Virtual Windows Through Glass Walls? Digitalization for Low-Mobility Female Entrepreneurs

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Abstract

Social norms and childcare responsibilities often constrain women's mobility and work. This paper investigates the promise of digitalization in unlocking the growth of home-based businesses, an economic lifeline for women in developing countries. To do so, Jordanian female entrepreneurs were offered access to virtual storefronts through Facebook business pages, as well as access to an online digital marketing training created in collaboration with local social media influencers. After six months of hands-on support, treated women had higher business survival, weekly revenue, and attracted more online clients. Machine learning heterogeneity analysis reveals that higher business performance and limitations on the owner's ability to leave her house at baseline are particularly predictive of effects. Together, results suggest that when constraints to technology adoption are lifted, digitalization can unlock windows of opportunity to talented female entrepreneurs, especially those mobility-constrained among them.

Keywords: Business Training and Outsourcing; Firm Growth; Female Entrepreneurship; Digital Marketing.
JEL Codes: O12, O17, J16, L25, L26, M31.

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1 Introduction

Can digitalization unlock growth for female entrepreneurs? Social norms and household demands often form 'glass walls' that restrict women's mobility and work outside the home (Jayachandran 2021). In France, 14% of the gender wage gap can be explained by differences in men and women's willingness to commute (Le Barbanchon, Rathelot, and Roulet 2021); in Pakistan, some women have to be paid half of their monthly household expenditure just to cross their village boundary for training (Cheema, Khwaja, Naseer, and Shapiro 2019); and in Saudi Arabia, strong gender norms limit women's work outside the home, even when households privately support it (Bursztyn, González, and Yanagizawa-Drott 2020). Around the world, women face substantial mobility constraints, yet few of those living in low-income communities are able to access remote employment from home[1]. Instead, millions of mobility-constrained women resort to home-based entrepreneurship for an economic lifeline[2]. Operating behind closed doors, however, many female entrepreneurs remain particularly market-constrained[3], selling mostly to friends and neighbors. With this backdrop, digitalization has been proposed as offering virtual windows of opportunities, allowing female entrepreneurs to reach broader markets from home[4].

Despite increasing access to the Internet in emerging markets[5], the promise of digital technologies for women in conservative settings remains uncertain. In principle, digitalization might enhance women's economic outcomes by offering flexibility (Mas and Pallais 2017). In conservative settings, however, this might not be enough. First, if constraints on female entrepreneurs are driven by concerns over their visibility and interactions with strangers, regardless of medium, then virtual spaces might fail to expand their markets. Second, mobility constraints are not randomly assigned. They likely result from norms and preferences that also constrain women's skills, aspirations, resources, and time (Martinez Dy, Martin, and Marlow 2018). Indeed, if home-based entrepreneurs are subsistence entrepreneurs with limited scope for growth, then the promise of digitalization might fail to materialize among them (Schoar 2010).

In this paper, I shed light on these issues by experimentally investigating the promise of online market access for female entrepreneurs in conservative settings. I do so in the context of Jordan, which, at 15%, has the world's third lowest female labor force participation rate[6] and one of the highest gender gaps in entrepreneurship[7]. While access to e-commerce has been growing in emerging markets, I focus on the promise of Facebook as a marketplace. With more than 2.93 billion users worldwide[8], Facebook has become one of the most accessible digital platforms in low and middle income countries[9] and is often used by business owners to reach customers[10].

To understand how female entrepreneurs use virtual markets in conservative settings, I start by

[1] Brussevich, Dabla-Norris, and Khalid 2020
[2] Bank 2023
[3] Hardy, Kagy, and Jimi 2022
[4] OECD 2022, Pergelova, Manolova, Simeonova-Ganeva, and Yordanova 2019
[5] Poushter, Bishop, and Chwe 2018
[6] World Bank, ILOSTAT database (last accessed in November 2023)
[7] World Bank, We-Data: Measuring the gap in female entrepreneurship around the world (2022)
[8] Meta Reports, First Quarter of 2022
[9] Pew Research Center (2016)
[10] The use of social media for 'informal online commerce' has been documented in Pakistan, Bangladesh, Myanmar (Roest and Bin-Humam 2021), Indonesia (Melissa, Hamidati, and Saraswati 2013, Wahyuningsih and Mustaqim 2021), Egypt (Beninger, Ajjan, Mostafa, and Crittenden 2016), and Tunisia (Brahem and Boussema 2022)

collecting qualitative observations from public online spaces in Jordan. First, I analyze hundreds of business marketing posts in Facebook groups and document significant differences in male and female users' posting behavior. Women are significantly more likely than men to conceal parts of their identity by using full names and real pictures on the profiles from which they market their businesses. Second, I document the existence of dozens of regional and national private women-only Facebook trading groups in Jordan, with thousands of members in each. These gender-segregated groups are often used as 'safe spaces' for female entreprenerus to interact and transact without male presence. Their popularity is consistent with existing evidence on female entrepreneurs generally segregating into female-dominated industries with less interactions with men (Ashraf, Delfino, and Glaeser 2019). Together, these observations suggest that cultural constraints on women's visibility and interactions are often mirrored online, but also that female entrepreneurs use digital platforms' features to operate *within* these constraints, potentially at the expense of their businesses' visibility.

