1.00. The labour disutility weight ($\psi = 5.00$) and liquidity utility weight ($\chi = 0.10$) are scaled to match steady-state labour supply and unconstrained money demand, respectively.

The regulatory structure of mobile money providers is also explicitly calibrated: the base money reserve ratio ($\rho^e = 0.10$) reflects the fractional reserve backing of the mobile money system, while the unremunerated asset ratio ($\rho = 0.05$) represents the highly liquid fraction of the trust. Transaction costs ($\theta^e = 0.01$) approximate the 1% average fee levied by digital providers.

A key novelty of our calibration lies in the parameterisation of the financial constraints (κ and γ), both of which are set to match steady-state targets rather than estimated freely. Setting $\kappa > 1$ reflects that physical cash serves not only as a medium of exchange but also as a store of value in developing economies, where households hold precautionary buffer stocks to insure against income and health shocks (Alvarez et al., 2009). Similarly, setting $\gamma > 1$ reflects the severe frictions inherent to the shadow economy, where unrecorded costs such as bribes or unregulated materials require cash stocks that strictly exceed the pure wage bill (Meghir et al., 2015).

To systematically match the empirical urban-rural divide documented in our difference-in-differences analysis, we construct three distinct calibration sets: a national baseline, an urban economy, and a rural economy. The national baseline serves as the aggregate average. For the urban economy, we specify a high cash-dependent environment corresponding to high informal sector density. The informal sector is heavily dependent on daily cash clearing ($\gamma = 1.70$), typical of retail and transit operations. Digital infrastructure is dense, represented by a large share of mobile money in liquidity services ($\omega_m = 0.70$), and physical cash and mobile money function as highly substitutable media of exchange ($\sigma = 1.30$). Furthermore, urban areas possess a lower share of purely hand-to-mouth constrained households ($\omega_p = 0.40$).

Conversely, the rural economy is predominantly agricultural and seasonal, meaning daily cash reliance is much lower ($\gamma = 0.30$). Digital infrastructure is sparse with very low mobile money coverage ($\omega_m = 0.10$). Crucially, cash and digital money act as complements rather than substitutes ($\sigma = 0.80$), because rural households cannot easily utilise digital balances for local agricultural transactions. The share of financially constrained households is correspondingly higher ($\omega_p = 0.65$).

The parameters governing the household-specific crime perception index ($\omega_y, \omega_{cash}, \omega_{wage}$) are calibrated to capture the differing nature of vulnerability across geographic divides. In urban areas, where populations are highly exposed to formal and informal employment shocks, households weight heavily on localised labour market desperation ($\omega_{wage} = 0.70$) and to a lesser extent on personal target vulnerability ($\omega_{cash} = 0.25$). The weight on the aggregate shadow economy is very low ($\omega_y = 0.05$). This urban calibration is essential for replicating the heterogeneous safety responses between constrained (cash-only) and unconstrained (mobile money) households observed in the data, as discussed in detail in the following subsection.

In contrast, rural households live in agricultural settings where wage desperation is less acute. Their survey responses regarding safety are heavily dominated by the presence or absence of aggregate illicit trading networks ($\omega_y = 0.60$), with much lower sensitivity to wage fluctuations ($\omega_{wage} = 0.20$) or personal cash targeting ($\omega_{cash} = 0.20$).

Finally, we calibrate the persistence and magnitude of the demonetisation shock to match the timeline of Kenya's 2019 currency transition. As discussed in Section 3, while the CBK's official retrospective characterises the changeover as smooth, commercial banks experienced severe, short-term shortages of new banknotes. Industry reporting indicates these frictions were largely resolved within a six-to-ten-week window, aligning with administrative data showing that 96.6% of old notes had been exchanged by the September 30 deadline (Central Bank of Kenya, 2019). We interpret this evidence as indicative of a liquidity shock that was materially disruptive yet temporally concentrated within the first one to two quarters. Accordingly, we set the persistence parameter to $\rho_\xi = 0.5$, implying a shock half-life of exactly one quarter and confining the structural macroeconomic disruption to the observed resolution window.

Because the acceptability parameter (ξ_t) captures the transactional efficiency of physical cash rather than a directly observable aggregate such as the base money supply, no administrative series permits a precise calibration of its initial magnitude. We therefore set the shock size to a 20 percent decline ($\epsilon_\xi = -0.20$) to qualitatively reflect the severity of the transitional frictions, representing peak transactional disruption characterised by precautionary hoarding, rigid KYC enforcement, and informal supply chain delays during the most acute phase of the currency transition. Paired with the lower persistence parameter, this ensures the simulated shock mimics a sudden, intense liquidity squeeze without mechanically extending the recession beyond the period supported by empirical evidence.

6.2 Impulse Response Dynamics and Economic Mechanisms

Figure 2 plots the dynamic transition paths for the three spatial calibrations over a 20-quarter horizon to a 20% drop in cash acceptability ($\epsilon_\xi = -0.20$) in period 1.

Before evaluating the dynamic results, it is necessary to establish the mapping between the theoretical agents in the model and the demographic cohorts in our empirical data. We align the unconstrained households in the model with the empirical mobile money users, as both groups possess the digital financial infrastructure necessary to substitute away from physical cash and smooth consumption. Conversely, we align the constrained households with the empirical cash-only users, as both are strictly bound by a cash-in-advance friction and lack alternative transaction mediums. We acknowledge that this bipartite mapping is a theoretical abstraction. In reality, empirical mobile money users may still face partial credit constraints, and financial inclusion exists on a spectrum rather than as a strict binary. Nevertheless, this alignment effectively captures the primary axis of technological vulnerability during a demonetisation.

Mechanism 1: The Liquidity Vacuum. The bottom row of Figure 2 provides the structural origin of the recession. When the transaction efficiency of cash (ξ_t) drops, informal firms are forced into precautionary cash hoarding to satisfy their working capital constraints (see the Cash Holding of Informal Sector panel, which spikes on impact by about 15% across all three spatial specifications). This hoarding acts as a liquidity drain, depriving the real economy of circulating currency and triggering a sharp collapse in the Real Wage Rate (bottom-middle panel).

The right column illustrates how this wage collapse is transmitted asymmetrically to households. Unconstrained households (mid-right panel) experience a relatively smooth and mild income decline because they utilise digital balances and bond yields to smooth consumption. In stark contrast, constrained households (bottom-right panel) suffer a large, instantaneous collapse in consumption at $t = 1$, because they rely heavily on physical cash and are unable to smooth consumption due to the hard cash-in-advance constraint. Notice that the Rural drop (red dashed, nearly -0.17%) is substantially deeper than the Urban drop (blue dotted, -0.05% in period 1 and -0.1% in period 2), visually confirming financial fragility in rural areas.

