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Abstract

This paper uses a unique data set with 1.1 million customer transactions from a microfinance institution in the Democratic Republic of Congo from 2017 to 2018. The paper provides evidence of assortative gender matching in agent banking transactions, as clients prefer to transact with agents of their own gender. Female clients show a robust preference for female agents even when they are less available, particularly when making high-value transactions and when they have higher account balances. The underrepresentation of female agents may contribute to the persistent gender gap in financial access and usage.

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The Role of Gender in Agent Banking: Evidence from the Democratic Republic of Congo[1]

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1. Introduction

Agent banking holds the promise of facilitating financial inclusion for underrepresented and marginalized groups, including women, through improved accessibility, convenience, and reduced costs. As an alternative to bank branches, agents represent physical access points that enable customers to make deposits, withdrawals and money transfers, and to repay loans (Lyman et al., 2006; Siedek et al., 2008; Flaming et al., 2011). In contrast to personnel of a bank branch that likely change from visit to visit, the agent is usually the same contact for clients. Customers therefore choose agents based on location, or personal characteristics of the agent such as gender, religion, ethnicity or age.

In this paper we investigate whether gender plays a role in the choice that customers make about which agents to transact with. Research to date says little about matching between agents and clients, or the potential implications of agent gender on clients' financial access and utilization. This is an important policy question since closing the gender gap in financial access is a goal of institutions such as the World Bank, the International Finance Corporation (IFC), and the United Nations. According to 2017 Global Findex data (Demirguc-Kunt et al., 2018), the gender gap in financial institutions account ownership was 9 percentage points (35% of males versus 26% of females had an account).

We study the role of gender in financial transaction decisions using data from FINCA DRC, one of the largest microfinance institutions (MFIs) in the Democratic Republic of Congo. The Democratic Republic of Congo is a country characterized by large gender inequalities–it was ranked 176th out of 189 countries in the 2018 Gender Inequality Index (United Nations Development Programme, 2018). These gender inequalities impede women's full participation in social and economic life.

Females only represent 39% of FINCA DRC's customers and 23% of all agents. In this context of male-dominated agent networks, both genders transact predominantly with male agents since there are simply more of them. But while male agents comprise the majority of the network, the distribution of male and female agents across locations is somewhat similar, suggesting that almost all FINCA DRC customers have a choice of the gender of the agent.

Our regression results indicate that clients are more likely to transact with agents of their own gender. In our main regression model, we find that women are significantly more likely to transact with female agents (odds ratio 1.518, p-value=0.000) and this tendency increases both with the value of transactions and the customer's balance. These patterns hold when controlling for customer, agent experience, and market-level covariates and when we restrict the analysis to markets with substantial representation of female agents. We also confirm gender matching using dyadic regressions. The results show that both men and women have broadly similar tendencies to transact with clients of their gender and similar age.

Given that women are underrepresented in the agent network, the preference for transacting with female agents could explain the gap in financial access and utilization among women. We explore potential reasons for gender homophily and find evidence consistent with gender assortative matching based on trust. Since the FINCA MFI agents see not only the amount transacted but also the customer's account balance, women in particular may prefer to go to a female agent, especially when they have large balances or want to make high-value transactions. Qualitative research in the Democratic Republic of Congo and three other African countries highlights the importance of anonymity and the lack of traceability as an advantage of digital financial services (Butter and de Bruijn, 2017; Heitmann et al., 2018). Safeguarding privacy therefore provides a motive for customers to seek out agents whom they trust not to disclose their financial information to others. The role of trust in explaining assortative matching is consistent with the literature showing that women's trust is more context sensitive than men's (Croson and Gneezy, 2009; Eckel and Wilson, 2004; Bohnet 2007; Greig and Bohnet, 2009). To further validate our findings, we use data from an experiment with banking agents from a large MFI in Senegal (Buri et al., 2018) and find similar matching patterns: customers tend to transact with agents of their own gender and among women, the probability that female clients use female agents increases with the size of the transaction.

The results from our study contribute to several strands of the literature. First, to the best of our knowledge, we provide the first analysis of the salience of gender in transaction decisions when banking with agents. The results are consistent with Barr et al. (2012) who run a lab-in-the-field experiment in 14 Zimbabwean villages to examine group formation under different conditions. They also find evidence of assortative matching along gender and religious lines. Second, there is a nascent literature explaining differences in banking agent performance. Cull et al. (2018) find that environmental factors (low income, densely populated areas with high levels of commercial development) are more important than the personal characteristics of agents in explaining the transaction volumes handled by agents. The authors also speculate that gender could play a role in promoting comfort as female clients may be more at ease when doing banking transactions with a female agent, but they do not directly test this hypothesis. Our paper expands on this area of research outlined in Cull et al. (2018).[2]

[2] This paper also relates to several studies suggesting that gender is relevant in different aspects of finance. In securities markets, males trade more aggressively than females, reducing their net returns in the process (Barber and Odean, 2001). Males are also more likely to hold stocks (rather than bonds) in their retirement portfolios (Sundén and Surette, 1998) and male corporate executives undertake more acquisitions and issue debt more often than female executives, though the announcement returns on those acquisitions and debt issues are lower for men than women (Huang and Kisgen, 2013). The literature also shows that MFIs with more women in their lending portfolios have lower default risk and higher repayment rates (D'Espallier et al., 2011). Credit decisions of female loan officers are associated with lower default rates than men's (Beck et al., 2013) and MFIs with female executives have significantly higher outreach efficiency than MFIs with male directors (Hartarska et al., 2014).

Finally, our research contributes to the literature on trust and financial privacy. Greig and Bohnet (2007) run a public goods game in a Nairobi slum and find that men and women in same gender pairs make higher contributions in a one-shot game, while mixed gender pairings reduce the contributions of women but not men. Thus, women appear to have more trust in other women in experimental settings.

Our findings suggest that the increased availability of female agents could enhance the usage of financial services and the benefits of financial inclusion for women. These recommendations are in line with policy option 8 of the G20 Global Partnership for Financial Inclusion (GPFI) which emphasize the need to encourage and provide appropriate incentives for financial service providers to increase the representation of women working in financial institutions and financial access points (G20 GPFI, 2020). The findings also relate to the literature highlighting the potential of digital financial services (DFS) and agent banking to contribute to financial access of previously excluded or underserved populations. Suri and Jack (2016) exploit variation in service rollout and estimate that access to DFS was associated with significant gains in consumption–gains which lifted 2% of Kenyan households out of poverty. They find that women-headed households benefitted more from DFS than male-headed households through increased financial resilience and changes in occupational choice, shifting out of agriculture and into business. In Sub-Saharan Africa, women are 7% more likely to be excluded from DFS and thus deprived of the social and economic benefits associated with the service (Demirguc-Kunt et al., 2018).[3]

The rest of the paper is structured as follows. Section 2 describes the study setting and data. The methods and results are presented in Section 3. Section 4 describes robustness checks of the results while Section 5 replicates the analysis in another market, Senegal. Section 6 discusses the implications of the findings and some limitations. Section 7 concludes.

2. Context and Data

FINCA DRC is a subsidiary of FINCA international, an MFI operating in 23 countries worldwide which pursues women's financial inclusion as part of its mission. FINCA DRC launched branchless banking in 2011 in an effort to expand outreach. FINCA's network has grown rapidly from 322 agents in 2014 (Gutin, 2015) to over 1,200 agents by April 2018, the end of our period of study.

