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“Reducing Disparities in Digital Financial Marketplace through Platform Interoperability: Micro Evidence from Mobile Money”

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Reducing Disparities in Digital Financial Marketplace through Platform Interoperability: Micro Evidence from Mobile Money

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Abstract

Markets for digital financial (DF) services have the potential to reduce poverty and improve welfare, yet vast and significant disparities exist. Many digitization and interoperability initiatives are transforming the DF marketplace. A first-order policy question is, "When and how does interoperability influence gender disparities?" We leverage a unique customer-level administrative dataset on mobile money and the first DF interoperable policy experiment in 2018 in sub-Saharan Africa to explore these issues in Ghana. In this environment, cashless payments and digital banking are essential subjects in financial access and banking discourse. Platform interoperability — a gender-neutral policy— (i) increases adoption **(+122%)**, (ii) eliminates gender gaps in DF markets only when combined with digital experience, and (iii) increases aggregate firm profits (**+52%**). We show that gender differences in endowment and price sensitivity are relevant channels through which interoperability effects may operate. The results have important implications for interoperability initiatives in DF markets.

KEYWORDS: Digital Finance, Gender Disparities, Interoperability, Mobile Money, Digital Literacy

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I. Introduction

> "…even with this significant growth, there is still a long way to go to bring those services to over a billion people worldwide who remain unbanked. The GSMA is therefore encouraging governments worldwide to keep developing the enabling policies that can support mobile money deployments and further boost the growth of this crucial ecosystem."
>
> — Max Cuvellier, Head of Mobile for Development for GSMA, 2023

The introduction of digital finance (DF) services, such as mobile money, agent banking, mobile banking, and point-of-sale devices, has revolutionized the global financial landscape. A testament to the rapid growth is the 20% increase in mobile payments between 2014 and 2021 (Annan et al., 2023). This evolution is crucial in developing regions where many people have been historically excluded from mainstream finance due to factors such as distance from banks or associated costs, resulting in significant inequalities (Aker & Wilson, 2013; Aron, 2018). In sub-Saharan Africa, 21% of adults[3] have embraced DF services like mobile money, granting them access to digital credit and insurance products (World Bank, 2020; World Bank, 2023). Such growth underscores DF's potential to drive financial inclusion and address historical access disparities.

Despite the advancements in digital financial (DF) markets, considerable gender disparities persist. This is evident in various contexts, including mobile money markets in Kenya and Ghana (Suri & Jack, 2016; Annan, 2021), agent banking in the Democratic Republic of Congo (Chambosko et al., 2021), and mobile banking in Bangladesh (Lee et al., 2022). These disparities particularly affect women, who represent a vulnerable consumer group. The failure to address these gender-based disparities can significantly impede women's ability to manage risks, stabilize consumption, or finance critical expenses like education (Dupas & Robinson, 2013; Cull et al., 2014). Moreover, such inequities can diminish their influence over resource allocation (Karlan et al., 2016) and weaken their bargaining power within households (Ashraf et al., 2006). Therefore, understanding and addressing these gender-based disparities is vital for mitigating existing inequalities and enhancing the efficiency of the DF market.

[3] Based on the Global Findex Database 2021, the adoption of mobile money accounts among adults rose from approximately 12% to 33%.

The DF marketplace is rapidly evolving with the introduction of innovative features contending with existing gender disparities. One of the key advancements in this domain is the concept of interoperability, a feature that allows transactions across different platforms, thereby widening the scope of usage. This innovation has universal applicability, ensuring equal benefits across all gender groups—gender neutral—and it is very significant in regions marked by notable disparities. For example, interoperability was introduced in Tanzania by Airtel, Tigo, and Zantel in 2014[4], and later in Ghana in 2018[5], through a joint effort by the government and central bank to enable seamless transfers across various mobile money platforms. While interoperability presents a promising avenue to boost DF adoption, it is still a subject of ongoing debate, with discussions focusing on its various advantages and potential limitations.

This study investigates the impact of interoperability—a gender-neutral policy—on gender inequality in DF and to what extent it affects the gender gap. In other words, does interoperability affect gender disparities in DF, and if so, how much? We leverage a unique customer-level administrative dataset on mobile money, the largest DF service in Ghana, which we obtain from the most prominent provider. Ghana is an ideal setting to answer our research question because it is a region where cashless payments and digital banking are essential subjects in its banking discourse and implemented its DF interoperable policy on May 10, 2018. In addition, mobile money, recognized for its potential to alleviate poverty and improve welfare (Suri & Jack, 2016; Bill & Melinda Gates Foundation, 2021) provides us a rich data source that offers valuable insights into consumer behavior. This enables us to identify disparities and take up and accurately estimate the policy's effects thus making our dataset exceptional for several reasons. Firstly, it is a panel data that tracks consumer transactions before and after the May 10, 2018, policy date. Second, our dataset is high-frequency and can be considered nationally representative[6]. This level of granularity provides a more comprehensive view of consumer behavior, allowing for a more nuanced analysis of the policy's impact. Finally, the nature of the data allows us to use a matched difference-in-differences framework to estimate the policy

[4]See https://www.zawya.com/en/press-release/tigo-pesa-now-the-largest-mobile-financial-service-eco-system-in-tanzania-wv1iouc1, accessed July 31, 2023.

[5] See https://carnegieendowment.org/2022/09/19/digital-financial-inclusion-and-security-regulation-of-mobile-money-in-ghana-pub-87949#:~:text=In%202018%2C%20Ghana%20launched%20one,(%2457%20million)%20by%202019, accessed July, 2023.

[6] The provider drew a random sample of consumers from its database.

effects. This approach helps us isolate the policy's impact by comparing the behavior of treated and control groups over time.

Our study highlights four main findings, which we have documented:

1. There is the existence of a larger and more significant gender gap, thus reaffirming previous work.
2. With interoperability, there is a gap closure in the adoption of DF
3. Introducing interoperability significantly improves transactions for women with more digital experience (i.e., years using the platform) than their male counterparts.
4. Gender differences in endowment and price sensitivity are relevant channels through which interoperability effects may operate.

Previous research on interoperability primarily centers on markets outside the realm of DF markets and is descriptive in nature. The works of Choi and Whinston (2000) and Kerber and Schweitzer (2017) exemplify this trend primarily by describing the benefits of interoperability, such as cost reduction and fair competition. However, our study stands out by using unique high-frequency data that aligns with the timing of an interoperability policy to test if the policy reduces the gender gap and estimate its impact. We also examine a context where interoperability can have a significant impact, that is, the DF marketplace. Our research shows that interoperability can close the gender gap and increase adoption.

Second, our research builds on previous studies that have explored gender disparities in areas such as risk preferences, competition, and beliefs (refer to Croson & Gneezy, 2009 for a comprehensive review; Gneezy et al., 2009; Filippin & Crosetto, 2016), as well as studies that have focused on women empowerment (Hendriks, 2019 Holloway et al., 2017). Empowered women are better equipped to make informed financial decisions, handle unforeseen challenges, and manage household resources. While we acknowledge gender gaps in uptake, we also highlight that interoperability in DF markets significantly empowers women to conduct more transactions. Interestingly, women with more digital experience transact more than their male counterparts. Our research provides detailed estimates that allow for comparison between digitally experienced women and men.

The structure of our paper is organized into several sections. Section II presents a stylized framework; Section III outlines the study setting; Section IV provides details on the data sources used in our analysis; Section V explains the empirical strategy employed; Section VI presents the results of our analysis; Section VII discusses the policy impacts of our findings; and Section VIII explores the implications of our study and includes a general discussion.

II. Stylized framework

This section presents a framework to guide our analysis to better understand disparities, take-up, and the impacts of interoperability.

The DF marketplace is essential to modern economies, offering convenient services to individuals and businesses (Gomber et al., 2017) and promoting financial inclusion by serving underserved populations (Suri, 2017; Aron, 2018). In many developing countries, mobile money has overcome the challenges of weak institutional infrastructure and high banking costs, making it a popular alternative to formal banking services. This has resulted in widespread adoption and "leapfrogging" in these regions (Aron, 2018, p. 182). Despite the advancements, certain studies have revealed the existence of gender inequalities in mobile money markets (Suri & Jack, 2016; Annan, 2021; Uwamariya et al., 2021).

Accordingly, regulations are crucial in promoting the adoption of financial services and closing the gap between consumers. They ensure financial stability, fair pricing, and consumer protection in DF markets (Gutierrez & Singh, 2013). Interoperability is one such regulation which offers numerous benefits, such as reduced costs and increased network effects, thereby increasing adoption in DF markets. Specifically, it promotes healthy competition among providers, leading to cost savings passed on to consumers (Consultative Group to Assist the Poor [CGAP], 2012) and creates network effects by attracting more people to join the network (Financial Access Initiative, 2012).

Figure 1 illustrates how interoperability operates in DF markets, particularly mobile money markets. These markets face several frictions that can impede adoption, including high transaction costs, low digital literacy, high price elasticity, and differences in mobile phone ownership (Jack & Suri, 2014; Kostov et al., 2015; Economides & Jeziorski, 2017; Aker & Wilson, 2013).

[Figure 1]

Before the introduction of interoperability, sending money across different networks incurred higher costs, creating a significant barrier to adoption. However, interoperability has helped to reduce these costs and has thus played a vital role in promoting adoption, particularly among underserved groups such as women and rural populations. By enabling cross-network transactions, interoperability helps reduce the barriers to financial access and empowers individuals with greater control over their off-network transactions.

In a heterogeneous population, we anticipate that males will embrace mobile money more than females due to women's significant obstacles in the marketplace. These obstacles include differences in financial literacy, societal norms, income, and available opportunities (see Figure 1). For instance, in certain regions, women are actively discouraged from engaging in financial transactions due to established social norms, significantly impacting their adoption of DF. Due to this, males have higher rates of mobile phone ownership, enabling them to do more cross-network transactions. However, a feature such as interoperability, which brings about cost savings to consumers, can facilitate off-network transactions among women who previously faced income barriers. This, in turn, might lead to closing gaps for women (i.e., reduction in disparities).

It is worth mentioning that although interoperability has many advantages, it also presents some challenges. Larger mobile network operators (MNOs) may resist interconnecting with smaller players to maintain dominance. Also, timing is critical for businesses to recover their investments before implementing interoperability and may conflict with existing business models, affecting customer loyalty (Kumar & Tarazi, 2012; Anderson & Reynolds, 2015). Some users may find it difficult on the consumer side due to the non-standard menu (Holloway et al., 2017). Therefore, users must have a certain digital experience or literacy level to effectively use interoperability. Women with more digital experience or literacy are more likely to benefit from interoperability. Considering the benefits and costs, we aim to test if interoperability reduces gender disparities, increases take-up, and whether it is profitable. We then describe the study setting.