Mechanism 2: The Digital Substitution Trap. The left column of Figure 2 explains the spatial divergence in technology adoption. In the Aggregate Mobile Money Adoption panel (top-left), the Urban (blue dotted) and National (black solid) lines shift strictly positive as populations utilise M-Pesa as a safety valve. However, the Rural line (red dashed) plunges negative.

Why does this happen? In urban areas ($\sigma = 1.30$), physical cash and digital money are substitutes, so unconstrained households who are frequent mobile money users seamlessly pivot to M-Pesa. However, in rural areas ($\sigma = 0.80$), they are complements. Since the aggregate recession causes a severe drop in rural income, and because rural households cannot easily substitute digital money for agricultural cash transactions, the rural unconstrained mobile money users, accustomed to digital platforms, substantially reduce their use of the costly digital ecosystem. (See red dashed lines in MM Adoption (Unconstrained HHs) panel). This drags aggregate rural mobile money adoption negative, providing a structural explanation for the technological divergence observed in the data.

Mechanism 3: The Multidimensional Crime Paradox. Finally, the middle column appears to resolve the empirical puzzle of why Urban unconstrained households were the singular demographic cohort to report feeling less safe following demonetisation in the Afrobarometer data.

By defining crime perception as a composite of macro-level shadow economy activity, micro-level target vulnerability, and localised labour market desperation, the model is able to fragment the household responses. The Crime Perception (Unconstrained HHs) panel in the centre reveals an instant positive spike of the blue dotted line (Urban). Because these users living in urban areas already held minimal physical cash, the target reduction benefit of demonetisation was negligible to them. Instead, their perceptions were dominated by localised labour market desperation as the real wage collapsed, driving up their fear of crime.

Conversely, the panel right below, Crime Perception (Constrained HHs), indicates a sharp decline in both lines into negative territory. These constrained households were forced to rapidly deplete their physical cash reserves to survive. For these households, the elimination of their vulnerability to theft and mugging overrode the wage desperation effect, resulting in significant improvements in perceived safety. This confirms theoretically what the data suggested: the security benefits of demonetisation accrued almost entirely to those who were previously carrying physical cash targets.

In summary, the structural transition paths isolate three interconnected general equilibrium mechanisms: a liquidity vacuum, a digital substitution trap, and a multidimensional crime paradox. These mechanisms shape the heterogeneous impacts of demonetisation. Crucially, the liquidity vacuum reveals a novel theoretical insight unattainable through reduced-form empirical analysis alone: the aggregate economic contraction is exacerbated by the precautionary cash hoarding behaviour of informal firms. By retaining physical cash to maintain production, these firms inadvertently tighten the cash-in-advance constraint of vulnerable, cash-dependent households, leading to acute consumption decline.

Meanwhile, the digital substitution trap demonstrates that this contraction is distributed asymmetrically across regions, disproportionately affecting rural populations that lack the technological infrastructure to substitute digital payments for physical currency.

Finally, the multidimensional crime paradox confirms that while aggregate illicit activity declines, the subjective security benefits of demonetisation accrue primarily to those forced to liquidate their physical cash holdings, leaving digitally integrated households exposed to the adverse psychological effects of depressed local labour market contraction.

6.3 Connecting Theory to Empirics: Survey Point Equivalents

The theoretical impulse responses in the previous subsection plot instantaneous, period-by-period percentage deviations, while our empirical DiD coefficients represent the average absolute point change across discrete, ordinal survey waves. To bridge the structural model with the empirical estimation, we construct theoretical survey point equivalents in two steps.

First, we map the survey fieldwork dates to the model's timeline. The 'Post' treatment indicator in our DiD framework pools Round 8 (August 28 to September 25, 2019) and Round 9 (November 12-30, 2021). Round 8 occurred prior to the CBK's September 30 exchange deadline. It captures the peak of the liquidity shock, corresponds to $t = 1$ in the model (June–August 2019) and straddles into the model's second quarter ($t = 2$, September–November 2019). Round 9 represents the post-shock recovery and corresponds to $t = 10$ in the model (September–November 2021). We therefore evaluate the model's dynamic paths using the discrete average of the impulse responses at these specific periods. Because Round 8 spans over the first and part of the second period of the model, we report calculations of survey point equivalents using both $t = 1$ and an average of $t = 1$ and $t = 2$.

Second, we scale these averaged percentage deviations by the total span of their respective survey indices (a factor of 2 for mobile money usage, 3 for crime perception, and 4 for income status). This scaling is dimensionally appropriate because it converts the model's percentage deviations from steady state into the ordinal survey units in which the DiD coefficients are expressed, without introducing any free parameter that could be tuned to improve the fit.

Table 8 presents these theoretical equivalents. The structural model successfully replicates the directional signs and the critical relative magnitudes of the empirical DiD findings (compare to Tables 3, 5, and 6).

Starting with income status, Table 8 shows that the model replicates the hierarchy of financial fragility observed in the survey data. Across all geographic specifications, the consumption drop for constrained (cash-only) households is an order of magnitude larger than the drop experienced by their unconstrained (mobile money) counterparts. The model confirms that the rural cash-only cohort experiences the most severe absolute income contraction (-0.3408), mirroring the empirical finding that this group bore the heaviest transitional costs of the policy due to a relative unavailability of digital alternatives. The unconstrained households, by contrast, utilise their digital liquidity to largely insulate their consumption paths.

For mobile money adoption, the model captures the aggregate spatial divergence that defines the empirical results. Aggregate mobile money adoption increases at the national level and in urban areas, driven by the high elasticity of substitution between cash and digital platforms in environments with dense technological infrastructure. However, in rural areas, the model correctly generates a negative aggregate adoption response (-0.0179). Since rural cash and digital money act as complements rather than substitutes in the agricultural economy, the income recession forces rural unconstrained households to abandon costly digital platforms.

The structural framework provides a theoretical insight into the sub-cohort dynamics underlying this aggregate figure. Due to data limitations, the Afrobarometer survey cannot observe the heterogeneous mobile money adoption responses within pre-existing user cohorts. The model fills this gap, predicting that the aggregate rural decline is driven by prior rural mobile money users reducing their use of the digital ecosystem (-0.0183), whereas cash-only rural households are forced into low-level adoption (0.0360) simply to survive the physical liquidity vacuum.

The model also aligns with the empirical observations regarding crime perception. At the aggregate level, crime perception falls across all regions, reflecting the universal benefit of the shadow economy contraction. By decomposing the household-specific crime index into macro-level illicit activity, micro-level target vulnerability, and localised wage desperation, the model generates the necessary heterogeneity between cohorts. It illustrates how cash-only households experience crime dynamics primarily through the sudden elimination of their physical cash hoards, leading to a reduction in perceived crime (-0.0259 in urban areas). Conversely, mobile money users, who already held minimal cash, evaluate safety primarily through the lens of localised labour market distress, generating an increase in perceived crime (0.0288 in urban areas). This multidimensional approach allows the theoretical framework to rationalise the divergent subjective safety evaluations reported in the Afrobarometer data.