Based on these findings, I set up an experiment aiming to increase businesses' online exposure without compromising owners' visibility. This is possible by setting up public Facebook business pages, which allow marketing a business without publicizing its owner's identity. To understand the impact of online markets on low-mobility women, including those with limited digital literacy, I also designed the intervention to lift informational, logistical, and financial barriers to technology adoption. Particularly, I work with 1,122 female entrepreneurs recruited from a database of microfinance clients, and I randomize their access to logistical support in setting up virtual storefronts for their businesses on Facebook. The support offered creating a public Facebook business page, marketing it for up to 6 months, and covering paid advertisements of up to $20 for active pages. The support package therefore provided a digital marketing outsourcing service for the treatment group. To help treated participants maintain their online presence, the logistical support was additionally bundled with access to a virtual asynchronous training on digital marketing. The training was designed and shot in collaboration with social media influencers in Jordan. It contained 30 short videos and covered locally-curated best practices for digital marketing, including tips on content-creation, photography, and ways to market the business without compromising one's privacy and well-being.

Conceptually, the intervention provides a 'market access technology' that expands customer reach beyond owners' social networks. In the offline world, high mobility entrepreneurs should already have access to such a technology: they can set up public storefronts, roam around neighborhoods, and market in public squares. With no constraints on interactions with distant strangers, all those who would benefit from an expanded market access technology would have already adopted it offline. Low-mobility female entrepreneurs, on the other hand, might have inefficiently low levels of adoption. Productive businesses that might benefit from higher market access might therefore fail to access it due to offline constraints on their owners' mobility. If the intervention successfully decreases the costs of expanded market access by digitizing it, we should expect significant business improvements for low-mobility entrepreneurs, and particularly those with high productivity among them.

To test this, I survey study participants six months after the intervention's start date. First, I find that around half the participants engaged with the logistical support by sending the required information, such as business name and pictures. After the support team created pages based on this information, 37% of treated participants became owners of a newly created Facebook page, and an additional 20% already had one. In parallel, 59% of treated participants opened the online training

and 16% watched an hour or more of it. Overall, treated women were more than twice as likely to report using a public Facebook business page for marketing, up from a control mean of 22%; they were also 12 percentage points more likely to market on public Facebook groups, up from a control mean of 19%.

Beyond take-up, I find that higher access to digital marketing translates to better business outcomes. Treated participants were 7 percentage points (p-value=0.02) more likely to have an active business, up by 9.3% from a control mean of 75% survival rate. They subsequently had 20% more distinct clients per month (p-value=0.05), up by around 2 distinct clients from a control mean of 9, and saw an 18% increase in weekly revenue, (p-value=0.05), up by 11 dollars from a control mean of $60. Increases in monthly revenue and profits are noisy, yet an index of business survival and performance increased by 0.13 SD (p-value=0.02). While these financial gains might be due to higher business survival in the treatment group, they provide suggestive evidence on the promise of market access interventions in supporting the livelihoods of female entrepreneurs.

Next, I investigate the impact of online market access on client composition. Given significant impacts on business ownership, looking at client composition outcomes among surviving businesses would reflect both the treatment effect and the selection effect into survival. Accordingly, I first impute outcomes with zeros among closed businesses for a causal interpretation of the intervention's impacts, then look at effects among operational businesses for descriptive insights.

Looking at the entire sample, I find that treated participants reported on average an increase in the number of online clients they got over a month period; they were also more likely to sell to strangers and customers from outside of their social network. Consistently, treated participants reported a lower share of store credit revenue out of total revenue. Store credit, a form of informal 'buy now pay later', is often requested by members of business owners' social network to smooth consumption. As owners sell to more people outside of their social network, store credit decreases, suggesting more formalization of practices among customers.

Looking at the sample of surviving businesses, I find that treated entrepreneurs still report a higher number of online clients and a lower share of store credit, compared to their counterparts in the control group. The likelihood of sales to strangers is also 5 percentage points higher in the treatment group, but the effect is insignificant at conventional levels (randomization inference p-value=0.15).

Importantly, these business effects do not come at the expense of more conservative gender norms. While increasing participants' ability to make income from home could reinforce conservative norms tying women to the domestic sphere, I find no evidence of such effects. If anything, treated participants are less likely to agree with a statement saying that a woman's value is best preserved at home. They are also equally likely to work outside the home and to hold a full-time job, compared to their counterparts in the control group.