The data we obtained from FINCA DRC are comprised of 1,124,331 transactions performed by 104,237 customers through 1,250 agents linked to 21 FINCA branches. Transactions were performed over a period of one year, between May 2017 and April 2018. The transaction-level data contain the value of each

[3] Barriers that impede women's participation in DFS include limited access to phones and internet connectivity, lack of information and assets, limited participation in the salaried labor force and lower socio-economic status (Chamboko et al., 2018).

transaction, the gender and age of the customer who executed the transaction as well as the gender and the age of the agent who assisted with the transaction. The data also include information on the type of transaction (cash deposit, withdrawal, funds transfer, or school fees payment) and the currency used (USD or CDF). Market level information such as the branch, the town and the dominant financial institution where the branch was located was also available.

About 61% of the FINCA DRC customers are males, a distribution similar to that of many other institutions in developing countries (Chamboko et al., 2018). In addition, males comprise 77% of FINCA DRC agents. This limited participation of females as agents may be explained in part by the fact that FINCA targets former or current clients as prospective agents (Cull et al., 2018). Targeted clients are individuals for whom FINCA has a reliable financial activity record and who have an existing shop which can double up as an agent (Cull et al., 2018).

Figure 1 shows the distribution of male and female agents across the 21 FINCA branches (henceforth referred to as markets). The representation of female agents ranges from 7% in Boma to 34% in Matete, indicating that there are both male and female agents in every market. Thus, while in every market the majority of agents were men, clients always had a number of male and female agents to choose from.

Panel A of Table 1 reports agent characteristics from the transaction data set. To complement these data, the authors were able to obtain the paper-based registration forms of the first 404 FINCA agents that signed up. These registration forms contain additional information that could be matched for 131 agents in the transaction data. Columns 1 and 3 of Table 1 report data on the sample of 131 matched agents, while Columns 2 and 4 report data from the remainder of the 1,119 unmatched agents. Column 5 reports the p-values for group differences between the sample of matched and unmatched female agents. Column 6 reports analogous p-values for male agents. Finally, Column 7 reports p-values of differences between male and female matched agents.

The comparisons in Columns 5 and 6 indicate significant differences between the matched and unmatched samples with respect to age of the agent and their business, as well as the frequency of some types of transactions. Significant differences in the age of agent and the business should not come as a surprise since we obtained registration records for the first agents that signed up, which therefore, would tend to be older.

Panel B of Table 1 reports the additional characteristics from registration records for the sample of matched agents. According to Column 7, male and female matched agents are similar along most characteristics. The only statistically significant difference is in the mean number of opening hours per day (female agents were open 10.7 hours and males 12.3 hours on average, $p = 0.042$). Both male and

female agents are open the same number of days in a week (6.6 days for females and 6.5 for male agents). Matched male agents had 3.5 employees on average while female agents had 3 employees. In this subsample, 11% of the stores of female agents were in the service sector, compared to 13% for males. Female agents had both higher average daily revenue (USD$815 versus USD$536 for males) and higher value of the stock (USD$9,857 versus USD$5,914), but the data are noisy and thus these differences were not statistically significant. The minimum balance of the point of sale (POS) terminal, which influences the volume of customer transactions the agent can execute, was higher for male agents (USD$655 versus USD$595 for females), but again not statistically significant. In line with FINCA's recruitment strategy, agents had been overwhelmingly FINCA clients at the time they registered as agents (90% of female agents and 97% of male agents had an existing FINCA bank account).

Table 2 reports characteristics of the customers related to the number of transactions per month and number of agents they regularly transact with. We use the full sample in columns 1-3 and a restricted sample of only markets where at least 25% of the agents are female in columns 4-6. The results are similar using either sample. In Panel A we find that male customers tend to make more transactions per month compared to female customers and to transact with more agents of either gender (Panel C). In Panel B, female customers tend to transact with one or more female agents only compared to male customers, although male customers are more likely to transact with multiple male and female customers.

Panel A of Table 3 presents the share and Panel B the value of transactions and currency disaggregated by the gender of customers and agents. According to Panel A of Table 3, 71.9% of all transactions were made by male clients, reinforcing the notion that transactions of male users were predominant in the network. Three quarters of their transactions were performed by male agents.

Most of the transactions were cash deposits (96.5%) and the remainder were withdrawals (3.1%), school fee payments (0.3%) and funds transfers (0.1%). There are statistically significant differences in the share of transactions performed by male and female clients as well as differences between male and female agents, which are however comparatively small in magnitude. Overall, female clients performed slightly more cash deposits than male clients (97.5% of female transactions versus 96.1% of male transactions were deposits, p-value = 0.000) while male clients performed more withdrawals than females (3.6% of male transactions versus 1.9% of females' transactions were withdrawals, p-value=0.000). Transactions at female agents were also 4.4 percentage points more likely to be conducted in US dollars (USD) than in Congolese francs (CDF), p-value = 0.000.[4] The share of transactions of female clients conducted in USD was 2.2 percentage points higher than that of male agents, p-value = 0.000.

[4] We note that clients transact with FINCA agents in both USD and Congolese Francs.

Panel B of Table 3 reports that transactions made by male clients were, on average of higher value than those made by female clients (USD$198 compared to USD$155).[5] Table 3 also shows that, on average, male clients made more transactions than female clients (12.7 compared to 7.8). Similarly, customers made on average 14.7 transactions at male agents and 6.2 at female agents. Finally, Table 3 reports account balances at the end of October 2017. These balances reflect the aggregate amount of money available across accounts owned by a customer (current, savings and other accounts). The mean account balance across all customers was USD$244. Female customers had, on average, a lower combined balance of USD$234 compared to USD$249 for men. Table 3 also indicates that average balance of customers transacting at male agents was higher than those transacting at female agents. (For more detailed descriptions of all variables, please refer to the Appendix.)

We also take a sample of 4,856 transactions from 2,509 unique customers transacting with 32 agents in May 2017, the first month of the transaction-level data, in order to construct a dyadic database.[6] The data set contains all possible client-agent pairs for each day of the month resulting in a total of 2,488,928 observations. The agents, clients and transactions included in the sample are representative of the whole sample.

3. Empirical Strategy and Results

Our goal is to investigate the relationship between customer and agent gender. To this end, we focus on two outcomes: a) the likelihood of transacting with a female agent, and b) the transaction amount.

Our empirical specification for the probability of transacting with a female agent is given by:

$$GenderAgent_{ji} = \alpha + \beta_1 GenderClient_i + \beta_2 Currency_{ji} + \beta_3 log(TransactAmount)_{ji} + \beta_4 TransactType_{ji} + \beta_5 CustomerAge_i + \beta_6 Market_{ji} + \beta_7 Month_{ji} + \varepsilon_{ji} \quad (1)$$

where $GenderAgent_{ji}$ is a dummy that takes the value of 1 if transaction j of customer i was done with a female agent. $GenderClient$ is a dummy which takes the value of 1 if the customer is female, and zero otherwise. $Currency$ captures whether a transaction was made in USD or CDF and $TransactType$ is a dummy for whether the transaction was a cash deposit (the most common transaction in our dataset). The logged transaction amount is given by $log(TransactAmount)$ which indicates the value of a transaction (in August 2017 USD). We control for $CustomerAge$ and characteristics of the local market and time effects using market and month dummies. We estimate these models using a logistic regression with

[5]All transaction values have been converted to USD.