Because the Round 8 survey fieldwork chronologically straddled the boundary between the first ($t = 1$) and second ($t = 2$) quarters of the policy window, we formally test the robustness of this temporal mapping. Table 9 reports the theoretical survey equivalents computed using the discrete average of $t = 1$ and $t = 2$ for the immediate post-shock wave. The structural directionality remains robust across all variables. Notably, the paradoxical increase in crime perception among urban mobile money users remains positive (0.0113) even when incorporating the subsequent quarter. This confirms that the acute wage desperation effect dominates the initial phase of the liquidity squeeze, validating the model's alignment with the institutional timeline.

6.4 Material Welfare Evaluation

While the average impulse response functions map cleanly to the difference-in-differences estimates, they primarily capture short-term disruptions. To quantify the long-term distributional cost of the policy, we compute the consumption equivalent (CE) variation as a standard measure of welfare change. This metric calculates the permanent percentage change in consumption that equates household welfare under the demonetisation path to the steady-state level.

In standard macroeconomic models, severe recessions can generate spurious welfare gains due to the mechanical increase in leisure from involuntary unemployment. Since our empirical data specifically measures financial hardship and cash shortages, we evaluate policy outcomes using *material welfare*—the discounted present value of the consumption stream. This isolates the true economic scarring of the liquidity shock. The recursive material value functions are:

$$V_{c,t} = \log(c_{c,t}) + \beta E_t[V_{c,t+1}] \tag{16}$$

$$V_{u,t} = \log(c_{u,t}) + \chi \log(\mathcal{S}_{u,t}) + \beta E_t[V_{u,t+1}] \tag{17}$$

The CE variation Δ_j for household j is derived analytically as:

$$\Delta_j = \exp\Big((1-\beta)\big(V_{j,0}^{shock} - V_{j,ss}\big)\Big) - 1 \tag{18}$$

Table 10 reveals the distributional consequences of the demonetisation policy. While the aggregate urban economy experienced the sharpest initial contraction in output due to the high cash-velocity of its informal sector, rural cash-only households incur the most severe lifetime welfare reductions (-0.539%).

This welfare loss is driven by the structural constraints of the rural agricultural economy. Rural households lack robust digital infrastructure ($\omega_m = 0.10$) and exhibit low technological substitutability between physical cash and digital payments ($\sigma = 0.80$). Therefore, they remain fully exposed to the firm-induced liquidity vacuum. Without mobile money acting as a buffer, their consumption paths are heavily constrained by the cash-in-advance friction. Conversely, unconstrained mobile money users across all regions experience substantially smaller welfare losses (ranging from -0.026% to -0.073%), as they successfully leverage digital liquidity and bond yields to smooth consumption over the transition path.

These welfare results offer a theoretical contribution to the literature on monetary shocks in developing economies. Existing macroeconomic studies often implicitly assume that regions experiencing the deepest aggregate output contractions naturally suffer the largest welfare losses. Our findings challenge this assumption by revealing a decoupling between aggregate macroeconomic severity and micro-level household welfare. Although the urban informal sector suffers the most acute production shock, the presence of alternative digital institutions mitigates the long-term consumption scarring for urban residents. In contrast, the absence of digital substitution in rural areas transforms a relatively milder aggregate output shock into a persistent, structural welfare loss for cash-dependent households. This demonstrates theoretically what our empirical data suggests: the welfare penalty of an aggressive monetary contraction acts as a regressive tax, falling almost entirely on the digitally excluded.

7 Conclusion and Policy Implications

Aggressive monetary interventions designed to accelerate digital formalisation are increasingly common in emerging markets, yet their distributional consequences remain poorly understood. This paper shows that the welfare costs of such interventions are not determined by the scale of the aggregate shock, but by whether households have access to viable digital alternatives when physical currency is withdrawn.

Kenya's 2019 demonetisation illustrates this mechanism with clarity. The policy simultaneously achieved its stated objectives: accelerating mobile money adoption and disrupting cash-based illicit activity, and inflicted severe, asymmetric welfare losses on the households it was intended to modernise. The difference between these two outcomes was not aggregate economic conditions but the geographic reach of digital infrastructure. Urban households with access to M-Pesa absorbed the liquidity shock through digital substitution and bond markets, suffering minimal welfare losses. Rural cash-only households, for whom physical cash and digital money remain technological complements rather than substitutes, were fully exposed to the firm-induced liquidity vacuum, incurring consumption equivalent welfare losses of -0.539% — an order of magnitude larger than their urban counterparts. Urban mobile money users, meanwhile, experienced a paradoxical deterioration in perceived safety not because crime rose, but because the wage collapse accompanying the liquidity vacuum dominated the negligible target-reduction benefit they received from holding less cash.

Three broader lessons follow. First, aggregate macroeconomic indicators such as output contractions, national adoption rates, average income losses are not informative guides to the welfare incidence of monetary shocks. They systematically mask the distributional asymmetries that determine whether a policy is progressive or regressive in practice. Second, the binding constraint on the welfare costs of demonetisation is not the size of the liquidity shock but the elasticity of substitution between cash and digital money at the household level. Where this elasticity is low, as in rural agricultural economies with sparse agent networks, no amount of aggregate digital penetration insulates the most vulnerable households. Third, and most practically, the sequencing of monetary reform matters. Expanding rural agent networks, subsidising digital infrastructure, and ensuring high cash-digital substitutability across geographic strata are not complementary policies to demonetisation, they are prerequisites for it. Imposing currency withdrawal before these conditions are met does not accelerate formalisation; it transfers welfare from the digitally excluded to those already integrated into the formal financial system.

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A Appendix: Model Equations and Optimisation

A.1 Constrained Household Optimisation

The Lagrangian for the constrained household is:

$$\mathcal{L}_c = E_0 \sum_{t=0}^{\infty} \beta^t \Bigg\{ \log c_{c,t} - \psi \frac{l_{c,t}^{1+\nu}}{1+\nu} + \lambda_{c,t} \left[w_t l_{c,t} + m_{c,t-1} + (1+r_t^e) m_{c,t-1}^e - c_{c,t} - m_{c,t} - (1+\theta^e) m_{c,t}^e \right] + \mu_{c,t} \left[\mathcal{S}_{c,t}(m_{c,t-1}, m_{c,t-1}^e, \xi_t) - \kappa c_{c,t} \right] \Bigg\} \tag{19}$$