III. Study setting

Mobile money has become the largest financial service in many developing regions of Sub-Saharan Africa. Over the past decade, it evolved from a niche service in Kenya to a prevalent global industry worth trillions of dollars. This transformation has been instrumental in providing countless people with access to financial services and improving their economic well-being.

Ghana has recently emerged as one of the fastest-growing mobile money markets (CGAP, 2018; International Trade Administration, 2022). It all started in 2009 when MTN introduced Ghana's first mobile money service, allowing citizens to send and receive money quickly. In the following years, three other mobile money services were launched: AirtelTigo cash, Vodafone cash, and GMoney, resulting in four nationwide mobile money services. MTN Ghana currently commands the largest market share, with 94% of the market, leaving its counterparts behind. By 2017, mobile money had gained significant traction in Ghana, with active accounts surpassing 11 million, and new products like savings, loans, pensions, and insurance were introduced. Despite this progress, mobile money wallets from different networks could not interconnect, making it inconvenient and expensive for consumers to transfer money across different networks. For instance, an MTN mobile money user could not send money directly to a Vodafone mobile money user or vice versa, forcing consumers to go to a mobile agent of Vodafone to send the money.

To address these challenges, the government and stakeholders, including the central bank and Ghana Interbank Payment and Settlement Systems, introduced interoperability on May 10, 2018, enabling seamless sending and receiving of money across networks. Since the launch of interoperability, both in-network and out-network transactions have surged in Ghana. In the first six months, the total value of transactions increased by about 85 times, from 96,907 to 8.31 million Ghanaian cedis (GHS) (Bank of Ghana, 2018). This growth has continued, with interoperable transactions expanding by over 400% from 2.5 million to 13.6 million money transactions between 2019 and 2020[7].

Although other forms of interconnectivity are used by other players in the DF ecosystems (such as aggregators), we study the consumer-side interoperability that involved the law passed on May 10, 2018, allowing consumers to perform cross-network transactions. In the next section, we describe the dataset used in our study.

IV. Data

IV.1 Transaction data

After signing a nondisclosure agreement, we obtained comprehensive administrative data from

[7] https://www.adfi.org/news/ghana-mobile-money-interoperability-transactions-rise-400-six-months, accessed August 9, 2023.

one of Ghana's largest mobile money providers. The dataset spans January 2017 to December 2018 and comprises 192,243 randomly sampled consumers from nationwide districts. The data were daily and contained over 99 million records. The event of interest in this study, interoperability, coincided with the span of the dataset, as it was instituted on May 10, 2018.

The dataset we obtained was anonymized, and consumers' names were not included. Instead, each record contained a customer ID and the corresponding ID of the consumer they transacted with, along with the amount, fee, and transaction date. Each transaction record also had a unique financial identification number for identification purposes. Additionally, the data included a column specifying the broad transaction types and their subcategories. The general transaction types were payments, debits, cash out, cash, and transfer, which constituted 41%, 17%, 16%, 14%, and 13% of the total volume of transactions, respectively. The service type field further disaggregated these transactions into subcategories. For instance, the service type for payment transactions comprised cross-network transfer (i.e., interoperability), talk time purchase, and loan repayments. Debit transactions involving automatic deductions had service types such as sports betting payments, loan repayments, and internet bundle purchases. Finally, some transactions had no fees and were labelled miscellaneous, including transaction history inquiry, balance history, and transaction reversals. In the next section, we describe the demographic characteristics of the consumers in our dataset.

IV.2 Demographic data

The firm provided a separate data table that includes consumers' demographic characteristics and unique IDs in the primary dataset. The unique IDs in the peripheral dataset allowed us to merge them with the transaction data. The demographic features include gender, date of birth, sign-up date, and customer profiles that determine the transaction limits of their mobile money wallets based on Know Your Customer rules. Using the date of birth and sign-up date, we determined the ages of customers and their digital experience, defined as the number of years they have been using the platform. In our dataset, the gender ratio is 5% females and 95% males, and the average age of consumers is 28 years, with a three-year digital experience. The firm also provided the consumers' location, including their state/region, administrative districts, and area of residence[8]. In the subsequent section, we describe our outcome variables.

IV.3 Transaction amount and business profits

The mobile money administrative data contains a wealth of information on an individual's transaction activity, including the amount involved in each transaction at any given time. Transactions can range from small amounts, such as 0.1 Ghana cedis, to large amounts in the thousands of Ghana cedis. However, the time frame in which individuals conduct transactions can be uneven. Therefore, the first step was to standardize the time frame by computing the average transaction amount involved in each type of transaction per month. This allowed us to determine the primary outcome of interest: the average transaction amount per transaction in a month. Regarding transactions, we categorize them into interoperable and non-interoperable types, which facilitates our analysis (the specifics of this classification are elaborated in the following two sections). Besides the categorization, our data also includes the associated fees, allowing us to determine monthly business profits. In the next section, we detail our empirical strategy.

V. Empirical strategy

Our main objective is to examine gender gaps, take-up, and how interoperability impacts business profits. We use a matched difference-in-differences design that combines our demographic and transaction datasets to achieve this. We selected this design based on the following reasons. Firstly, it allows us to establish a causal relationship between interoperability and its effects on transaction amounts (adoption) and business profits. Secondly, the matched design enables us to match identical controls (non-interoperable transactions) with our treated transactions (interoperable transactions), making it possible to attribute any changes or variations in interoperable transactions to the interoperability policy. Thirdly, this design helps us to compare pre-treatment trends and determine the variables for matching. We use age and digital

[8] We classified these locations into rural and urban areas using the Ghana Statistical Service district reports, with 64% urban and 36% rural.

experience as the characteristics and previous monthly average transaction amounts before the policy date (from January 2017 to April 2018) as the behavioural variables for matching.

We begin our analysis by examining existing gaps and the uptake of mobile money. To capture these gaps, we estimate the following equations:

$$Y_{it} = \beta_0 + \beta_1 Female_i + \emptyset_i + \vartheta_t + \varepsilon_{it} \quad (1)$$

where Y_{it} is the average transaction amount for a district i in month t. $Female_i$ is a dummy variable which is 1 when a transaction is a female initiated, otherwise, 0 for male. In other words, the coefficient β_1 measures the average difference in transactions between females and males, with male as the baseline. $\emptyset_i$ and ϑ_t capture district and the month-fixed effects, and ε_{it} capture the random error term. In our more robust version, we interact district and month-fixed effects.

Afterward, we estimate the first stage equation that captures the gender differences in mobile money take-up:

$$\mathrm{SoI}_{it} = \beta_0 + \beta_1 Female_i + \emptyset_i + \vartheta_t + \varepsilon_{it} \quad (2)$$

The definitions here are similar to Eqn. 1 except that SoI_{it} is the share of interoperable transactions (in percentage) for district *i* in month *t*, the coefficient β_1 in Eqn.2 captures the gender differences in the share of interoperable transactions with male as the baseline and ϑ_t and ε_{it} capture the month-fixed effects and the random error term, respectively. Similarly, interact district and month-fixed effects in our more robust version.

After the first stage regressions, we estimate a matched Difference-in-Differences (DiD) equations that capture the effect of interoperability:

$$Y_{i(i')td} = \beta_0 + \beta_1 Treat_{i(i')} \times Post_t + \cdots + \mu_{i(i')} + \delta_{td} + \theta' Treat_{i(i')} \times Trend_t + \vartheta' Treat_{i(i')} \times X^j + \varepsilon_{i(i')td} \quad (3)$$

where $Y_{i(i')td}$ is the average transaction amount for transaction type match (i') in month *t*. $Treat_i$ is 1 if i is an interoperable transaction. Our main parameter of interest β_1 captures the average effect of treatment on the treated (ATT). In our case, the ATT is the average effect of interoperability in the post-treatment period (i.e., after May 10, 2018). $Post_t$ is 1 if $t \in [May, 10,\ 2018 - \text{December},\ 31,\ 2018]$, $Trend_t$ represents the linear time trend, $\mu_{i(i')}$ is matched transaction-pair fixed effects, δ_{td} is the month x district fixed effects and X^j is a controls vector that contains age, digital experience and ε_{it} capture the random error term.

Next, we examine the gender differences in interoperability by estimating the following model on our unmatched sample:

$$Y_{it} = \beta_0 + \beta_1 Female_i \times Post_t + \cdots + \mu_i + \delta_{t'd} + \theta' Treat_i \times Trend_t + \vartheta' Treat_i \times X^j + \varepsilon_{it} \quad (4)$$

where Y_{it} is the transaction amount for a consumer i in day t. The coefficient β_1 captures the gender differences in transaction amounts (adoption) after interoperability. Similar to Eqn. 3 $Trend_t$ represents the linear time trend, μ_i is the consumer fixed effects , $\delta_{t'd}$ is the month x district fixed effects and X^j is a controls vector that contains age, digital experience and ε_{it} capture the random error term. It is worth noting that equation (4) is usually plaque with issues because it does not distinguish between interoperable and noninteroperable transactions. Also, if there are spillovers from males and females within interoperable transactions, it isn't easy to establish a counterfactual. Therefore, we complement our gender differences analysis with a matched triple difference-in-differences model, which offers detailed insights and estimates when measuring the varying effects of the treatment (interoperability) on males and females. The advantage of a triple difference model is that it provides more nuanced insights and estimates when estimating the differential impact of treatment on men and women (Olden & Møen, 2022). We specify a triple-matched difference-in-differences (DDD)) that captures the differential impacts of gender-interoperable transactions:

$$Y_{i(i')td} = \beta_0 + \beta_1 Treat_{i(i')} \times Post_t \times Female^j + \cdots + \mu_{i(i')} + \delta_{td} + \theta' Treat_{i(i')} \times Trend_t + \vartheta' Treat_{i(i')} \times X^j + \varepsilon_{i(i')td} \quad (5)$$

The definitions in Eqn.5 are similar to Eqn. 3 except that $Female^j$ =1 is when the consumer is a female**.** Also, our main parameter of interest β_1 (the triple difference-in-difference) captures the differential interoperability impact by gender (with a male as the baseline).