[6] For clients that made more than one transaction with the same agent during the same day, we collapse the data at a daily level for each agent-client pair. This led us to finally to a total of 4,236 transactions.

standard errors clustered at the customer-level and report odds ratios and average marginal effects for customer gender.

We complement this analysis with a dyadic regression model using the sample of transactions drawn from May 2017. The dependent variable is a dummy variable indicating whether a transaction between these potential pairings occurred that day of the month. In particular, the model that we run is as follows:

$$Transaction_{acn} = \alpha + \beta_1 SameGender_{ac} + \beta_2 SameMarket_{ac} + \beta_3 BothFemale_{ac} + \beta_4 AgeDifference_{ac} + \varepsilon_{ac} \quad (2)$$

where $Transaction_{acn}$ is the dummy variable which takes the value of 1 if a transaction took place between agent a and client c on day n of May 2017, $SameGender_{ac}$ is a dummy variable that takes the value of 1 if both agent a and client c are of the same gender, $SameMarket_{ac}$ is a dummy variable that takes the value of 1 if both agent a and client c are located in the same market area and finally, $AgeDifference_{ac}$ is the absolute value of the difference between the agent of the agent and that of the client. This model is estimated with ordinary least squares (OLS) using two-way clustered standard errors both at agent and client level. We also include client and agent location fixed effects.

The empirical specification for the amounts transacted at male and female agents is similar to that in equation (1) and given by:

$$\log(TransactAmount)_{ji} = \alpha + \beta_1 GenderClient_i + \beta_2 GenderAgent_{ji} + \beta_3 (GenderClient_i * GenderAgent_{ji}) + \beta_4 Currency_{ji} + \beta_5 TransactType_{ji} + \beta_6 CustomerAge_i + \beta_7 AgentAge_{ji} + \beta_8 Market_{ji} + \beta_9 Month_{ji} + \varepsilon_{ji} \quad (3)$$

where $log(TransactAmount)$ indicates the logged transaction amount of transaction j of customer i. The independent variables are almost identical to those in equation (1). Most notably, we introduce an interaction between $GenderAgent$ and $GenderClient$ to estimate the effect of gender on transaction amounts. We estimate these models using ordinary least squares (OLS) regressions with standard errors clustered at the customer-level. Appendix Table 1 contains more details about the variables.

Probability of transacting

Table 4 reports the determinants of transacting with female agents. Column 1 excludes controls and market and time fixed effects while Column 2 includes market and time fixed effects but still excludes other controls. The odds ratio that a female client transacts with a female agent is 1.531 (p-value is 0.000) in Column 1 and 1.520 (p-value is 0.000) in Column 2. When control variables are added in Column 3 and market and time fixed effects (in addition to controls) in Column 4, the effect declines only slightly (odds ratio = 1.514, p-value = 0.000 in Column 3 and odds ratio = 1.518, p-value = 0.000, in Column 4).

Comparing Columns 1 and 2 and 3 and 4 respectively, we note that the inclusion of market and time fixed effects does not significantly impact the coefficient of interest. Column 4 corresponds to our preferred specification described in equation (1) above. The results indicate that transactions of female clients are 1.514 (p-value is 0.000) times more likely to be conducted at female agents than the transactions of male clients. We also report the marginal effect of client gender on the probability of transacting with female agents which is 0.074. In Column 4, none of the other control variables (currency, transaction type, customer age) is significant.

In Column 5, we explore how location affects transaction behavior. Since customers make multiple transactions over the course of a year, they may behave differently when visiting agents in markets that they do not typically visit. To explore this, we create a dummy variable called "outside modal market" that takes the value of 1 if the transaction is made in a market different from the one where the customer makes most of the transactions. The results in Column 5 indicate that transactions of customers (of both genders) are 1.232 (p-value = 0.000) times more likely to be with female agents when a customer is visiting a less familiar market. We also interact customer gender and the modal market dummy to investigate whether this behavior differs along gender lines. We find that the increased likelihood of customers transacting with female agents outside their modal market applies to both genders as women are not significantly more likely to transact with females outside their modal market compared to males (odds ratio 1.048, p-value = 0.792).

In practice, when a customer transacts at an agent, she reveals not only the transaction amount but also her account balance. If female customers' preference for female agents is (at least partially) driven by a desire to conceal financial information from male agents, we would expect female customers to also be more likely to transact with female agents when they have higher account balances. We matched data on account balances at one point in time (end of October 2017) with customer transaction data. For the analysis, we restrict the data to all customer transactions occurring within 10 days after the time point for which the balance data is available and thus posit that the balance information will affect transaction behavior within the 10-day window after the date for which we have knowledge about customers' balances.

In Column 6 of Table 4, we add the customer balance variable and an interaction term between customer gender and account balance to our main specification. The coefficient on account balance in logs is smaller than 1 (odds ratio= 0.937, p-value = 0.000), indicating that customers (of both genders) with higher balances are less likely to transact with female agents. This is consistent with the results from descriptive statistics showing that customers at male agents had higher balances. For female customers, however, the effect reverses its direction, indicating that female customers are more likely to transact with

female agents when they have higher balances (odds ratio = 1.128, p-value = 0.006). We note that the coefficient for client gender is smaller and no longer significant, but since our data is only 2.4% the size of our full data, we may suffer from lower statistical power to detect effects.

Table 5 reports results from dyadic regressions in specification (2) to complement the analysis of Table 4. The results confirm the gender homophily found in Table 4. The coefficient for agent and client having the same gender is positive and significant at the 5% or 10% level depending on the specification. The effect is large, suggesting that transactions between clients and agents of the same gender are 1.7 times more likely than of different gender. In addition, the coefficient for a female gender match is not significant, suggesting that both male and females have a similar degree of gender homophily and that there are no differential effects by gender. Columns 2 and 4 include the absolute value of the age difference between the client and agent. The coefficient is negative and significant in column 4 when location fixed effects are included. It suggests that clients tend to transact with agents of similar age as them. As expected, clients are also far more likely to transact with agents in the same market area where they registered as customers. We note that the results are virtually unchanged when we use different samples drawn from the transaction-level data.

These results provide additional support for the role of gender homophily, and while it appears to be similar in strength among males and females alike, the implications are different by gender: female agents are less available, and as a result, an increase in the number of female agents could increase participation in financial markets among females.

Transaction amounts

Table 6 reports the correlates of the value of individual transactions performed by clients. The dependent variable is the log of the transaction value in USD. Similar to Table 4, Column 1 and Column 2 report the specification without controls and, in Column 1, without market and time fixed effects. Based on the coefficients in Column 1, females performed lower-value transactions than male clients. When accounting for additional covariates, the magnitude of the negative association between female gender and transaction amounts increases in size from -0.370 and -0.352 in Columns 1 and 2 to -0.548 and -0.543 in Columns 3 and 4 (all p-values are 0.000). The comparison between Columns 3 and 4, our preferred specification, shows that our results are again robust to the inclusion of market and time fixed effects.