The First Order Conditions (FOCs) are:

$$c_{c,t}^{-1} = \lambda_{c,t} + \kappa \mu_{c,t} \tag{20}$$

$$\psi l_{c,t}^{\nu} = \lambda_{c,t} w_t \tag{21}$$

$$\lambda_{c,t} = \beta E_t \left[\lambda_{c,t+1} + \mu_{c,t+1} (1-\omega_m) \xi_{t+1}^{\frac{\sigma-1}{\sigma}} \left(\frac{\mathcal{S}_{c,t+1}}{m_{c,t}} \right)^{\frac{1}{\sigma}} \right] \tag{22}$$

$$\lambda_{c,t}(1+\theta^e) = \beta E_t \left[\lambda_{c,t+1}(1+r_t^e) + \mu_{c,t+1} \omega_m \left(\frac{\mathcal{S}_{c,t+1}}{m_{c,t}^e} \right)^{\frac{1}{\sigma}} \right] \tag{23}$$

A.2 Unconstrained Household Optimisation

The Lagrangian for the unconstrained household is:

$$\begin{aligned} \mathcal{L}_u = E_0 \sum_{t=0}^{\infty} \beta^t \Bigg\{ & \log c_{u,t} - \psi \frac{l_{u,t}^{1+\nu}}{1+\nu} + \chi \log \mathcal{S}_{u,t}(m_{u,t-1}, m_{u,t-1}^e, \xi_t) \\ & + \lambda_{u,t} \Big[w_t l_{u,t} + m_{u,t-1} + (1+r_t^e) m_{u,t-1}^e + (1+i_{t-1}) b_{t-1} \\ & + \Pi_{1,t} + \Pi_{2,t} - T_t - c_{u,t} - m_{u,t} - (1+\theta^e) m_{u,t}^e - b_t \Big] \Bigg\} \end{aligned} \tag{24}$$

The FOCs are:

$$\frac{\partial \mathcal{L}_u}{\partial c_{u,t}} : \quad c_{u,t}^{-1} = \lambda_{u,t} \tag{25}$$

$$\frac{\partial \mathcal{L}_u}{\partial l_{u,t}} : \quad \psi l_{u,t}^{\nu} = \lambda_{u,t} w_t \tag{26}$$

$$\frac{\partial \mathcal{L}_u}{\partial b_t} : \quad \lambda_{u,t} = \beta E_t \left[\lambda_{u,t+1}(1+i_t) \right] \tag{27}$$

$$\frac{\partial \mathcal{L}_u}{\partial m_{u,t}} : \quad \lambda_{u,t} = \beta E_t \left[\lambda_{u,t+1} + \frac{\chi}{\mathcal{S}_{u,t+1}} \left(\frac{\mathcal{S}_{u,t+1}}{\xi_{t+1} m_{u,t}} \right)^{\frac{1}{\sigma}} (1-\omega_m) \xi_{t+1} \right] \tag{28}$$

$$\frac{\partial \mathcal{L}_u}{\partial m_{u,t}^e} : \quad \lambda_{u,t}(1+\theta^e) = \beta E_t \left[\lambda_{u,t+1}(1+r_{t+1}^e) + \frac{\chi}{\mathcal{S}_{u,t+1}} \left(\frac{\mathcal{S}_{u,t+1}}{m_{u,t}^e} \right)^{\frac{1}{\sigma}} \omega_m \right] \tag{29}$$

A.3 Firm Optimisation

Informal Firms (Type 1):
The informal firm maximises the present discounted value of real dividends $\Pi_{1,t} = Al_{1,t}^{\alpha} - w_t l_{1,t} + m_{t-1}^f - m_t^f$, subject to the WCC $\gamma w_t l_{1,t} \leq \xi_t m_{t-1}^f$. Let $\lambda_{u,t}\phi_t$ be the Lagrange multiplier on the constraint, where $\lambda_{u,t}$ is the marginal utility of wealth of the unconstrained owners. The firm's Lagrangian is:

$$\mathcal{L}_{firm1} = E_0 \sum_{t=0}^{\infty} \beta^t \lambda_{u,t} \left[Al_{1,t}^{\alpha} - w_t l_{1,t} + m_{t-1}^f - m_t^f + \phi_t(\xi_t m_{t-1}^f - \gamma w_t l_{1,t}) \right] \tag{30}$$

The First Order Conditions (FOCs) with respect to $l_{1,t}$ and m_t^f are:

$$\frac{\partial \mathcal{L}_{firm1}}{\partial l_{1,t}} : \quad \alpha A l_{1,t}^{\alpha-1} = w_t(1 + \gamma\phi_t) \tag{31}$$

$$\frac{\partial \mathcal{L}_{firm1}}{\partial m_t^f} : \quad \lambda_{u,t} = \beta E_t \left[\lambda_{u,t+1}(1 + \phi_{t+1}\xi_{t+1}) \right] \tag{32}$$

Comparing the firm's intertemporal cash demand Euler equation with the unconstrained household's bond Euler equation ($\lambda_{u,t} = \beta E_t[\lambda_{u,t+1}(1 + i_t)]$) reveals that in the deterministic steady state ($\xi_{ss} = 1$), the shadow price of the working capital constraint exactly equals the nominal interest rate: $\phi_{ss} = i_{ss}$. Thus, the constraint strictly binds as long as $i_{ss} > 0$.

Formal Firms (Type 2):
The formal firm faces no financial frictions and simply solves a static profit maximisation problem each period:

$$\max_{l_{2,t}} \ \Pi_{2,t} = Al_{2,t}^{\alpha} - w_t l_{2,t} \tag{33}$$

Taking the derivative with respect to $l_{2,t}$ yields the standard marginal product condition:

$$\alpha A l_{2,t}^{\alpha-1} = w_t \tag{34}$$

B Appendix: Steady State Solution

To solve the steady state analytically, we predetermine the structural parameters ($\beta, \psi, \nu, \kappa, \omega_m, \sigma, \omega_p, \chi, \theta^e, \rho, \rho^e$) and the exogenous real money supply ($\bar{m}^s$). In the steady state, $\xi_{ss} = 1$. The nominal interest rate is $i_{ss} = \frac{1}{\beta} - 1$, and the WCC shadow price is $\phi_{ss} = i_{ss}$. The optimal steady-state portfolio ratio $\Omega \equiv \frac{m_c^e}{m_c} = \frac{m_u^e}{m_u}$ is:

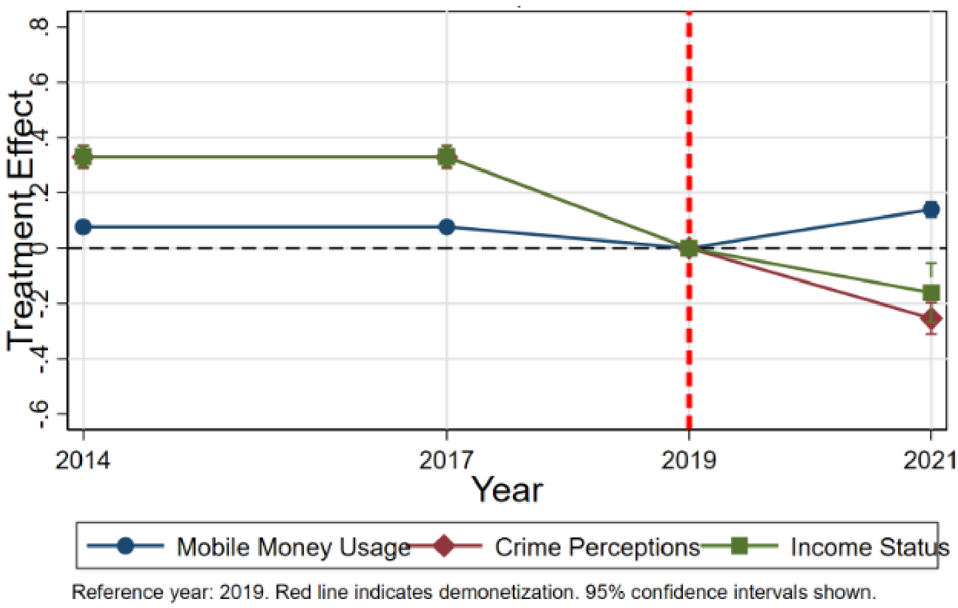
$$\Omega = \left[\frac{1-\beta}{\beta^{-1}(1+\theta^e) - (1 + r_{ss}^e)} \frac{\omega_m}{1-\omega_m} \right]^{\sigma} \tag{35}$$

Given ϕ_{ss}, labour demands are analytically linked to the wage w_{ss}:

$$l_{2,ss} = \left(\frac{w_{ss}}{\alpha A} \right)^{\frac{1}{\alpha-1}}, \quad l_{1,ss} = \left(\frac{w_{ss}(1 + \gamma i_{ss})}{\alpha A} \right)^{\frac{1}{\alpha-1}} \tag{36}$$

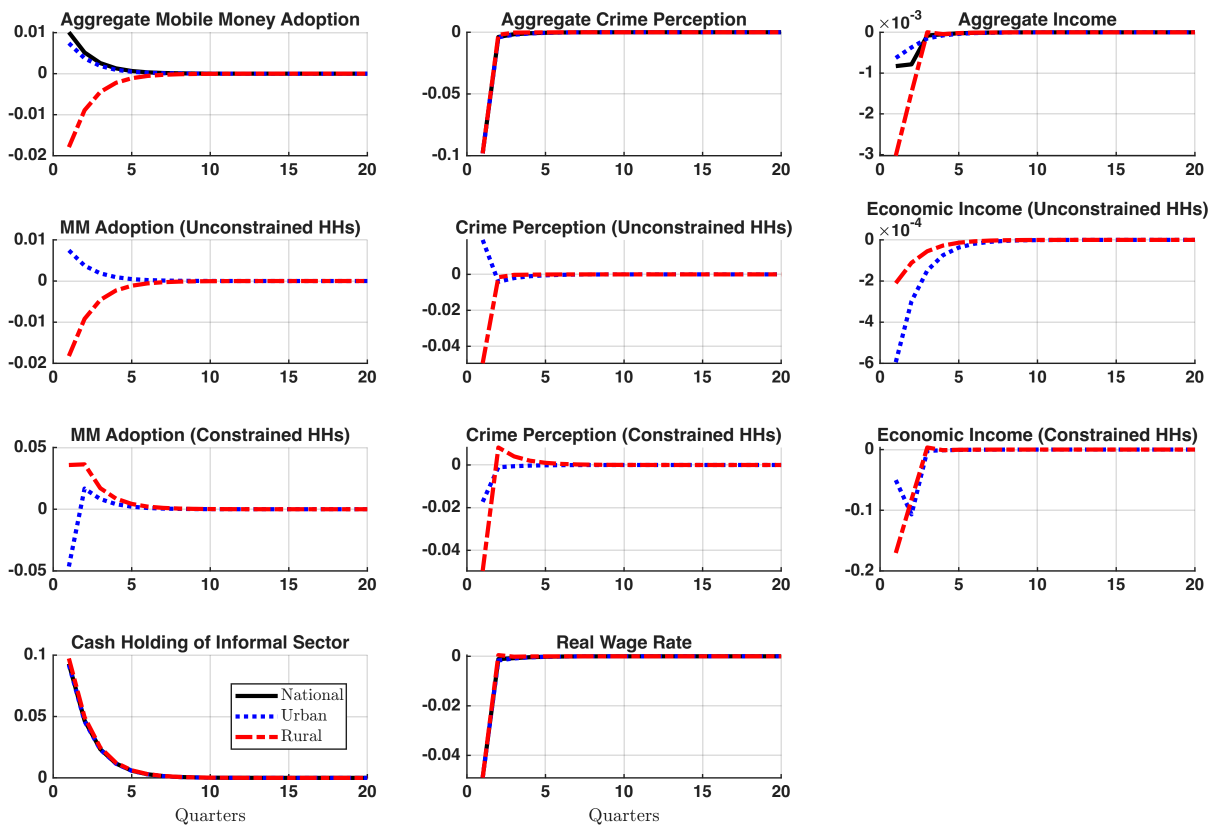
We then use a numerical root-finding algorithm to simultaneously find w_{ss}, $m_{c,ss}$, and $m_{u,ss}$ that clear the goods and money markets.

Figure 1: Parallel Trends Test of Demonetisation using an Event Study Design



Note: Pre-trends for crime perception and income status are almost collinear.

Figure 2: Simulated Impulse Responses to a 20% Demonetisation Shock



Note: Panels display percentage deviations from the steady state for National (black solid), Urban (blue dotted), and Rural (red dashed) calibrations.

Table 1: Variable Construction and Definitions

Variable Name	Category	Definition and Coding	Source/Notes
OUTCOME VARIABLES			
mobile_money_cat	Primary Outcome	Mobile money usage intensity. 0=No usage, 1=Occasional usage, 2=Regular usage. Higher values indicate greater digital financial integration.	Afrobarometer mobile money questions. Positive coefficients indicate increased adoption.
crime_handling	Primary Outcome	Crime perception and safety. 1=Very safe, 2=Fairly safe, 3=Fairly unsafe, 4=Very unsafe. Lower values indicate better safety perception.	Afrobarometer crime and safety questions. Negative coefficients indicate improved safety.
income_status	Primary Outcome	Self-reported economic status. 1=Very bad, 2=Fairly bad, 3=Neither good nor bad, 4=Fairly good, 5=Very good. Higher values indicate better economic conditions.	Afrobarometer economic condition questions. Positive coefficients indicate improved welfare.
TREATMENT VARIABLES			
Kenya	Treatment Indicator	Binary indicator for Kenya. 1=Kenya, 0=Control country. Identifies treatment country in DiD specification.	Constructed from country identifiers.
Post	Time Indicator	Binary indicator for post-demonetisation period. 1=2019-2021, 0=2014-2017. Captures post-treatment period.	Constructed from survey year.
Kenya × Post	DiD Interaction	Key interaction term. 1=Kenya in post-period, 0=otherwise. Coefficient captures causal effect of demonetisation.	Interaction of Kenya and Post variables.
Kenya × Post × Urban	Triple Interaction	1=Urban Kenya in post-period, 0=otherwise. Captures differential urban effects of demonetisation.	Used in heterogeneity analysis.
CONTROL GROUP VARIABLES			