Next, we will investigate whether interoperability leads to increased profits. To achieve this, we estimate the following equation:

$$Y_{i(i')td} = \beta_0 + \beta_1 Treat_{i(i')} \times Post_t + \cdots + \mu_{i(i')} + \delta_{td} + \theta' Treat_{i(i')} \times Trend_t + \vartheta' Treat_{i(i')} \times X^j + \varepsilon_{i(i')td} \quad (6)$$

The definitions in Eqn.6 are like Eqn. 3 except that our outcome of interest $Y_{i(i')td}$ which is business profits for $\boldsymbol{i(i')}$ =transaction type match, $\boldsymbol{t}$ =time(month), d=district

In our design, we establish identification by comparing monthly trends for interoperable and non-interoperable transactions after introducing interoperability. This approach assumes that both transactions would have followed similar trends if the policy had not been introduced. To confirm this assumption, we plot parallel trends for our difference-in-differences (DiD) specifications as shown in the appendix Figures A1, A2, and A3. The matching procedure is critical to our design, enabling us to create pairs of identical customer transactions through one-to-one matching. The procedure is further described in the subsequent section.

V.1 Construction of matched sample
V.1.1 Matching procedure

Interoperability, being a national policy, impacted every consumer in our dataset. For this reason, we examined transaction types to determine the effects of interoperability, as some transactions were affected while others were not. During matching, we had to classify between interoperable transactions and those not. For instance, when transferring money across networks, interoperability can have a second-order effect on cash-out transactions. If a consumer withdraws money received through an interoperable transfer, interoperability can affect the cash-out process. However, these types of transactions violate the Stable Unit Treatment Value Assumption (SUTVA), which requires treatment to be well-defined and without interference between units in different treatment groups. Therefore, we exclude cash-out transactions from our analysis. Additionally, there are more transactions unaffected by interoperability than those that are, suggesting that the distribution of interoperable and non-interoperable transactions may differ.

Furthermore, to ensure a similar distribution of the treated (interoperable) and control (non-interoperable) transactions, we perform a coarsened matching (CEM) technique. Coarsened matching is a form of exact matching but has an added advantage. It retains most of the observation, unlike exact matching, which excludes many because it matches exactly on the same covariates. The main advantage of CEM is that it coarsens the data to reduce the level of granularity. Specifically, it coarsens the data by binning covariates. In our case, it bins the ages of our consumers and their digital experience on the platform. We use CEM matching to obtain a customer transaction pair that is 1:1, which we then utilize for our difference-in-difference estimates.

To ensure a credible control group, we match individuals not only by age and digital experience but also by the values of the dependent variable (average transaction amount) before the policy date. In the next section, we will present the results of our study.

VI. Results

VI.1 Existing disparities and take-up

We present results that indicate existing disparities in gender in Tables 1 and 2 based on Eqn. 1. In each of the Tables, column (1) is our basic specification that controls for no fixed effects, column (2) accounts for district and month fixed effects, and column (3) our preferred model accounts for the interaction of district and month fixed effects. The coefficient, Female, is negative and significant across all columns. This implies that there are existing disparities in mobile money adoption between males and females; on average, males transact higher than females by almost 2 GHS ($\frac{2.02}{7.64} \approx +26\%$), as shown in Table 1. We present the disparities before the policy in Table 2. Table 2 indicates that the coefficient for females is 1.46 GHS less than that of males representing a $\frac{1.46}{3.13} \approx +47\%$ gender gap. These estimates are robust to confounders because we control for the interaction of district and month-fixed effects.

Next, we analyze the take-up or adoption of interoperability using Eqn. 2. Our preferred model using the district and month-fixed effects interaction indicates an estimated difference of 1.37 pp. The estimated difference corresponds to a $\frac{1.37}{6.90} \times 100 \approx +20\%$ higher incidence of interoperable transactions for females. Conditional on district x month fixed effect that absorbs potential confounding variation, we interpret this as a gender gap in adoption (see appendix Table A1). To assess the evolution of interoperability, we plot the share of interoperable transactions over time (Figure 2) and gender differences in the share of interoperable transactions (Figures 3 and 4). Figure 2 indicates that the share of interoperability seems to have grown to about 12% after the policy; and continued to grow till it plateaued at about 20%, then declined steadily and peaked at 15%.

Regarding the number and amount, the share of interoperability for females surpassed males throughout time after the policy, as indicated in Figures 3 and 4 which reemphasizes the closure of the gender gap. In the following sections, we present policy estimates since these unconditional plots suggest strong policy effects.

VI.2 Policy impacts on disparities

Table 3 reports the effect of interoperability (as shown in Eqn. 3). Controlling differential trends by treatment groups and by characteristics in addition to customer transaction-pair and interaction of month and district fixed, we obtain a positive coefficient on $Treat_{i(i')} \times Post_t$. This suggests that introducing interoperability increased adoption by almost 9 GHS – approximately a +122% increase in mobile money adoption.

VI.3 Gender differences and heterogeneous impact of interoperability

In this section, we present estimates of gender differences in interoperability and explore its heterogeneous impacts. We first estimate a gender difference in interoperability and explore the moderating role of digital experience in Table 4. Table 4 shows that after interoperability, male transactions surpass that of females with approximately 1.68 GHS. In column (2), we examine gender differences post interoperability and our coefficient of interest $Female_i \times Post_t$ is not statistically different from 0, which indicates there are no gender differences in adoption post interoperability. However, these estimates are more likely to be affected if there are spillovers from males and females within interoperable transactions (as stated in section V). To distinguish between interoperable and non-interoperable transactions and explore heterogeneity, we estimate a triple difference-in-differences model and perform some heterogeneity analysis in in Table 5.

In Table 5, we conducted our DDD estimates (Eqn. 5) in column (1) of Table 5. We split the sample into above-median and below-median digital experience in columns (2) and (3), respectively. The last column involves the interaction of DDD with a continuous measure of digital experience. Per column (1), interoperability can eliminate gender gaps to eliminate gaps for DF markets, as shown by the non-statistical triple difference coefficient, which implies that interoperability has the potential to eliminate gender gaps to eliminate gaps for DF markets.

According to column (3), there are no gender differences in adoption when we examine customers with digital experience higher than the median. However, interoperability decreases adoption for females when we examine consumers with digital experience below the median—approximately 27% (see column 3). The last column indicates that interoperability has the potential to eliminate gender gaps only if combined with digital literacy.

VI.4 Word cloud

One concern we had regarding digital literacy or experience is its potential confounding effect with awareness. To address this concern, we conducted a word cloud analysis using news articles from popular press sources in Ghana before and after the implementation of interoperability. We utilized Factiva, a standard business information system that aggregates news from popular press sources to gather these articles.

We sampled news articles from January 1, 2017, to March 31, 2018[9], for the pre-policy period. Similarly, for the post-policy period, we sampled news articles from May 10, 2018, to October 31, 2018. The word cloud analysis revealed minimal mention of "interoperability" before the policy change compared to the post-policy period (Figure 5). In other words, the news articles during that time did not effectively communicate the details and potential benefits of the new feature to the public compared to the post-period. Consequently, many people may have been unaware of the existence of interoperability or the potential value it could provide. Specifically, the word cloud analysis for the pre-policy period shows that the word "interoperability" represented less than 3% of the content, while for the post-policy period, interoperability represented about 12%, indicating a significant increase in its prominence.

Considering this finding, we are confident that the gap closure is driven by pre-existing digital experience rather than awareness.

VI.5 Profitability

In this section, we investigate the impact of interoperability on profitability using our difference-in-differences approach. Our analysis is based on a robust model, as shown in Table 6,

[9] To prevent any anticipation effects, we have decided to remove two months. Furthermore, the inclusion of these two months does not significantly alter the results.

specifically column (2). We can provide a comprehensive assessment by incorporating district and month-fixed effects and their interaction. Our findings reveal a notable result: interoperability is associated with a significant increase in profitability, with a gain of about $\frac{0.80}{1.54} = 52\%$.

VII. Mechanisms

In this section, we explore possible explanations for our findings. Specifically, we examine gender differences in endowment and price sensitivity as possible mechanisms through which interoperability operates. We analyze data from multiple sources, such as surveys and additional mobile money records, to accomplish this. Further details on our methodology can be found in the subsections that follow.

VII.1 Endowment effect

Interoperability's effectiveness in bridging gender gaps in the DF marketplace relies on its combination with increased digital experience. One crucial factor contributing to this phenomenon is the gender disparity in cell phone ownership or endowment before the policy intervention.

The endowment effect, which refers to individuals attaching greater value to objects they already possess (Dommer & Swaminathan, 2013), plays a significant role in interoperability. It means that individuals who already own multiple cell phones (signifying multiple networks), typically males, might be less inclined to adopt new services like interoperability that facilitate transactions across networks. This is because they can already transact easily across different networks. Conversely, females, who were less likely to engage in interoperability due to not owning multiple phones historically because of barriers such as financial constraints, social norms, or lack of awareness, exhibit a higher likelihood of adopting interoperability compared to their male counterparts (i.e., their increased interoperable transactions rise to levels that eliminate the overall gender gap).

To examine this mechanism or channel, we obtained data on cell phone ownership from the Ghana Living Standards Survey (GLSS) conducted by the Ghana Statistical Service (GSS) from October 22, 2016, to October 17, 2017. The survey has been a reliable data source since 1986 for researchers and policymakers studying the living conditions and well-being of the

Ghanaian population. Specifically, the survey has a section on information communication technology that looks at computer ownership, and usage, mobile phone ownership. Thus, we can analyze gender gaps in cell phone ownership pre-policy using the GLSS data and assess whether differences closed post-policy using our mobile money dataset. Figures 6 and 7 indicate that males surpass females in gender ownership of cell or mobile phones pre-policy. We analyzed the distribution of cell phone ownership based on gender in different regions. Our findings reveal that men tend to own cell phones more than women, as evidenced by the gender gap (Female-Male) column in Table A2 of the appendix. Based on the descriptives in Table A2, we rank the gender gaps in ascending order of widening gaps. Afterward, we calculate the median and split them into regions with high gender gaps vs. low gender gaps. Accra, Eastern, Ashanti, Volta and Central regions emerged above the median, while the rest remained below the median (See Table A2).