The regression coefficients in Column 4 indicate that female clients transacted smaller amounts on average (-0.543, p-value = 0.000). Transforming regression coefficients to obtain mean predicted transaction values for male and female customers shows that males transact on average USD$240 while females transact on average USD$160 after accounting for control variables, and the difference is

significant (p-value = 0.000). Table 7 reports the mean predicted values by agent and customer gender based on the results from Column 4. The results show that males transact on average USD$250 with male agents whereas females transact about half as much (53%) with male agents (USD$133). By contrast, females' transactions are on average 66% larger at female agents than at male agents (USD$221 on average). This is also indicated by the positive interaction between female customer and female agent in Column 4 of Table 4 (0.481, p-value = 0.000). The average amount among males is reduced by 17% when transacting at female agents compared to when they transact at male agents, suggesting that the reduction in transaction amounts is larger for females than males when transacting at opposite-gender agents.

Columns 5 and 6 of Table 6 analyze effects separately for transactions done at female and male agents, respectively, in order to shed light on how the correlates of transaction size vary by agent gender. The coefficient for female clients in Column 5 is negative and significant for transactions done at male agents (coefficient = -0.543, p-value = 0.000) indicating that the mean transaction amount of female clients at male agents is significantly lower than that of male clients. In Column 6, the coefficient for client gender is close to zero and becomes statistically insignificant for transactions performed at female agents (coefficient = -0.036, p-value = 0.777). Thus, female clients conducted transactions of approximately the same value as male clients at female agents but of significantly lower value at male agents. The pattern further supports our finding that female clients tend to visit female agents when transacting larger amounts. Table 7 also reports that transaction values among males and females are much more similar in size at female agents compared to male agents.

4. Robustness Checks

Markets with high and low female agent presence

One potential threat to the validity to our results in Tables 3 and 5 is that we include all markets in our analysis, even those with very low representation of female agents.[7] It could be argued that males and females in these markets have insufficient choice for us to establish whether they actually prefer agents of their gender. To address this concern, we restrict our analysis to markets where at least 25% of agents are female and compare with results obtained for markets with less than 25% female agents. The results presented in Columns 7 and 8 of Table 4 show that our results are robust to using either subsample. In markets with less than 25% female agents, females are more likely than male clients to transact with female agents (odds ratio = 1.537, p-value = 0.000). In markets with greater than 25% female agents, the

[7] Recall from Figure 2 that the share of female agents can be as low as 7% in some markets.

odds ratio is 1.500 (p-value = 0.000). This is rather remarkable in that it suggests that female clients continue to transact with female agents, even when they are more difficult to access.

With respect to transaction values, the pattern described in Columns 1 to 6 of Table 6 is also evident when restricting the data set in Columns 7 and 8 to markets with high and low presence of female agents. In both markets with more and less than 25% female agents, females make lower value transactions than male customers overall (coefficients = -0.517 and -0.556 with p-values = 0.000 in Columns 7 and 8, respectively), but transaction amounts are again significantly higher for females transacting at female agents (coefficients = 0.500 and 0.436 with p-values = 0.000 in Columns 7 and 8 of Table 6, respectively).

Agent characteristics

A second threat to validity is unobservable differences in agent and customer characteristics. For example, female clients may transact more with female agents simply because female agents tend to also sell other goods or services more demanded by females. While we lack customer-level data, we were able to obtain rich data from the agent registration records. According to Column 7 of Table 1, there are no differences between male and female agents across almost all dimensions including number of employees, sector, existing client relationship with FINCA, opening days per week, daily revenue, stock value, and minimum POS balance (only opening hours per day are significantly lower for female agents). We conclude that based on the data we have available, male and female agents are largely similar and thus differences in the shops or what they sell cannot mainly account for the assortative matching by gender we observe in our data.

We also run our main specifications on a data set which only includes customers transacting at matched agents (i.e., those for whom registration and transaction data could be matched). We do this to ensure that our results hold when we limit observations to transactions with agents that are largely similar. We create two different data sets: one with only transactions at matched agents and another that includes all transactions of customers who transacted at least once with a matched agent. The results are reported in Columns 9 and 10 of Table 4, respectively. Columns 9 and 10 report odds ratios of 2.098 and 1.825, respectively (both p-values are 0.000) and indicate an even stronger association between agent and customer gender with the restricted data set than in our preferred specification in Column 4 of Table 4 (odds ratio = 1.518, p-value = 0.000). Columns 9 and 10 of Table 6 also confirm the findings of Column 4, Table 6 that females transact larger amounts at female agents. Since matched male and female agents are comparable (Table 1), these robustness checks suggest that our results are not driven by unobservable factors.

5. Evidence from Senegal

We now assess whether the patterns we find in FINCA DRC transactions also hold in another African context – Senegal. Senegal is more financially developed, slightly more gender equal (ranked 166 in the UN Gender Equality Index compared to 179 for the Democratic Republic of Congo) and a more stable, higher-income country than the Democratic Republic of Congo (Senegal is a lower-middle income while the Democratic Republic of Congo is a low-income country).

We use data from an experiment with banking agents from Baobab (previously known as Microcred), a large MFI in Senegal (Buri et al., 2018). Baobab offers savings and microcredit products, mostly focused on low income clients. The company started its activities in Senegal in 2007 and launched its network of banking agents in 2014. Baobab is now one of the largest microfinance institutions in Senegal, with more than 500 agents and 37 branches in both urban and rural areas of the country.

The data from Buri et al. (2018) include withdrawals and deposits made by Baobab customers at a few banking agents between February 2015 and April 2016. Baobab was expanding its network of agents at the time of the experiment and, for the purposes of the experiment design, Buri et al. (2018) selected a small number of agents recently established in the suburbs of the capital Dakar, in Thies (the third most populous city), and in a rural area outside Thies.[8] Thus, the Senegalese sample consists of only 936 transactions made by 44 female and 54 male clients (98 clients in total).

Table 8 presents summary statistics for our sample from Senegal. Each transaction was made with one of the 74 male or 12 female agents (86 agents in total) that operated in 20 markets. All transactions were made in West African CFA francs and the values were converted to US dollars as of January 2015.

As shown in Table 8, among the 936 transactions, 34.8% were made by a female client and only 9.6% were made at a female agent. The average transaction amount was USD$105 and 46.6% of all transactions were withdrawals. Consistent with data from the Democratic Republic of Congo, most of the transactions made by female customers were made at a female agent.

Table 9 presents the estimates of the probability that a transaction was done with a female agent, predicted by the gender of the client, using the same specification from Columns 1 and 3 of Table 4 with data from FINCA DRC. Following the Democratic Republic of Congo specification, we cluster the standard errors at the client level. Since we have data on only 98 clients in 20 markets, the inclusion of

[8] For more details on the experiment design, see Section 2 of Buri et al, 2018.

market or time fixed effects leads to collinearity issues and lack of power and thus they are not included. We note, however that in Table 4, the inclusion of fixed effects does not significantly affect the results.