Table 1 – *Continued from previous page*

Variable Name	**Category**	**Definition and Coding**	**Source/Notes**
control_westafrica	Control Definition	1=West African countries (Ghana, Côte d'Ivoire, Senegal), 0=Kenya. Primary control group specification.	Main control group in baseline specifications.
control_eastafrica	Control Definition	1=East African countries (Rwanda, Tanzania, Uganda), 0=Kenya. Regional control group for robustness.	Used in robustness checks with regional neighbors.
control_allafrica	Control Definition	1=All non-Kenya African countries, 0=Kenya. Broadest control group specification.	Maximum sample size for statistical power.
GEOGRAPHIC VARIABLES			
urban_area	Geographic	Binary indicator. 1=Urban area, 0=Rural area. Used for stratification and as control variable.	From URBRUR_COND variable.
rural_area	Geographic	Binary indicator. 1=Rural area, 0=Urban area. Complementary to urban_area indicator.	Constructed as inverse of urban_area.
area_type	Geographic	Categorical variable for detailed area types. Range 1-8 for finer geographic distinctions.	More detailed geographic classification.
FIXED EFFECTS VARIABLES			
i.COUNTRY	Fixed Effects	Country fixed effects. Controls for time-invariant country characteristics including institutions, geography, culture.	Standard country identifier.
i.year	Fixed Effects	Year fixed effects. Controls for temporal trends affecting all countries including global economic conditions.	Survey year indicators.
i.country_location_id	Fixed Effects	Location fixed effects at district/city/village level. Controls for local economic and social conditions.	Most granular geographic controls.

Table 1 – *Continued from previous page*

Variable Name	Category	Definition and Coding	Source/Notes
Region FE	Fixed Effects	Regional fixed effects. Alternative to location FE to avoid multicollinearity in some specifications.	Used when location FE not feasible.
ECONOMIC CONTROL VARIABLES			
female_income	Economic Control	Female primary income earner. 1=Female earns primary income, 0=Otherwise. Controls for household gender dynamics.	From Q101 (gender) and Q95 (employment).
financial_welloff	Economic Control	Household financial stability. 1=Rarely/never cash shortages, 0=Often cash shortages. Controls for baseline wealth.	From Q7E or Q7E_clean depending on round.
employment_status	Economic Control	Employment situation. 1=Not working, 2=Employed (full/part-time), 3=Self-employed. Controls for labour market status.	From Q95. Categories capture different economic vulnerabilities.
SOCIAL CONTROL VARIABLES			
educ_clean	Social Control	Education level. 1=Primary or less, 2=Secondary, 3=Post-secondary. Controls for human capital differences.	From Q97. Higher values indicate more education.
religion_group	Social Control	Religious affiliation. 1=Christian, 2=Muslim, 3=Traditional/ethnic, 4=None, 5=Other. Controls for cultural influences.	From Q98A. May affect financial behaviour through social networks.
occupation_group	Social Control	Occupation type. 1=Professional, 2=Service, 3=Skilled manual, 4=Unskilled manual, 5=Agricultural, 6=Other/not working.	From Q96A. Controls for cash dependence by occupation.
METHODOLOGICAL VARIABLES			

Table 1 – *Continued from previous page*

Variable Name	**Category**	**Definition and Coding**	**Source/Notes**
age_cat	Matching Variable	Age category groups for CEM matching. Categorical age brackets for life-cycle controls.	Created for matching procedures.
weight_urban_mm	CEM Weights	Coarsened Exact Matching weights for urban mobile money users. Creates balanced treatment/control groups.	Generated through CEM procedure.
weight_urban_cash	CEM Weights	CEM weights for urban cash-only users. Balances observables between treatment and control.	Used in robustness analysis.
weight_rural_mm	CEM Weights	CEM weights for rural mobile money users. Addresses selection on observables in rural areas.	Separate weights for rural heterogeneity.
weight_rural_cash	CEM Weights	CEM weights for rural cash-only users. Final weight category for matching analysis.	Completes rural cash user balance.
LOCATION IDENTIFIERS			
LOCATION_CLEAN	Identifier	Cleaned location variable for geographic identification and merging datasets.	Data management variable.
country_location_id	Identifier	Country-specific location identifier for implementing location fixed effects in regressions.	Technical variable for fixed effects.
household_id	Identifier	Household identifier for clustering standard errors and accounting for within-household correlation.	Used for robust standard error calculation.

Table 2: Descriptive Statistics: Kenya, Pre vs. Post Demonetisation

	Mean	Std. Dev.	Min	Max
Pre				
Mobile Money	0.7508	0.4044	0.00	2.00
Crime Handling	2.9636	0.9852	1.00	4.00
Income Status	3.0944	1.5940	1.00	5.00
Post				
Mobile Money	1.7843	0.5151	0.00	2.00
Crime Handling	2.0597	1.0454	1.00	4.00
Income Status	2.4793	0.9398	1.00	5.00

Table 3: Effects of Demonetisation on Mobile Money Use, Crime Perception, and Income: Household-Level Estimates

	Mobile Money Usage				Crime Perception				Income Status			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Loc FE	Loc+Ctry	Loc+Year	All FE	Loc FE	Loc+Ctry	Loc+Year	All FE	Loc FE	Loc+Ctry	Loc+Year	All FE
Interaction Term												
Kenya × Post	1.063***	1.041***	1.055***	1.046***	−1.682***	−1.695***	−1.677***	−1.695***	−0.930***	−0.780**	−0.930***	−0.780**
	(0.166)	(0.161)	(0.167)	(0.161)	(0.329)	(0.341)	(0.334)	(0.349)	(0.333)	(0.339)	(0.333)	(0.339)
Fixed Effects & Controls												
Location FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Year FE	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Model Statistics												
Observations	22,699	22,699	22,699	22,699	22,351	22,351	22,351	22,351	22,457	22,457	22,457	22,457
Adjusted R^2	0.680	0.682	0.685	0.687	0.144	0.145	0.146	0.147	0.326	0.329	0.326	0.329

Notes: Robust standard errors clustered at the household level in parentheses. Sample includes Kenya as treatment with West African countries (Ghana, Côte d'Ivoire, Senegal) as control. Economic and social controls are included in all specifications. * p<0.10, ** p<0.05, *** p<0.01.