Our next step is to carry out a difference-in-differences analysis, considering the gender gaps that exist in different regions. We aim to ascertain whether interoperability has resulted in a decrease in the gender gap in areas where the gap is wider than the median:

$$Y_{i(i')td} = \beta_0 + \beta_1 Treat_{i(i')} \times Post_t \times Female^j \text{x } RegionDiff_i + \cdots + \mu_{i(i')} + \delta_{td} + \varepsilon_{i(i')td} \quad (7)$$

$Equation$ (7) definitions are similar to $Equation$ (3), except where $RegionDiff$ is an indicator that represents the regional difference of cellphone ownership (Female-Male), therefore our main parameter of interest β_1 captures the differential interoperability impact by gender (with male as the baseline) taking into account the regional gap differences in mobile phone ownership. If β_1 is positive and significant, females do more transactions after interoperability in regions with larger pre-existing gaps. As indicated by Table 7, β_1 is positive and significant (9.276), indicating a wider gap reduction therefore, in regions where the pre-existing gaps are larger, females do more transactions after interoperability.

VII.2 Price Sensitivity

Based on previous studies, we have explored the gender differences in the price sensitivity channel (Gao et al., 2020; Wakefield & Inman, 2003; Umashankar et al., 2017; Santana and Morwitz, 2021). Our goal is to better understand how price sensitivity varies with gender in the context of premium and freemium transactions. We define premium transactions as those that attract a fee, such as checking transaction history and peer-to-peer transfers, while freemium transactions do not, such as ATM withdrawals and checking of balance. For our study, we have selected transaction history transactions and ATM withdrawals as our premium and freemium transactions, respectively. Checking history serves as our transactions in the treatment group, while ATM withdrawals are our transactions in the control group. We have selected these transaction types based on our pre-treatment plots because they trend in the same direction. We believe that interoperability may benefit females by generating cost savings, making them less price sensitive or indifferent to males after the policy. To explore this possibility, we will estimate the following regression specification.

$$Y_{it}^{j} = \beta_0 + \beta_1 Premium_i \times Post_t \times Female^j + \cdots + \gamma_j + \delta_t + \varepsilon_{it} \quad (8)$$

where Y_{it}^{j} = Number of transactions for j =individual, t =time in month, $Premium_i$=1 if i is a premium transaction, $Post_t$ =1 if $t \in [May, 10,\ 2018 - December,\ 31,\ 2018]$, $Female^j$=1 is when the consumer is a Female, γ_j =user-specific fixed effects and δ_t =month FE. Our main coefficient of interest β_1 captures the gender differences in the number of premium transactions conducted (i.e., a measure of price sensitivity) for males and females (with males as baseline) after the policy. We present the results in Table 8. According to Table 8, β_1 is not statistically significant, meaning there are no gender differences in the number of premium transactions conducted after interoperability, implying no price sensitivity differences between males and females. Therefore, we conclude that one of the channels through which interoperability can eliminate gaps for DF markets is the price sensitivity channel.

VIII. Discussions and implications

Interoperability initiatives have become increasingly important in recent years as DF markets evolve. However, research has shown that there are often significant gender differences in take-up. Our research has examined the gender disparities in adoption and discovered that the adoption gap could be bridged by a feature (i.e., interoperability) in the DF marketplace. However, this cannot be accomplished without digital literacy or experience. Additionally, our research demonstrates that gender differences in endowment and price sensitivity are relevant channels through which interoperability effects may operate.

The results of this study have significant implications for the future of research and practice in the DF marketplace. It emphasizes the importance of creating a user-friendly DF marketplace that ensures a positive experience, especially for women with limited digital experience or literacy. This will lead to an increased adoption of new features in DF markets. Also, to decrease the gender gap in take-up, policymakers and companies should consider the price sensitivity nature of women when setting prices for their products and services. They can achieve this by reducing adoption and usage costs and offering rewards for adoption. This will in turn encourage more women to participate in the DF marketplace.

Another way to promote the participation of women in DF markets is to offer digital literacy training that will encourage less experienced users to participate in the DF marketplace. In addition, clear and accessible messaging is crucial in increasing public awareness and adopting new features in the DF marketplace. Therefore, future releases should prioritize effective communication and marketing strategies. This will ensure that the public has the awareness and understanding needed to increase the adoption of new features in DF markets.

In conclusion, this paper has explored the gender differences in adoption in the DF marketplace and argued that interoperability can decrease the gender gap in take-up, and the impacts of interoperability are more significant for women with more digital experience.

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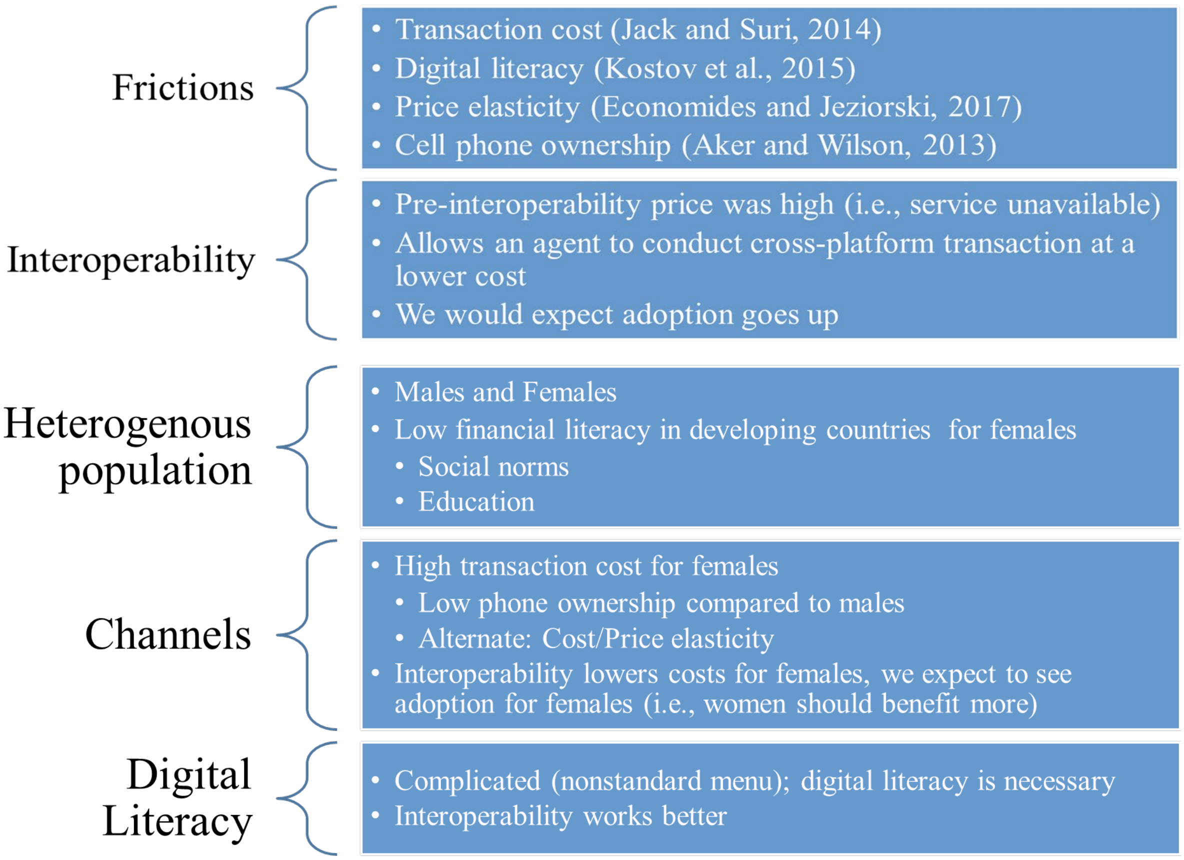
Figure 1: Summary of stylized framework



Notes: This figure is a summary of a stylized framework. It begins by summarizing the frictions in DF markets and then shows how interoperability combined with digital literacy reduces such frictions.

Table 1: Effect of gender on the transaction amount

DV: Transaction amount, GHS

	(1)	(2)	(3)
Female	**-2.130*****	**-2.020*****	**-2.020*****
	(0.0827)	**(0.0820)**	**(0.0821)**
Constant	7.880***	7.868***	7.868***
	(0.0339)	(0.0334)	(0.0334)
District FE	No	Yes	No
Month FE	No	Yes	No
Month x District FE	No	No	Yes
Observations	2,459,376	2,459,376	2,459,352
Mean DV	7.644	7.644	7.644

Notes: The dependent variable is the monthly average transaction amount. Model (1) is the basic Model that controls no fixed effects. Model (2) contains district and month-fixed effects, while Model (3), the primary model, controls district interaction with month-fixed effects. Clustered (transaction-pair matched) standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Effect of gender on the transaction amount before interoperability

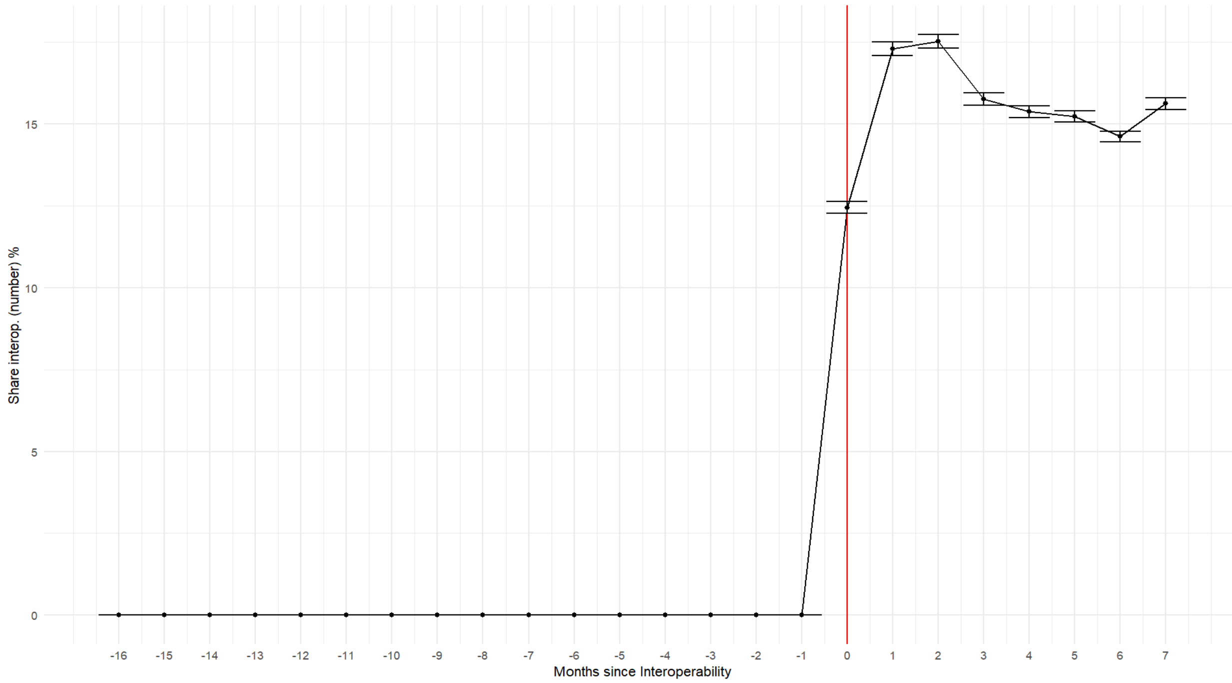
DV: Transaction amount, GHS

	(1)	(2)	(3)
Female	**-1.483*****	**-1.457*****	**-1.457*****
	(0.0369)	**(0.0370)**	**(0.0370)**
Constant	3.294***	3.291***	3.291***
	(0.0199)	(0.0198)	(0.0198)
District FE	No	Yes	No
Month FE	No	Yes	No
District x Month FE	No	No	Yes
Observations	1,625,264	1,625,264	1,625,248
Mean DV	3.127	3.127	3.127

Notes: The dependent variable is the monthly average transaction amount. Model (1) is the basic Model that controls no fixed effects. Model (2) contains district and month-fixed effects, while Model (3), the primary model, controls district interaction with month-fixed effects. All estimations are before interoperability. Clustered (transaction-pair matched) standard errors in parentheses.