The odds ratio reported in Column 1 of Table 9 is 5.83 (p-value=0.016) This odds ratio is substantially larger than the one in the Democratic Republic of Congo in Table 4. The point estimate for the female client dummy implies a marginal effect of 12 additional percentage points in the probability of transacting with a female agent for female clients (marginal effects are reported at the bottom of the table and evaluated at the average probability of a client being female). In Column 2, we include as regressors the type of transaction (an indicator for withdrawals) and the log of the transaction amount. The logit point estimates and marginal effects are virtually unchanged. The marginal effects estimated for the data in Senegal are about 12 percentage points, a bit larger than our estimates for the Democratic Republic of Congo using similar specifications, which range from 8.1 percentage points in Column 1 to 8.4 percentage points in Column 3 of Table 4.[9]

Table 10 displays the results from the dyadic regressions in equation (2) using all of the transaction-level data from Senegal (instead of the sample used in the case of the Democratic Republic of Congo). Our findings are remarkably similar to those obtained for the Democratic Republic of Congo, suggesting again that both males and females have gender homophily. Transactions between clients and agents of the same gender are 1.6 times more likely than transactions between individuals of different gender. Similarly, we also find that clients are more likely to make transactions with those agents located in their same area. As in the case of the Democratic Republic of Congo, there is no gender differential effect, and this is reflected in the fact that the coefficient associated with the binary variable that indicates that both the client and the agent are women is not statistically significant. Since the data from Senegal do not include the age of clients or agents, we cannot include the difference in age as a regressor.

In Table 11, we run the analysis of the transaction amount, analogous to that in Columns 1 and 3 of Table 6. In particular, we run OLS regressions where the dependent variable is the log of the transaction amount (in US dollars of January 2015) against an indicator for female agents, female clients and their interaction. Again, standard errors are clustered at the client level and, due to collinearity issues, we do not include market nor time fixed effects. In Column 1 of Table 10 the estimates suggest that female agents on average perform transactions 72% or 70$USD smaller than male agents when dealing with male customers, but that difference vanishes when the female clients transact with them (p-value of the test that

[9] When we use the sample of matched agents in Column 10, the marginal effects are 12.8 and 12.5 percentage points for the specification in columns 1 and 3, respectively (results not shown).

the 3 coefficients add up to zero is 0.453). In Column 3 we control for the type of transaction performed and results are virtually unchanged.

6. Discussion

Our results from both the Democratic Republic of Congo and Senegal provide two pieces of evidence indicating that gender matters in agent banking transactions. First, both male and female clients exhibit assortative gender matching. Perhaps surprisingly, for female clients this preference for female agents seems largely unimpacted by variation in the availability of female agents. When we restrict our analysis to markets where at least 25% of agents are female, same gender preference does not increase, as would be expected if convenience were the driving mechanism. This suggests that gender matching for females is not mainly driven by what Barr et al. (2012) describe as 'opportunity', i.e. the availability of female agents. Rather, the behavior is more consistent with the notion of 'homophily' as customers exhibit a stable preference to transact with agents of their gender.

Second, we use the transaction amounts and account balances to explain gender homophily. We find that female clients are more likely to use female agents the larger their transactions and account balances. We thus posit that gender-based trust may be driving the observed gender homophily as female clients have a stronger tendency to use female agents for larger transactions: larger amounts are riskier, and thus when the stakes are higher, female clients rely more heavily on female agents. Table 7 shows that both men and women transact higher average amounts at agents of their gender (men USD$250 and women USD$221). When visiting agents of the opposite gender, the average female transaction declines to USD$133 (a 40% reduction) while transactions of males only show a 17% reduction (to USD$207).

The balance data provide additional support for our conjecture that gender-based trust could be an important underlying mechanism. Since agents know the customer's balance when a transaction is made, there is a risk that financial information is disclosed to others without the client's consent. Visiting a female agent can be a strategy for women to mitigate this risk since female agents may be less likely to disclose information to other clients, compared to male agents.

7. Conclusion

The research findings have practical implications for financial service providers. While the preference for same gender agents appears to be similar in strength between males and females, the implications vary along gender lines. Since females prefer female agents but only 23% of agents are female, female customers will have to travel farther on average to transact with an agent of their gender. The underrepresentation of female agents may thus represent a barrier to greater financial inclusion,

contributing to the persistent gender gap in financial access. Taking steps towards gender balance in agent networks could therefore potentially increase uptake and usage of DFS by female customers, though further research is needed to more directly test this conjecture.

Another implication is the importance of investigating the root causes of female underrepresentation among agents. While recruitment criteria of agents based on business type or asset ownership could be considered gender-blind when taken at face value, they may de facto exclude females from becoming agents given women's greater difficulty in fulfilling these criteria under present gender disparities. A better understanding of the gender-lensed impacts of existing hiring procedures could thus contribute to policies and procedures that facilitate greater participation of women in agent networks.

While this paper presents evidence on the existence of gender differences in transaction behavior with agents, further research that uses careful causal identification strategies to isolate the precise pathways through which the observed effects operate is needed.