Table 4: Effects of Demonetisation Placebo Treatment

	(1) Mobile Money Usage	(2) Crime Perception	(3) Income Status
Kenya × Placebo	0.099	1.115***	0.985***
	(0.173)	(0.138)	(0.092)
Observations	10,759	10,511	10,534
Country FE	NO	NO	NO
Year FE	NO	NO	NO
Demographic	YES	YES	YES
Economic	YES	YES	YES
R-squared	0.233	0.098	0.098

Notes: Standard errors clustered at the household level in parentheses. Sample restricted to rounds 6 (2014) and 7 (2017), using West African countries (Ghana, SenegalCôte d'Ivoire) as the control group. The placebo treatment is a fake demonetisation assigned to 2017, prior to the actual 2019 policy. * p<0.10, ** p<0.05, *** p<0.01.

Table 5: Heterogeneity Analysis: Urban vs. Rural Areas

	Urban Areas			Rural Areas		
	(1) MM	(2) Crime	(3) Income	(4) MM	(5) Crime	(6) Income
Kenya	-0.585^{***}	1.621^{***}	0.764^{***}	0.235^{*}	1.098^{**}	0.420
	(0.085)	(0.296)	(0.270)	(0.130)	(0.413)	(0.469)
Post	-0.850^{***}	0.308^{*}	1.692^{***}	-1.510^{***}	0.392	1.521^{***}
	(0.063)	(0.183)	(0.222)	(0.130)	(0.317)	(0.430)
Kenya × Post	0.624^{***}	-1.678^{***}	-1.314^{***}	-0.250^{*}	-1.088^{**}	-0.410
	(0.092)	(0.333)	(0.275)	(0.132)	(0.422)	(0.475)
Constant	1.732^{***}	1.755^{***}	1.902^{***}	1.791^{***}	1.766^{***}	1.588^{***}
	(0.048)	(0.147)	(0.220)	(0.128)	(0.307)	(0.425)
Observations	8,289	8,214	4,588	7,139	6,989	4,330
Adjusted R^2	0.285	0.109	0.299	0.723	0.086	0.213
All Fixed Effects	YES	YES	YES	YES	YES	YES

Table 6: Heterogeneity Analysis for Mobile Money Users and Cash-Only Users

	Urban MM Users		Urban Cash Only		Rural MM Users		Rural Cash Only	
	(1) Crime	(2) Income	(3) Crime	(4) Income	(5) Crime	(6) Income	(7) Crime	(8) Income
Kenya × Post	1.088^{**}	-0.314^{**}	-1.419^{***}	-0.782	-0.860^{**}	-1.068^{***}	-2.839^{***}	-2.241^{***}
	(0.467)	(0.140)	(0.523)	(0.634)	(0.328)	(0.224)	(0.153)	(0.207)
Observations	5,841	3,012	2,354	1,572	4,024	2,016	2,908	2,286
Adjusted R^2	0.085	0.196	0.254	0.393	0.138	0.296	0.047	0.091
All Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES

Table 7: Model Calibration

Parameter	**Symbol**	**Value**	**Description**
Preferences & Technology			
Subjective discount factor	β	0.98	Implies steady-state interest rate $\approx 8\%$ annually
Labour disutility weight	ψ	5.00	Scales steady-state labour supply
Inverse Frisch elasticity	ν	1.00	Standard macro literature
Liquidity utility weight	χ	0.10	Matches unconstrained money demand
Labour share in production	α	0.65	Standard labour share
CIA constraint tightness	κ	1.20	Average cash-to-consumption ratio
Production technology	A	1.00	Time-invariant nationwide technology normalised to one
Persistence of demonetisation shock	ρ_ξ	0.50	Demonetisation shock follows a non-persistent AR(1) process
Financial / Mobile Money			
MMP reserve requirement ratio	ρ^e	0.10	Fractional reserve backing of M-Pesa trust
Unremunerated asset ratio	ρ	0.05	Fraction of trust not earning interest
MMP transaction cost	θ^e	0.01	1% average deposit/withdrawal fee
Spatial Divide			
1. Urban Calibration			
Constrained pop. share	ω_p	0.40	Lower share of financially constrained households
Mobile money weight	ω_m	0.70	High M-Pesa penetration
Elasticity of substitution	σ	1.30	Cash and mobile money are highly substitutable
WCC tightness	γ	1.70	High reliance on cash clearing in urban retail/transit sectors
Crime sensitivity weights	$\omega_y, \omega_{cash}, \omega_{wage}$	0.05, 0.25, 0.70	Highly sensitive to local wage desperation
2. Rural Calibration			
Constrained pop. share	ω_p	0.65	High share of financially constrained households
Mobile money weight	ω_m	0.10	Sparse M-Pesa penetration
Elasticity of substitution	σ	0.80	Cash and MM are complements in agricultural economies
WCC tightness	γ	0.30	Low reliance on daily cash clearing in agriculture
Crime sensitivity weights	$\omega_y, \omega_{cash}, \omega_{wage}$	0.60, 0.20, 0.20	Highly sensitive to shadow economy collapse

Table 8: Model-Generated Demonetisation Effects (Baseline Survey Point Equivalents)

Variable	**National**	**Urban**	**Rural**
Crime Perception			
Aggregate	−0.1472	−0.1473	−0.1472
MM Users (Unconstrained)	–	0.0288	−0.0742
Cash-Only (Constrained)	–	−0.0259	−0.0745
Mobile Money Adoption			
Aggregate	0.0101	0.0074	−0.0179
MM Users (Unconstrained)	–	0.0075	−0.0183
Cash-Only (Constrained)	–	−0.0463	0.0360
Income Status			
Aggregate Income	−0.0017	−0.0013	−0.0061
MM Users (Unconstrained)	–	−0.0012	−0.0004
Cash-Only (Constrained)	–	−0.1007	−0.3408

Table 9: Model-Generated Demonetisation Effects (Sensitivity Test)

Variable	**National**	**Urban**	**Rural**
Crime Perception			
Aggregate	−0.0765	−0.0767	−0.0752
MM Users (Unconstrained)	–	0.0113	−0.0383
Cash-Only (Constrained)	–	−0.0138	−0.0311
Mobile Money Adoption			
Aggregate	0.0076	0.0056	−0.0134
MM Users (Unconstrained)	–	0.0056	−0.0137
Cash-Only (Constrained)	–	−0.0148	0.0362
Income Status			
Aggregate	−0.0016	−0.0010	−0.0045
MM Users (Unconstrained)	–	−0.0009	−0.0003
Cash-Only (Constrained)	–	−0.1572	−0.2528

Note: In the sensitivity test, theoretical equivalents were computed using the discrete average of $t = 1$ and $t = 2$ for the immediate post-shock survey wave, addressing the chronological straddle of the Round 8 survey.