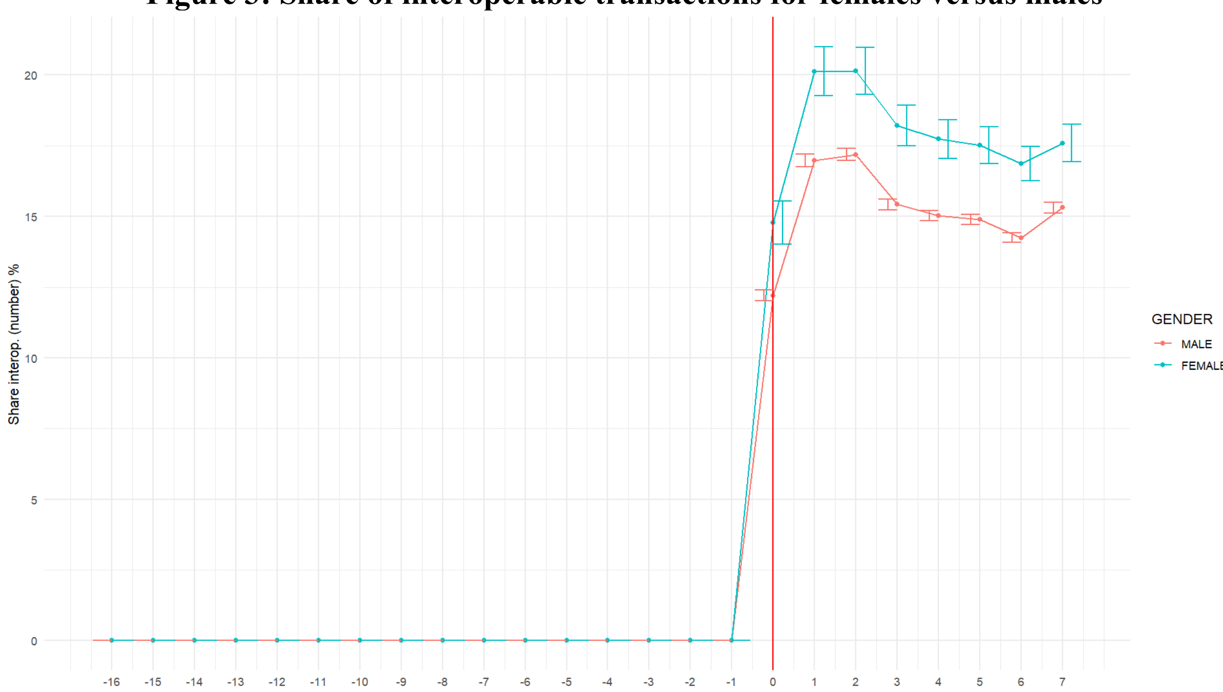
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 2: Share of interoperable (number) transactions



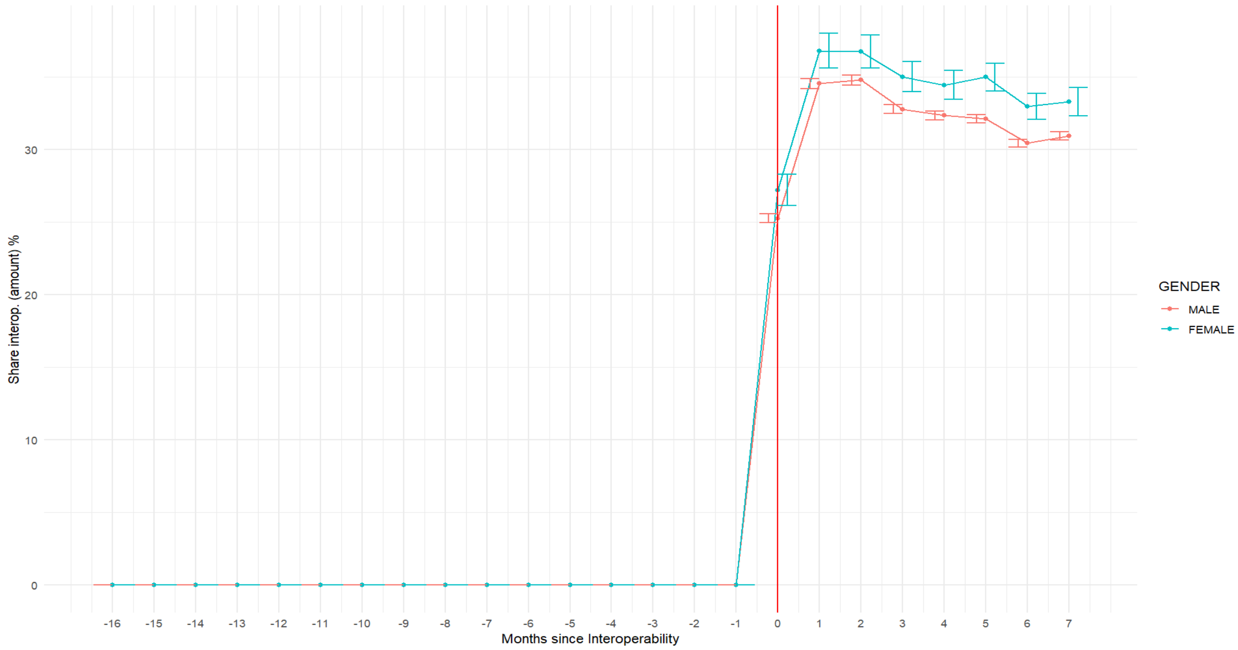
Notes: This Figure is an unconditional plot of the share of interoperable transactions (%) against months since the introduction of mobile money interoperability (May 10, 2018). The share is zero in the pre- interoperability regime and takes on post-policy values by construction.

Figure 3: Share of interoperable transactions for females versus males



Notes: This Figure is an unconditional plot of the share of interoperable transactions (%) against months since mobile money interoperability (May 10, 2018) for males versus females. After the policy, the female share of interoperable transactions on average surpasses that of males. By construction, the share is zero in the pre-interoperability regime and takes on post-policy values for females and males.

Figure 4: Share of interoperable (amount) transactions for females versus males



Notes: This Figure is an unconditional plot of the share of interoperable transactions (%) against months since mobile money interoperability (May 10, 2018) for males versus females. After the policy, the female share of interoperable transactions on average surpasses that of males. By construction, the share is zero in the pre-interoperability regime and takes on post-policy values for females and males.

Table 3: Difference-in-differences model comparing differences in transaction amounts across Interoperable versus non-Interoperable transactions

DV: Transaction amount, GHS	
	(1)
Treat	-2.130***
	(0.136)
Treat x Post	**9.260*****
	(0.133)
Constant	-2.088*
	(1.069)
Customer Transaction-Pair FE	Yes
Month FE	No
Month x District FE	Yes
Treat x Controls	Yes
Treat x Trend	Yes
Observations	2,459,352
Mean DV	7.644

Notes: The dependent variable is the average transaction amount per month. The model is difference-in-differences models that control for customer transaction-pair fixed effects. Notably, we get customer transaction pairs via Coarsened Exact Matching. Also, the model controls for controls for month interaction with district fixed effects and the interaction effects of treatment and control variables (age and digital experience) and also interaction effects of treatment and trend. Clustered (transaction-pair matched) standard errors in parentheses controls district interaction with month fixed effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Gender differences model comparing differences in females and males after interoperability

DV: Transaction amount, GHS

	(1)	(2)
Female	-1.684**	
	(0.702)	
Post		4.006***
		(0.579)
Female x Post		0.567
		(0.555)
Constant	49.689**	31.502***
	(0.178)	(3.272)
Customer FE	No	Yes
Month x District FE	Yes	Yes
Treat x Controls	No	Yes
Treat x Trend	No	Yes
Observations	84,334,874	84,332,134
Mean DV	49.689	49.611

Notes: The dependent variable is the daily transaction amount. Model 1 captures the effect of gender on interoperability. Model 2 examines gender differences in transaction amount post interoperability. Model 1 controls for the interaction of month and district fixed effects while Model 2 controls for month interaction with district fixed effects and the interaction effects of treatment and control variables (age and digital experience) and interaction effects of treatment and trend. Clustered (customer) standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Triple difference-in-differences model comparing the differences in transaction amounts across Interoperable versus non-Interoperable transactions for different gender groups