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Figures and Tables

Figure 1: Distribution of agents by market and gender

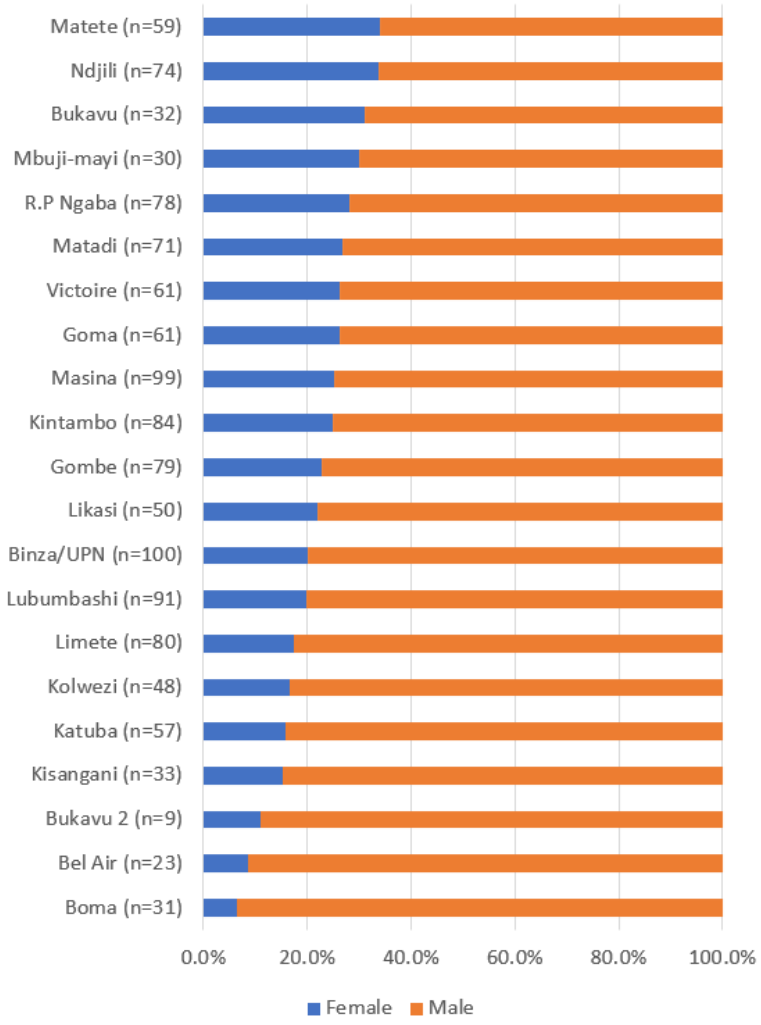

Figure 2: Distribution of transactions by market and gender

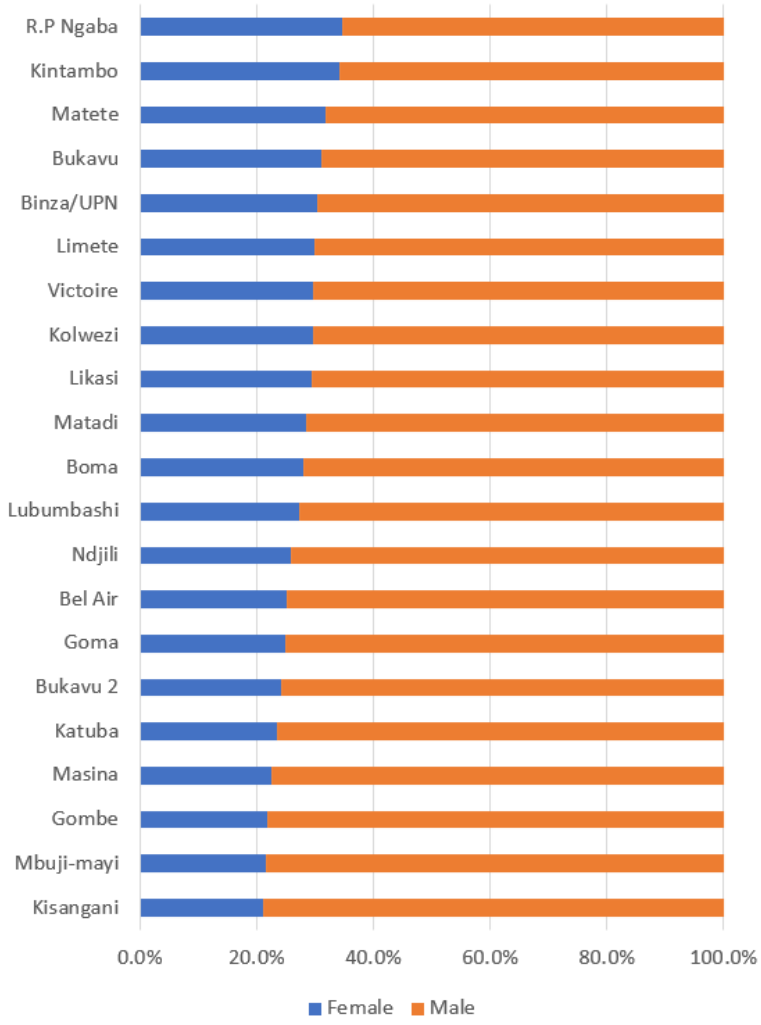

Table 1. Agent characteristics in the Democratic Republic of Congo

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Female Agents		Male Agents		P-value of t-test that (1)=(2)	P-value of t-test that (3)=(4)	P-value of t-test that (1)=(3)
	Matched	Unmatched	Matched	Unmatched			
Panel A: Transaction data							
Agent business age	11	9.8	10.8	9.2	0.025	0.000	0.719
Agent age	48.2	41.2	46.5	40.2	0.000	0.000	0.358
Number of transactions	1271.4	940	1677.1	781.9	0.349	0.000	0.300
Transaction amount in USD	175.9	174.6	173.8	162	0.972	0.583	0.959
Share of transactions made in USD	0.6219	0.615	0. 638	0. 572	0.900	0.022	0.777
Share of deposits	0.921	0.886	0.918	0. 873	0.381	0.046	0.931
Share of withdrawals	0.069	0.105	0.080	0.122	0.338	0.067	0.772
Share of funds transfers	0.001	0.001	0.001	0.000	0.983	0.224	0.992
Share of school fees payments	0.008	0.006	0.000	0.001	0.826	0.008	0.328
Panel B: Registration data							
= 1 if previous FINCA client	0.897		0.971				0.226
= 1 if service sector	0.107		0.134				0.698
Employees	3		3.5				0.589
Days open per week	6.6		6.5				0.637
Opening hours (per day)	10.7		12.3				0.042
Revenue (per day)	815.3		535.7				0.196
Value of stock	9857.1		5914.2				0.149
Minimum POS balance	595.2		655.2				0.243
Number of agents	29	262	102	857			

Note: This table presents summary statistics of agents based on whether they could be matched with agent registration records. Records were obtained by digitizing all available agent registration forms (the forms of the first 404 agents FINCA signed-up). 131 of those agents could be matched with one of the 1250 agents in the dataset using their FINCA agent ID. Of the 1250 agents, 959 were males and 291 females. We report the p-value of a simple mean comparison t-test in columns 5, 6 and 7. All the transactions are made either in USD or CDF and converted to USD dollars of August 2017. See Appendix 1 for descriptions of the variables.

Table 2. Customer characteristics about transactions in the Democratic Republic of Congo

	Full sample			Restricted sample		
	Proportion of customers			Proportion of customers		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Male	Female	All	Male	Female
A. Number of Transactions						
Less than 1 transaction per month	80.8%	77.0%	86.7%	83.9%	80.8%	88.7%
Between 1 and 5 transactions per month	17.0%	20.3%	11.9%	14.4%	17.1%	10.2%
More than 5 transactions per month	2.2%	2.7%	1.4%	1.7%	2.1%	1.1%
B. Type of Agents Customer Transacts with						
One male agent only	26.9%	25.1%	29.8%	28.7%	26.8%	31.7%
One female agent only	12.4%	10.8%	14.9%	17.9%	15.9%	21.0%
Multiple male agents only	20.9%	21.9%	19.4%	14.5%	15.3%	13.2%
Multiple female agents only	3.1%	2.8%	3.6%	4.6%	4.5%	4.8%
One or more male and female agent	36.6%	39.5%	32.3%	34.3%	37.5%	29.3%
C. Average Number of Agents Customer Transacts with						
Average number of male agents	2.1	2.4	1.7	1.6	1.8	1.3
Average number of female agents	0.9	0.9	0.8	0.9	1.0	0.8
Total number of customers	104,237	63,313	40,924	49,895	30,158	19,737

Notes: The restricted sample is limited only to those 9 markets where at least 25% of agents are female. This yields a dataset with 452,290 transactions from 49,895 customers.

Table 3. Customer transactions in the Democratic Republic of Congo

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Gender of the customer		P-value of test statistic that (2)=(3)	Gender of the agent		P-value of test statistic that (5)=(6)
		Male	Female		Male	Female	
Panel A. Share of transactions							
All transactions	1	0.719	0.282	-	0.748	0.252	-
Withdrawal	0.031	0.036	0.019	0.000	0.032	0.028	0.000
Cash Deposit	0.965	0.961	0.975	0.000	0.964	0.967	0.000
Funds transfer	0.001	0.002	0.000	0.000	0.002	0.001	0.000
School fees payment	0.003	0.002	0.006	0.000	0.003	0.004	0.000
Transactions in CDF	0.388	0.394	0.372	0.000	0.399	0.355	0.000
Transactions in USD	0.612	0.606	0.628	0.000	0.601	0.645	0.000
Panel B. Value of transactions (USD)							
All transactions	186.11	198.34	154.91	0.000	189.69	175.49	0.000
Transactions in CDF	52.51	55.49	44.29	0.000	53.32	49.73	0.000
Transactions in USD	279.69	302.00	225.62	0.000	291.09	248.94	0.000
Panel C. Number of Transactions and Balances							
Number of transactions	10.79	12.76	7.73	0.000	14.71	6.18	0.000
Account balance in USD	244.06	248.54	233.46	0.076	549.91	464.34	0.080

Note: This table presents summary statistics of 1,124,331 transactions from 104,237 customers with 1250 agents. Of those customers, 63,313 were males and 40,924 females. The account balance in USD was available only for end of October 2017 and the data includes 28,445 transactions from 11,454 customers at 768 agents. We report the p-value of a simple mean comparison t-test in Panel B and C, Columns 4 and 7. Panel A Columns 4 and 7 report the p-value of a t-test for proportions. All the transactions are made either in USD or CDF and converted to USD dollars of August 2017. See Appendix 1 for descriptions of the variables.