Table 10: Material Welfare Changes (Consumption Equivalent Variation %)

Group	**National**	**Urban**	**Rural**
Aggregate	−0.321	−0.163	−0.376
MM Users (Unconstrained)	–	−0.026	−0.073
Cash-Only (Constrained)	–	−0.368	−0.539

Note: A negative value indicates a welfare loss, expressed as a permanent percentage reduction in baseline consumption without the demonetisation regime.

Long Appendix — Not for Publication

Table LA1: Household-Level Estimates of the Effects of Demonetisation with East Africa Control

	Mobile Money Usage				Crime Perception				Income Status			
	(1) Loc FE	(2) Loc+Ctry	(3) Loc+Year	(4) All FE	(5) Loc FE	(6) Loc+Ctry	(7) Loc+Year	(8) All FE	(9) Loc FE	(10) Loc+Ctry	(11) Loc+Year	(12) All FE
Main Variables												
Kenya	-0.690^{**}	-0.677^{**}	-0.522	-0.549	1.457^{***}	0.670^{**}	1.306^{***}	0.589^{*}	0.625^{***}	0.420^{*}	0.532^{***}	0.356
	(0.320)	(0.323)	(0.326)	(0.333)	(0.281)	(0.310)	(0.289)	(0.307)	(0.194)	(0.240)	(0.191)	(0.228)
Post-demonetisation	-1.439^{***}	-1.418^{***}	-1.894^{***}	-1.913^{***}	0.146	-0.484^{***}	0.542^{***}	-0.184	1.342^{***}	1.190^{***}	1.590^{***}	1.432^{***}
	(0.293)	(0.290)	(0.322)	(0.325)	(0.145)	(0.140)	(0.198)	(0.197)	(0.108)	(0.163)	(0.118)	(0.195)
Interaction Term												
Kenya $\times$ Post	0.910^{***}	0.884^{***}	0.737^{**}	0.754^{**}	-1.596^{***}	-0.891^{***}	-1.442^{***}	-0.809^{**}	-0.915^{***}	-0.748^{***}	-0.820^{***}	-0.682^{***}
	(0.324)	(0.316)	(0.327)	(0.324)	(0.335)	(0.313)	(0.369)	(0.325)	(0.216)	(0.245)	(0.228)	(0.242)
Fixed Effects & Controls												
Location Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country Fixed Effects	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Year Fixed Effects	NO	NO	YES	YES	NO	NO	YES	YES	NO	NO	YES	YES
Economic Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Social Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Model Statistics												
Observations	20,644	20,644	20,644	20,644	20,284	20,284	20,284	20,284	20,401	20,401	20,401	20,401
R^2	0.613	0.613	0.618	0.618	0.115	0.164	0.124	0.168	0.349	0.351	0.352	0.353

Notes: Robust standard errors clustered at the household level in parentheses. Sample restricted to Kenya and East African countries (Rwanda, Tanzania, Uganda) as control group. The Kenya $\times$ Post coefficient represents the difference-in-differences estimator, measuring the causal effect of Kenya's 2019 demonetisation policy. Location FE models include district/city/village fixed effects. Economic controls include female primary income earner, financial well-being, and employment status. Social controls include education, religion, urban/rural location, and occupation group. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table LA2: Household-Level Estimates of the Effects of Demonetisation with Whole Africa Controls

	Urban Areas			Rural Areas		
	(1) MM	(2) Crime	(3) Income	(4) MM	(5) Crime	(6) Income
kenya	-0.124	1.066***	0.619***	0.747***	1.502***	0.623**
	(0.078)	(0.381)	(0.238)	(0.052)	(0.310)	(0.272)
post	-0.363***	-0.373***	0.560***	-0.975***	-0.612***	0.341***
	(0.018)	(0.065)	(0.088)	(0.025)	(0.152)	(0.059)
kenya_post	0.139*	-1.017***	-0.126	-0.673***	-0.221	0.895***
	(0.072)	(0.287)	(0.183)	(0.047)	(0.307)	(0.228)
_cons	1.276***	2.286***	2.000***	1.277***	1.384***	1.375***
	(0.038)	(0.288)	(0.181)	(0.050)	(0.169)	(0.177)
Observations	51,551	50,704	29,484	62,028	60,892	35,579
Adjusted R^2	0.304	0.148	0.251	0.619	0.133	0.217
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Location FE	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors clustered at the household level in parentheses. Sample restricted to All African countries as control group. The Kenya × Post coefficient represents the difference-in-differences estimator, measuring the causal effect of Kenya's 2019 demonetisation policy. Location FE models include district/city/village fixed effects. Economic controls include female primary income earner, financial well-being, and employment status. Social controls include education, religion, urban/rural location, and occupation group. * p<0.10, ** p<0.05, *** p<0.01.

Table LA3: Household-Level Estimates of the Effects of Demonetisation with CEM Weighted Controls

	Urban Areas			Rural Areas		
	(1) MM	(2) Crime	(3) Income	(4) MM	(5) Crime	(6) Income
Kenya	0.265	1.434***	1.514***	−0.024	1.474***	1.339***
	(0.218)	(0.111)	(0.071)	(0.018)	(0.231)	(0.162)
Post	−1.235***	1.011***	2.977***	−2.011***	1.059***	1.883***
	(0.083)	(0.080)	(0.016)	(0.015)	(0.190)	(0.270)
Kenya × Post	0.644***	−1.809***	−1.786***	0.241***	−1.636***	−0.679**
	(0.219)	(0.216)	(0.109)	(0.027)	(0.266)	(0.324)
Constant	1.235***	1.489***	1.023***	2.011***	1.497***	1.199***
	(0.083)	(0.080)	(0.016)	(0.015)	(0.146)	(0.141)
Observations	8,289	8,214	4,588	7,139	6,989	4,330
Adjusted R^2	0.312	0.203	0.340	0.760	0.162	0.340
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES

Notes: Robust standard errors in parentheses. CEM-weighted regressions using matched samples for urban and rural areas separately, following the approach of (Ho ,2007). The Kenya × Post coefficient represents the difference-in-differences estimator, measuring the causal effect of Kenya's 2019 demonetisation policy. MM refers to Mobile Money adoption. * p<0.10, ** p<0.05, *** p<0.01.

Table LA4: Robustness Check: Alternative Standard Error Clustering

Clustering Level	Mobile Money	Crime Perception	Income Status
Household (Baseline)	1.046***	-1.695***	-0.780**
	(0.161)	(0.349)	(0.339)
Country	1.046***	-1.695**	-0.780*
	(0.187)	(0.421)	(0.389)
Survey Round	1.046***	-1.695***	-0.780**
	(0.172)	(0.378)	(0.351)
Statistical Significance	Robust	Robust	Robust
Economic Significance	Large	Large	Moderate

Notes: Kenya × Post coefficients shown. Standard errors in parentheses. While country-level clustering increases standard errors as expected, the direction, magnitude, and overall significance patterns remain consistent across clustering approaches. * p<0.1, ** p<0.05, *** p<0.01