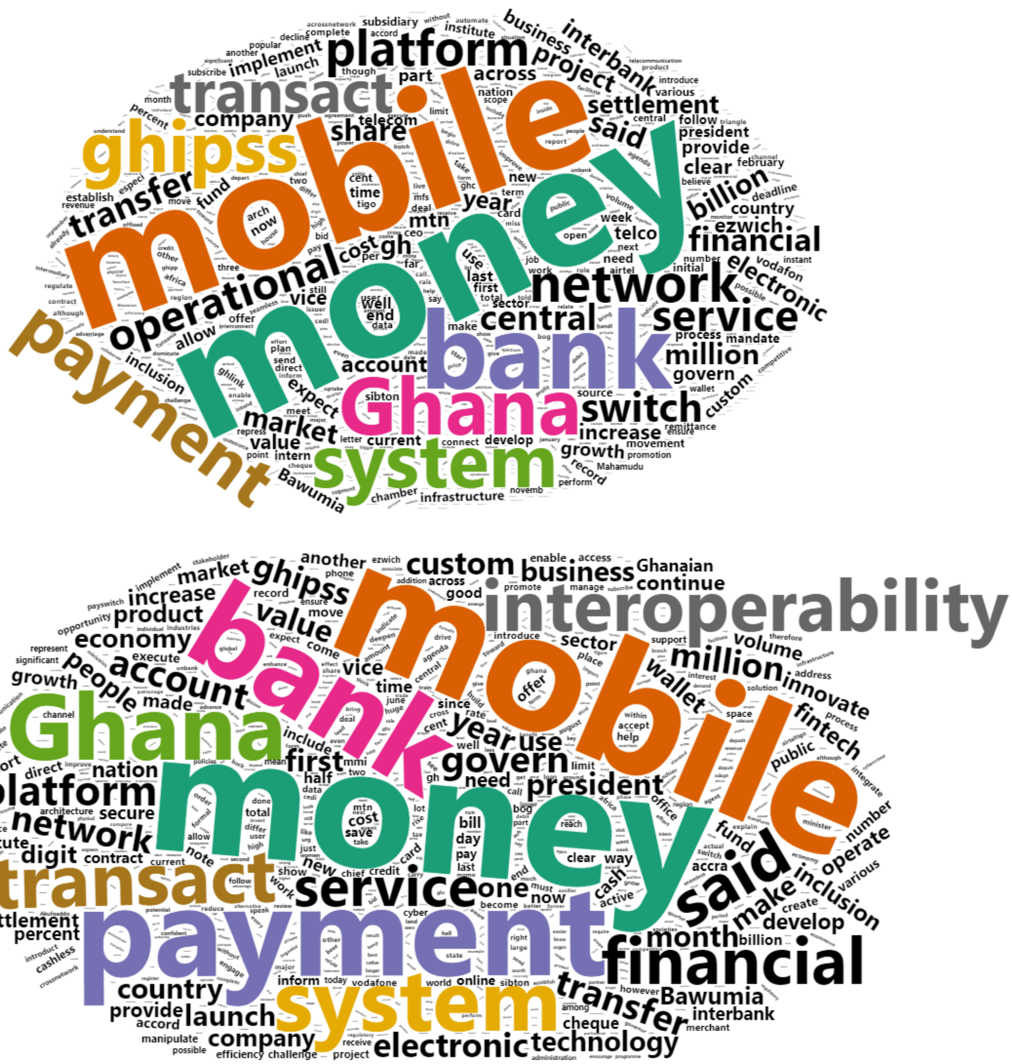
DV: Transaction amount, GHS

	(1)	(2)	(3)	(4)
Treat	-2.146***	-1.675***	-2.429***	-2.210***
	(0.138)	(0.223)	(0.211)	(0.135)
Treat x Post	**9.171*****	8.023***	10.50***	11.66***
	(0.141)	(0.193)	(0.208)	(0.213)
Female	0.0148	-0.137	0.319	0.257
	(0.141)	(0.209)	(0.201)	(0.191)
Treat x Female	-0.639***	-0.105	-0.867***	-0.620***
	(0.128)	(0.260)	(0.152)	(0.139)
Post x Female	-1.501***	-1.760***	-1.585***	-1.672***
	(0.234)	(0.393)	(0.297)	(0.294)
Treat x Post x Female	**0.0709**	**0.789**	**-1.715*****	-1.706***
	(0.398)	**(0.677)**	**(0.502)**	(0.501)
Treat x Post x Female x Experience				**2.429*****
				(0.843)
Constant	-1.841*	1.233	-3.884*	-1.674
	(1.065)	(1.507)	(2.240)	(1.060)
Customer Transaction-Pair FE	Yes	Yes	Yes	Yes
District x Month FE	Yes	Yes	Yes	Yes
Treat x Controls	Yes	Yes	Yes	Yes
Treat x Trend	Yes	Yes	Yes	Yes
Observations	2,437,872	1,221,792	1,216,056	2,437,872
Mean DV	7.593	8.724	6.456	7.593

Notes: The dependent variable is the monthly average transaction amount. Models are triple difference-in differences models comparing differences in transaction amounts across Interoperable versus non-Interoperable transactions for different gender groups. Specifically, Model (1) is a triple difference-in-differences model comparing differences in transaction amounts across Interoperable versus non-Interoperable transactions for different gender groups. Model (2) is a triple difference-in-differences model comparing differences in transaction amounts across Interoperable versus non-Interoperable transactions for different gender groups. Model (3) is a triple difference-in-differences model comparing differences in transaction amounts across Interoperable versus non-Interoperable transactions for different gender groups when we restrict the data to consumers who have a mean lesser than the median digital experience (< 0.87 years). Model (3) is a triple difference-in-differences model comparing differences in transaction amounts across Interoperable versus non-Interoperable transactions for

different gender groups that interacted with the continuous measure of digital experience. All the models are saturated in that they control for customer transaction pair FE, an interaction of district and month fixed effects, an interaction of treatment and controls (i.e., age and experience) and finally and an interaction of treatment and trend variables. Notably, we get customer transaction pairs via Coarsened Exact Matching. Clustered (transaction-pair matched) standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 5: Word clouds for pre- and post-interoperability



Notes: The figure above represent word clouds we built pre (top) and post-interoperability (bottom). We collected news articles from January 1, 2017, to March 31, 2018, for the pre-policy period, and from May 10, 2018, to October 31, 2018, for the post-policy period. The analysis of the pre-policy period shows that the word "interoperability" appeared in less than 3% (76/3661) of the total keywords whereas in the post-policy period, it appeared in approximately 12% (190/1592) of the total keywords. This indicates that the policy change had a significant impact on the frequency of the word.

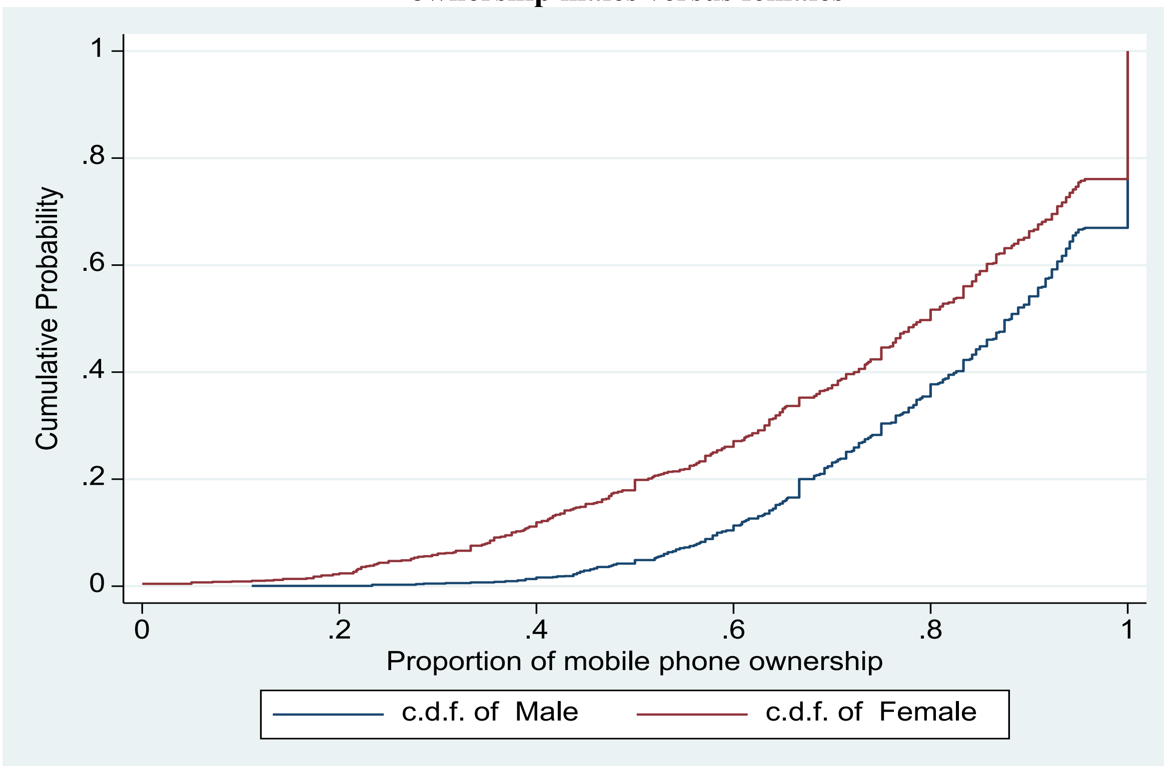
Table 6: Difference-in-differences model comparing differences in transaction fees across Interoperable versus non-Interoperable transactions

DV: Total transaction fees, GHS

	(1)	(2)
Treat	2.785***	2.791***
	(0.0302)	(0.0303)
Treat x Post	**0.811*****	**0.801*****
	(0.0352)	**(0.0350)**
Constant	0.355***	0.355***
	(0.00958)	(0.00960)
Customer Pair FE	Yes	Yes
Month FE	Yes	No
Observations	1,581,631	1,581,628
Mean DV	1.537	1.537