Table 4. Probability of transacting at female agents in the Democratic Republic of Congo

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	= 1 if female agent									
Sample	All	All	All	All	All	Customers with balance data (Oct 2017)	Markets >25% female agents	Markets <25% female agents	Matched agent only	All customers transacting at matched agents
= 1 if female client	1.531***	1.520***	1.514***	1.518***	1.519***	1.113	1.500***	1.537***	2.098***	1.825***
	(0.121)	(0.113)	(0.128)	(0.119)	(0.105)	(0.163)	(0.155)	(0.145)	(0.372)	(0.211)
= 1 if currency USD			1.321***	1.037	1.039	1.031	0.936	1.150**	0.711***	0.910
			(0.067)	(0.046)	(0.045)	(0.077)	(0.042)	(0.072)	(0.063)	(0.053)
= 1 if cash deposit			1.152	1.136	1.145	1.124	1.269	0.995	1.097	1.066
			(0.203)	(0.213)	(0.219)	(0.264)	(0.232)	(0.305)	(0.390)	(0.197)
Log of transaction amount in USD			0.994	1.006	1.002	1.014	1.009	1.009	1.001	0.980
			(0.018)	(0.017)	(0.016)	(0.019)	(0.021)	(0.017)	(0.045)	(0.021)
=1 if transaction outside modal market					1.232***					
					(0.063)					
Female client*transaction outside modal market					1.048					
					(0.187)					
Customer age			0.996*	0.999	0.999	1.000	0.999	0.999	1.008**	1.001
			(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)
Log customer balance in USD						0.937***				
						(0.013)				
Female client*log customer balance in USD						1.128***				
						(0.049)				
Number of transactions	1,087,340	1,087,340	1,087,340	1,087,340	1,087,340	26,900	452,290	635,050	164,054	711,191
Number of clients	101,824	101,824	101,824	101,824	101,824	10,691	49,895	64,896	29,184	36,217
Pseudo R-squared	0.006	0.087	0.009	0.087	0.088	0.104	0.039	0.097	0.166	0.099
Mean dep var omitted category	0.229	0.229	0.097	0.097	0.101	0.088	0.119	0.082	0.023	0.090
Marginal effect	0.084	0.075	0.081	0.074	0.075	0.113	0.088	0.064	0.111	0.104
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*Note: This table reports the estimates of a logit model where each observation is a transaction made a by a single client at a given FINCA DRC agent between May 2017 and April 2018. The dependent variable is a dummy which takes the value 1 if the agent is female. In all columns, we cluster the standard errors at the client level. We include market and time fixed effects in all columns, except columns 1 and 3. Marginal effects are reported at the bottom of the table and are estimated using the mean of the dummy variable for female clients. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. See Appendix 1 for descriptions of the variables.*

Table 5. Dyadic regressions in the Democratic Republic of Congo

	(1)	(2)	(3)	(4)
	A transaction was done between agent *a* and client *c* that month (1=Yes)			
Client and agent have the same gender (1=Yes)	0.000791**	0.000792**	0.000459*	0.000442*
	(0.000315)	(0.000315)	(0.000226)	(0.000221)
Client and agent are both female	-0.000719	-0.000726	-0.00000749	0.0000175
	(0.000582)	(0.000584)	(0.000416)	(0.000411)
Absolute age difference between client and agent		-0.000011		-0.000023***
		(-0.0000167)		(0.0000074)
Agent and client are located in the same area (1=Yes)	0.0152***	0.0152***	0.0156***	0.0156***
	(0.00254)	(0.00253)	(0.00260)	(0.00260)
Mean of the Dependent Variable among pairs with dummies = 0	0.00044	0.00044	0.00044	0.00044
Observations	2,488,928	2,488,928	2,488,928	2,488,928
R-squared	0.010	0.010	0.011	0.011
FEs	No	No	Yes	Yes
Number of clients	2509	2509	2509	2509
Number of agents	32	32	32	32

*Note: This table reports the results of dyadic regressions where each client is paired with every agent in the dataset. The dependent variable takes value 1 if client c transacted with agent a in a particular day of the month. The mean of the dependent variable among pairs with dummies = 0 refer to the mean when "Client and agent have the same gender", "Client and agent are both female" and "Agent and client are located in the same area" are all set to 0. In columns 3 and, 4 the regression includes client and agent location fixed effects. Standard errors are clustered at the client and agent level using the STATA command reghdfe. *** p<0.01, ** p<0.05, * p<0.1.*

Table 6. Transaction amounts in the Democratic Republic of Congo

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10
	Log of transaction amount in USD									
Sample	All	All	All	All	Male agents	Female agents	Markets >25% female agents	Markets <25% female agents	Matched agent only	All cust transact matched
= 1 if female client	-0.370***	-0.352***	-0.548***	-0.543***	-0.543***	-0.036	-0.517***	-0.556***	-0.307***	-0.335
	(0.093)	(0.088)	(0.066)	(0.060)	(0.060)	(0.127)	(0.081)	(0.077)	(0.093)	(0.07
= 1 if female agent	0.078	0.042	-0.159***	-0.123***			-0.133***	-0.092*	-0.251***	-0.187
	(0.066)	(0.057)	(0.042)	(0.033)			(0.037)	(0.048)	(0.068)	(0.04
= 1 if currency USD			1.817***	1.793***	1.853***	1.586***	2.026***	1.620***	1.468***	1.637
			(0.040)	(0.036)	(0.042)	(0.044)	(0.054)	(0.047)	(0.054)	(0.04
= 1 if cash deposit			-1.407***	-1.385***	-1.421***	-1.283***	-1.508***	-1.269***	-1.163***	-1.163
			(0.086)	(0.082)	(0.075)	(0.166)	(0.109)	(0.091)	(0.151)	(0.09
Customer age			0.009***	0.009***	0.008**	0.011***	0.007**	0.010***	0.012***	0.013
			(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.00
Agent age			0.014***	0.010***	0.013***	-0.002	0.006***	0.013***	-0.017***	0.00
			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.00
Agent gender* customer gender			0.477***	0.481***			0.500***	0.436***	0.759**	0.454
			(0.132)	(0.131)			(0.165)	(0.106)	(0.301)	(0.18
Number of transactions	1,087,340	1,087,340	1,087,340	1,087,340	813,302	274,038	452,290	635,050	201,655	711,1
Number of clients	101,824	101,824	101,824	101,824	85,847	53,257	49,895	64,896	36,217	36,2
R-squared	0.007	0.050	0.248	0.263	0.276	0.229	0.290	0.246	0.236	0.24
Mean dep var omitted category	4.071	4.071	4.071	4.071	4.083	3.749	4.113	4.045	4.084	4.08
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Ye
Market FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Ye
Time FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Ye

*Note: This table reports the estimates of an OLS model where each observation is a transaction made a by a single client at a given FINCA DRC agent between May 2017 and April 2018. dependent variable is the log of the transaction amount in USD. In all columns, we cluster the standard errors at the client level. We include market and time fixed effects in all columns, ex columns 1 and 3. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. See Appendix 1 for descriptions of the variables.*

Table 7. Mean transactions amount in USD and gender in the Democratic Republic of Congo

	(1)	(2)	(3)
	Transaction value in USD		P-value of t-test that (1)=(2)
	At male agents	At female agents	
Female customers	132.77	220.76	0.000
Male customers	249.51	206.90	0.000

Note: This table presents predicted values for transaction values at male and female agents of 787,413 male and 299,927 female customers controlling for all variables included in the regression in Column 4 of Table 4 (values are transformed back from logged USD to USD values). We report the p-values of a simple mean comparison t-test for the predicted values in Column 4. All the transactions are made either in USD or CDF and converted to USD dollars as of August 2017. See Appendix 1 for descriptions of the variables.

Table 8. Summary statistics for Senegal

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Overall	Gender of the customer		P-value of t-test that (2)=(3)	Gender of the agent		P-value of t-test that (5)=(6)
		Male	Female		Male	Female	
Transaction made by female customer (1=Yes)	0.348	0.000	1.000	-	0.309	0.722	0.000
Transaction made at a female agent (1=Yes)	0.096	0.041	0.199	0.000	0.000	1.000	-
Withdrawal (1=Yes)	0.466	0.497	0.408	0.009	0.474	0.389	0.124
Transaction amount (Jan 2015 USD)	105.38	96.14	122.67	0.05	107.60	84.49	0.280

Note: This table presents summary statistics from data on 936 transactions made between February 2015 and April 2016 by 98 clients at 86 Microcred/Baobab agents in 20 markets in Senegal. Among the 86 mobile money banking agents, 74 were male and 12 were female. There are 54 male clients and 44 female clients. In columns 4 and 7, we report the p-value of a simple mean comparison t-test of the previous two columns. All the transactions are made in local currency but converted to USD dollars of January 2015.

Table 9. Probability of transacting at female agent in Senegal

	(1)	(2)
	=1 if female agent	
=1 if female client	5.828**	5.796**
	(4.249)	(4.043)
=1 if withdrawal		0.812
		(0.306)
Log of transaction amount in Jan15 USD		0.751
		(0.151)
Number of transactions	936	936
Number of clients	98	98
Pseudo R-squared	0.098	0.122
Mean dep var omitted category	0.041	0.029
Marginal effect	0.120	0.118
Clustered SE	Yes	Yes
Market FE	No	No
Time FE	No	No

*Note: This table reports the odds-ratio estimates of a logit model where each observation is a transaction made a by a single client at a given Microcred/Baobab agent between February 2015 and April 2016. The dependent variable is a dummy that takes value 1 if the agent was female. In all columns, we cluster the standard errors at the client level. Marginal effects reported at the bottom of the table are estimated using the mean of the dummy variable for female clients. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table 10. Dyadic regressions in Senegal

	(1)	(2)
	Transaction between agent *a* and client *c* in month (1=Yes)	
Client and agent have the same gender (1=Yes)	0.00181*	0.00169**
	(0.000915)	(0.000812)
Client and agent are both female	-0.000782	-0.000630
	(0.00138)	(0.00141)
Agent and client are located in the same area (1=Yes)	0.00894***	0.0118***
	(0.00252)	(0.00333)
Mean of the Dependent variable among pairs with dummies = 0	0.00113	0.00113
Observations	121,770	121,770
R-squared	0.003	0.005
FEs	No	Yes
Number of client clusters	99	99
Number of agent clusters	82	82

*Note: This table reports the results of dyadic regressions where each client is paired with every agent in the dataset. The dependent variable takes value 1 if client c transacted with agent a in a particular month. The mean of the dependent variable among pairs with dummies = 0 refer to the mean when "Client and agent have the same gender", "Client and agent are both female" and "Agent and client are located in the same area" are all set to 0. In column 2 the regression includes client and agent location fixed effects. Standard errors are clustered at the client and agent level using the STATA command reghdfe. *** p<0.01, ** p<0.05, * p<0.1.*

Table 11. Transaction amounts in Senegal

	(1)	(2)	(3)	(4)
	Log of transaction amount in Jan15 USD			
=1 if female agent	-0.721**	-0.487	-0.698**	-0.481
	(0.321)	(0.310)	(0.324)	(0.312)
=1 if female client	0.0933	0.171	0.0849	0.167
	(0.311)	(0.278)	(0.310)	(0.276)
=1 if female agent and female client	0.157	0.536	0.112	0.524
	(0.677)	(0.602)	(0.691)	(0.606)
=1 if withdrawal			-0.155	-0.0572
			(0.124)	(0.144)
Number of transactions	936	909	936	909
Number of clients	98	97	98	97
R-squared	0.008	0.049	0.009	0.050
Mean dep var omitted category (USD)	98.4	97.09	107.4	103.5
Clustered SE	Yes	Yes	Yes	Yes

*Note: This table reports the estimates of an OLS model where each observation is a transaction made a by a single client at a given Microcred/Baobab agent between February 2015 and April 2016. The dependent variable is the log of the transaction amount in USD dollars of January 2015. Standard errors in parentheses. In all columns, we cluster the standard errors at the client level. In columns 2 and 4 we include market fixed effects, but some markets do not have enough clients and in these cases, observations are lost due to collinearity. *** p<0.01, ** p<0.05, * p<0.1.*

Appendix

Appendix Table 1. Descriptions of variables

Variable	Definition
Absolute age difference	Absolute age difference in years between a customer and an agent
Account balance in USD	Customer's account balance (combined across all account types: current, savings and other on October 31, 2017)
Agent age	Agent's age
Agent business age	Number of years the agent's business has been in operation
Days open per week	Number of days per week the agent's location is open for business
Deposits	Deposit transactions (cash-ins)
Employees	Number of employees in the agent's shop
Funds transfers	Customer transfers funds to another person's account
Minimum POS balance	Minimum balance of point of sale (POS) terminal the agent uses to conduct customer transactions
Number of transactions	Number of transactions over the study period (2017-2018)
Opening hours (per day)	Number of hours per day the agent's location is open for business
Outside modal market	Dummy variable, indicates whether a customer transacts outside the modal market, i.e. his/her most frequently used transaction location (1=outside modal market, 0=inside modal market)
Previous FINCA client	Dummy variable, indicates whether an agent had a FINCA account prior to becoming an agent (1 = yes, 0=no)
Revenue (per day)	Daily revenue of the business the agent operates
School fees payments	School fees payment made through FINCA account
Service sector	Dummy variable, indicates whether agent's shop operates in service sector (1 = yes, 0=no)
Transaction amount in USD	Amount transacted in USD (August 2017 exchange rate in DRC data, January 2015 exchange rate in Senegal data)
Transactions in CDF	Dummy variable, indicates whether the transaction was conducted in CDF (1=CDF, 0=USD)
Transactions in USD	Dummy variable, indicates whether the transaction was conducted in USD (1=USD, 0=CDF)
Value of stock	Current inventory value in USD
Withdrawals	Withdrawal transactions (cash-outs)