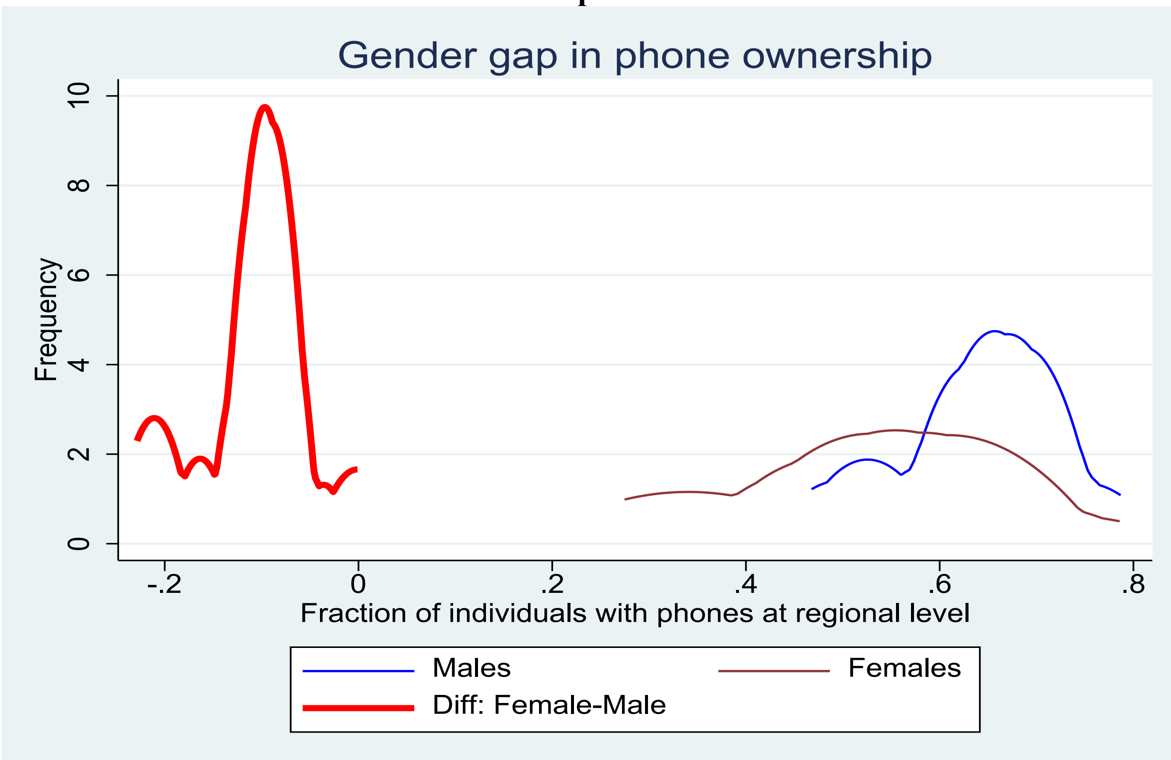
Notes: The dependent variable is the monthly average transaction amount. Models (1) and (2) are simple difference-in-differences models that control for customer transaction-pair fixed effects. Notably, we get customer transaction pairs via Coarsened Exact Matching. Also, Model (1) controls for month-fixed effects while (2) controls for month interaction with district-fixed effects. Models (3) and (4) capture the interactive effect of trends. At the same time, our preferred Model (4) controls for the trends' interactive effects and captures the interactive effects of control variables (age and digital experience). Clustered (transaction-pair matched) standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 6: Cumulative probability density plot showing the proportion of cell phone ownership males versus females



Notes: Based on the cumulative probability distribution plots (CDFs) for cellphone ownership among males and females, it can be observed that males have a greater percentage of cellphone ownership in comparison to females at different points on the distribution.

Figure 7: A graph displaying the disparity between male and female ownership of cell phones



Notes: This graph illustrates the difference in cellphone ownership between genders. On the left side, the x-axis displays negative values indicating that male ownership exceeds female ownership. The right side of the graph displays separate distributions for males and females, highlighting that the distribution for males is higher than that of females. Ultimately, the data concludes that male phone ownership surpasses that of females.

Table 7: Difference-in-differences model comparing gender and regional differences in gender gaps after interoperability

DV: Transaction amount, GHS

	(1)
Treat x RegionDiff	3.280***
	(0.353)
Post x RegionDiff	-260.123
	(234.833)
Treat x Post x RegionDiff	79.802***
	(1.630)
Female x RegionDiff	-5.547***
	(1.695)
Treat x Female x RegionDiff	2.428*
	(1.391)
Post x Female x RegionDiff	-15.631***
	(2.669)
Treat x Post x Female x RegionDiff	9.276**
	(4.429)
Constant	12.0844**
	(4.876)
Customer Pair FE	Yes
Month FE	Yes
Observations	2,437,872
Mean DV	7.592

Notes: The dependent variable is the monthly average transaction amount. The model is a triple difference-in-differences model that examines if interoperability has led to a reduction in the gender gap in regions with wider gaps pre-policy. In the model, we control for customer transaction-pair and month-fixed effects. Notably, we get customer transaction pairs via Coarsened Exact Matching. Clustered (transaction-pair matched) standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Triple difference-in-differences model comparing gender differences in price sensitivity.

DV: Number of transactions

	(1)	(2)
Premium	-1.053***	-1.045***
	(0.060)	(0.057)
Post	0.147	0.134
	(0.181)	(0.181)
Premium x Post	0.522***	0.534***
	(0.082)	(0.085)
Premium x Female		-0.08
		(0.194)
Post x Female		0.312
		(0.204)
Premium x Post x Female		-0.269
		(0.215)
Constant	2.370***	2.367***
	(0.042)	(0.042)
Customer FE	Yes	Yes
Month FE	Yes	Yes
Observations	37,382	37,382
Mean DV	1.746	1.746

Notes: The dependent variable is the number of transactions. Model (1) examines the impact of premium transactions on the number of transactions after interoperability. Model (2) is a triple differences model that explores how price sensitivity varies with gender in the context of premium and freemium transactions. Premium transactions are those that incur a fee, such as checking transaction history and peer-to-peer transfers. In contrast, freemium transactions do not incur a fee, such as ATM withdrawals and balance checks. For this study, we selected transaction history transactions as our premium transactions and ATM withdrawals as our freemium transactions. In both models, we account for customer and month-fixed effects. Our Coarsened Exact Matching analysis provides us with the customers we use in our models. Clustered (districts) standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Supplementary Material

Reducing Disparities in Digital Financial Marketplace through Platform Interoperability: Micro Evidence from Mobile Money

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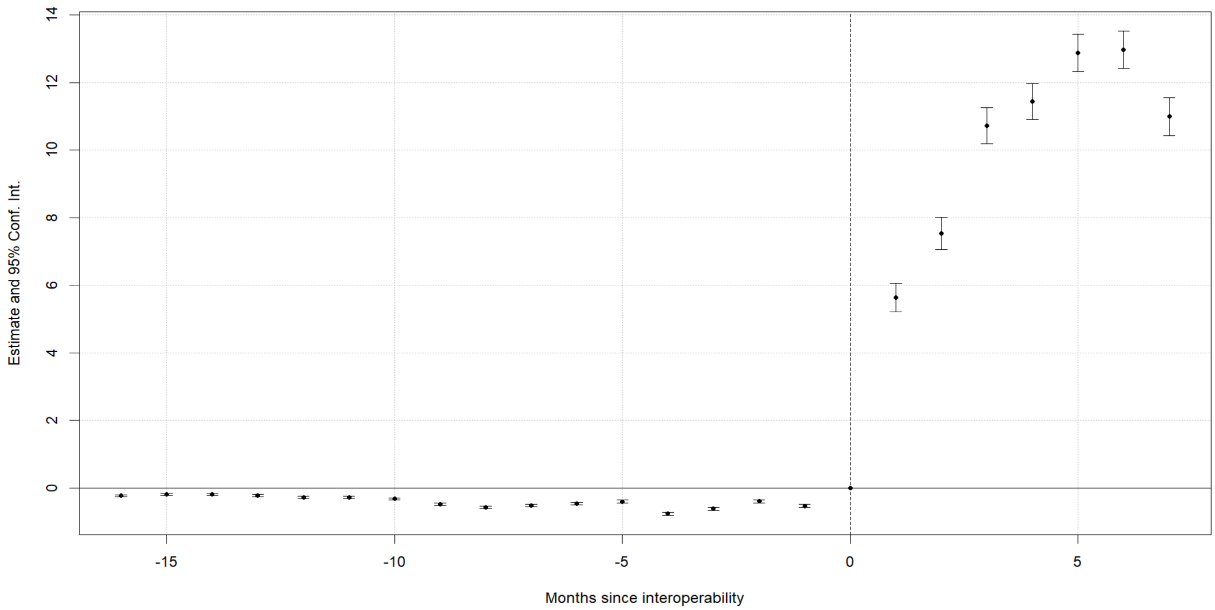
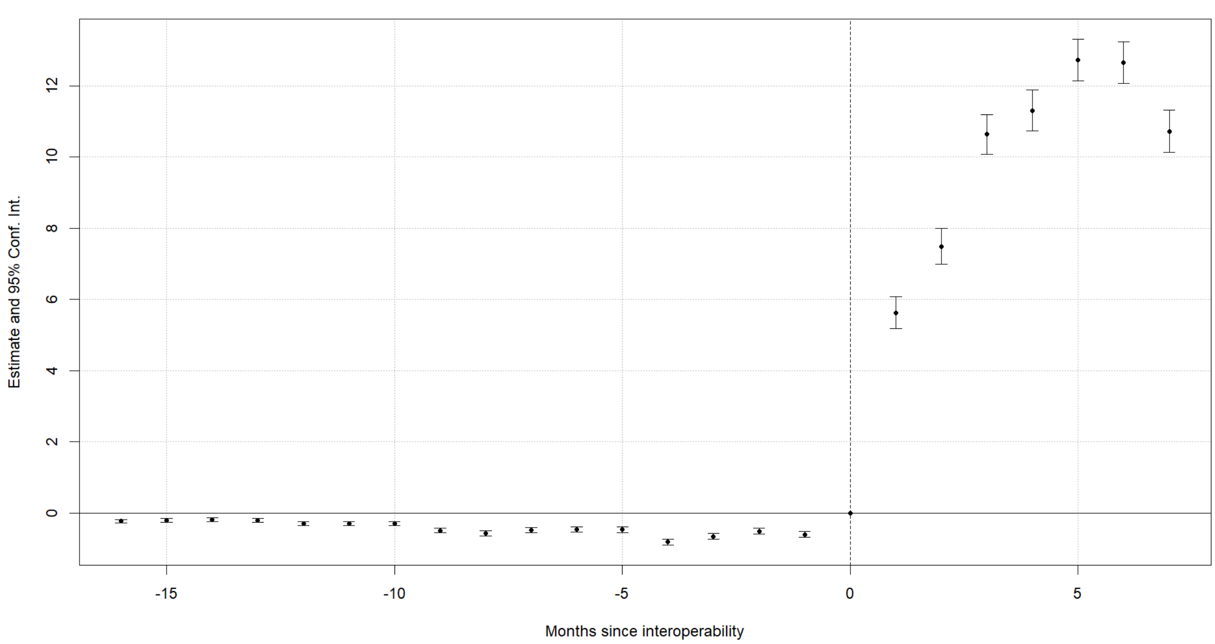
Figure A1: Visual Evidence of the Parallel Trends Assumption for the entire sample



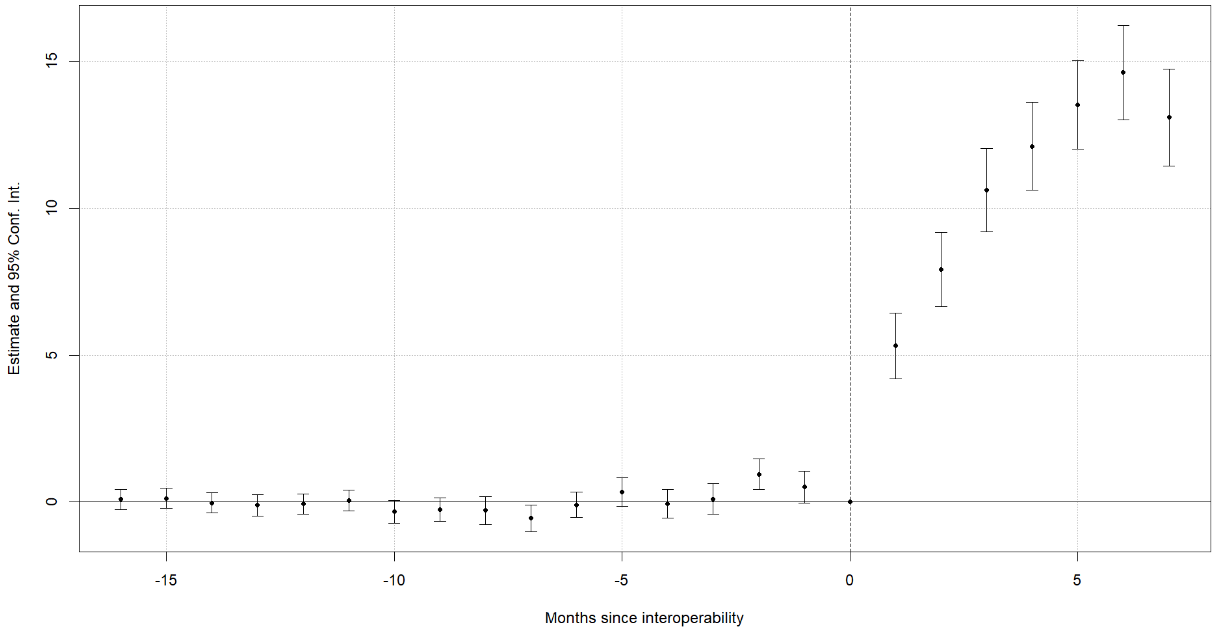
Notes: The plots represent parallel trend plots for the average transaction amount for the entire sample. The dashed lines in each indicate when the government enacted interoperability (May 10, 2018).

Figure A2: Visual Evidence of the Parallel Trends Assumption focusing on males



Notes: The plots represent parallel trend plots for the average transaction amount when the sample is restricted to males. The dashed lines in each indicate when the government enacted interoperability (May 10, 2018).

Figure A3: Visual Evidence of the Parallel Trends Assumption focusing on females



Notes: The plots represent parallel trend plots for the average transaction amount when the sample is restricted to females. The dashed lines in each indicate when the government enacted interoperability (May 10, 2018).

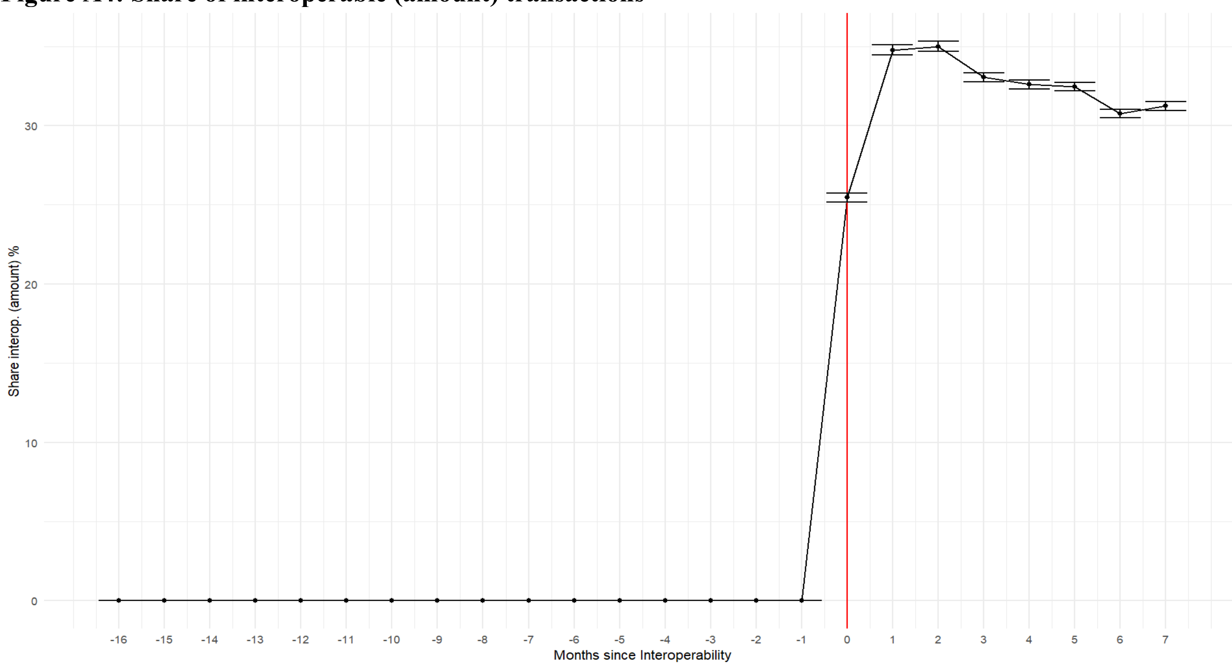
Table A1: Effect of gender on the share of interoperable transactions

DV: Share of interoperable transactions (%)

	(1)	(2)	(3)
Female	2.718***	1.349***	1.374***
	(0.129)	(0.120)	(0.120)
Constant	6.692***	6.794***	6.792***
	(0.0296)	(0.0274)	(0.0274)
District FE	No	Yes	No
Month FE	No	Yes	No
District x Month FE	No	No	Yes
Observations	1032390	1032390	1032383
Mean DV	6.895	6.895	6.895

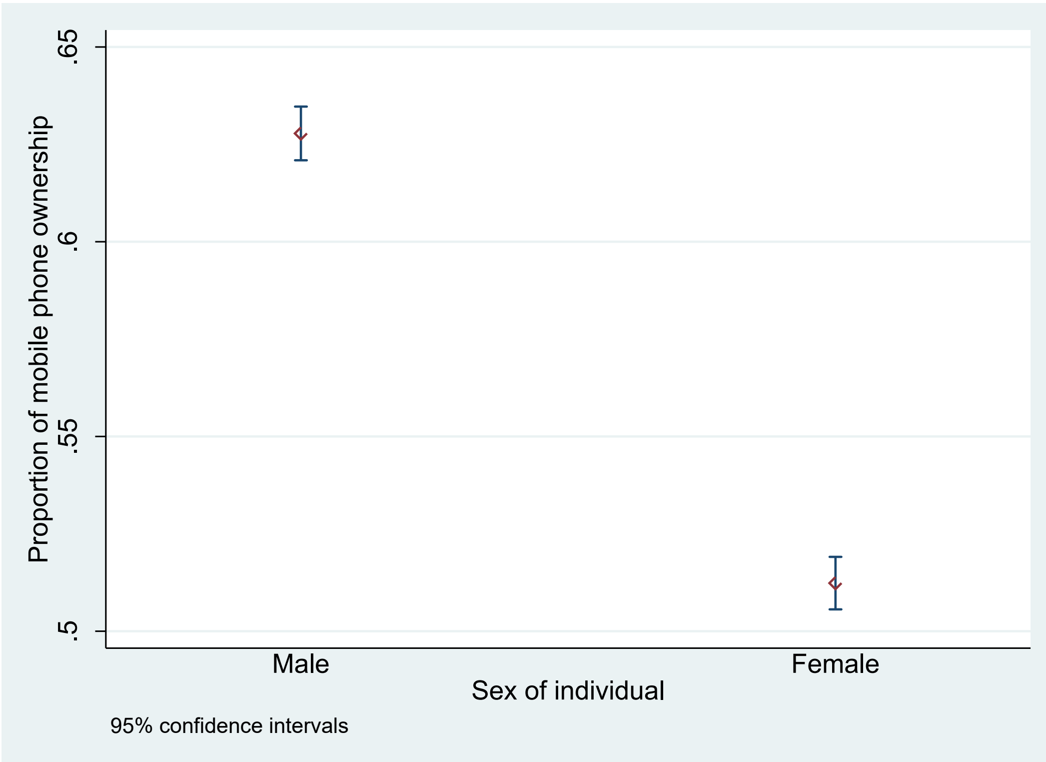
Notes: Model (1) is the basic model which controls for no fixed effects. Model (2) controls for district and month fixed effects, while Model (3), the main model, controls district interaction with month fixed effects. Standard errors (transaction-pair matched) in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A4: Share of interoperable (amount) transactions



Notes: This Figure is an unconditional plot of the share of interoperable transactions (%) against months since the introduction of mobile money interoperability (May 10, 2018). The share is zero in the pre-interoperability regime and takes on post-policy values by construction.

Figure 5: Gender differences in cell phone ownership



Notes: This graph illustrates the difference in cellphone ownership between genders. On the left side, the x-axis displays the male proportion of mobile phones, while females are on the right. Ultimately, the data concludes that male phone ownership surpasses that of females.

Table A2: Regional gender gap in cell phone ownership

Region	Gap (Female-Male)	Median	Classification
Accra	-0.0009723	-0.096151	↑ Median
Eastern	-0.0711853		↑ Median
Ashanti	-0.0859199		↑ Median
Volta	-0.089605		↑ Median
Central	-0.0913764		↑ Median
Brong Ahafo	-0.1009245		↓ Median
Western	-0.1033762		↓ Median
Upper East	-0.1339334		↓ Median
Upper West	-0.1930459		↓ Median
Northern	-0.2285553		↓ Median

Notes: The ownership of cell phones by gender varies by region. To calculate this difference, the proportion of female cell phone owners is subtracted from that of males, and the results are aggregated by region. The table divides regions into those with gaps above (↑) and below (↓) the median, as indicated by the classification column.