Next, I investigate differential treatment effects across women with varying mobility levels. To do so, I construct a baseline mobility index for participants by averaging the z-scores from mobility variables collected at baseline (following Kling, Liebman, and Katz 2007)[11]. Looking at heterogeneity in results, I find that female entrepreneurs with a below-median mobility index ('low-mobility women') had higher business survival, revenues, profits, online clients, and sales to strangers, compared to their

[11]The baseline mobility index averages the z-scores from the following variables: number of times out alone last month, willingness to leave the house weekly to attend an in-person training, and willingness to operate the business outside the home if rent is covered.

counterparts in the control group. In contrast, female entrepreneurs with above median mobility index at baseline ('high-mobility women') experienced economically and statistically insignificant improvements in outcomes, despite having similar take-up rates as women with below median mobility. These differences likely suggest less market constraints among high-mobility women, or lower returns to them from the marketing support provided at the level of the intervention.

These results are qualitatively maintained when looking at the sample of surviving businesses: among low-mobility women, treated business owners report 20 more dollars in weekly revenue (p-value<0.05) and 40 more dollars in monthly revenue, although the latter effects are noisy (randomization inference p-value=0.18). They are also more likely to sell to strangers and have a significantly smaller share of store credit out of revenue, compared to surviving businesses in the control group. High mobility women, on the other hand, have null effects except on the number of online clients, which increases by 0.74 (p-value=0.1), up from a control mean of 2.19. This might suggest some substitution for high-mobility women: they might be reaching clients online instead of in-person as their Facebook marketing activities increase.

These heterogeneous effects are consistent with those predicted using a data-driven approach. I employ machine learning algorithms to detect differential treatment effects and explore their sources, following Chernozhukov, Demirer, Duflo, and Fernandez-Val 2018. While under-powered, estimates suggest sizable heterogeneity in the sample, with a heterogeneous treatment effect size four times bigger than the average effect size. Exploring its sources, I find that indeed, baseline mobility is predictive of treatment effects. Other predictors of treatment effects include baseline measures of business productivity, such as a baseline business index[12], ownership of a fixed business asset, and an indicator of above median baseline revenue.

Given results from the machine learning predictions and existing evidence on the relevance of entrepreneurial skill (Banerjee, Breza, Duflo, and Kinnan 2019, Gompers, Kovner, Lerner, and Scharfstein 2006, Hussam, Rigol, and Roth 2022), I further look at the interaction of baseline mobility and productivity. I find that treatment effects are particularly high for productive and mobility constrained women, where productivity is defined as above median revenue or ownership of business assets at baseline. Since financial measures of business performance might reflect access to capital, as opposed to skill, I also use an alternative measure of business talent that rates business pictures received from a selected subset of participants from the treatment and control groups at baseline. Overall, results from picture ratings and from financial measures of business productivity suggest that most effects are coming from mobility-constrained and relatively productive female entrepreneurs. These results underscore existing findings in the literature showing that baseline ability is predictive of business interventions' impact (Banerjee et al. 2019, Hussam et al. 2022), and provide new evidence on the relevance of cultural factors for interventions targeting female entrepreneurs.

This study contributes to several literatures. First, I add to an extensive body of work examining constraints to entrepreneurship and firm growth. Many studies have investigated production-side factors like liquidity (De Mel, McKenzie, and Woodruff 2008; Herkenhoff, Phillips, and Cohen-Cole 2021; Kerr, Lerner, and Schoar 2014; Lerner, Schoar, Sokolinski, and Wilson 2018), labor (De Mel, McKenzie, and Woodruff 2019), and managerial ability (Bloom, Eifert, Mahajan, McKenzie, and Roberts 2013); a recent literature also examines market access factors by studying the role of

[12]The baseline business index averages the z-scores from baseline monthly revenues, profits, and clients.

marketing skills and outsourcing (Anderson, Chandy, and Zia 2018; Anderson, Chintagunta, Germann, and Vilcassim 2021; Anderson and McKenzie 2022), access to national markets through ecommerce (Couture, Faber, Gu, and Liu 2021), and access to foreign markets through trade (Atkin, Khandelwal, and Osman 2017). I add to these literatures by documenting market access constraints faced by female entrepreneurs and testing the effectiveness of a virtual and light-touch digital marketing outsourcing intervention in alleviating these. Additionally, I add to a growing literature hilighting heterogeneity in entrepreneurial potential and skill as a key determinant of business performance (Banerjee, Breza, Duflo, and Kinnan 2019; Gompers, Kovner, Lerner, and Scharfstein 2006; Hussam, Rigol, and Roth 2022). Results in this experiment echo existing evidence on the relevance of ability and highlight mobility and cultural constraints as another key determinant of entrepreneurial success among female business owners.

In addition to the literature on entrepreneurship, this paper contributes to an overlapping literature on digitalization and social media. Existing evidence highlights the implications of digitalization and the Internet on businesses (Goldfarb and Tucker 2019; Hjort and Poulsen 2019; Otis, Clarke, Delecourt, Holtz, and Koning 2023) and the future of work (Bloom, Liang, Roberts, and Ying 2015; Cullen and Farronato 2021; Ho, Jalota, and Karandikar 2023; Horton, Kerr, and Stanton 2017). Recent evidence particularly suggests that the arrival of 3G Internet increases business ownership among women, but also increases their work in unpaid jobs (Chiplunkar and Goldberg 2022). Evidence from Jordan also highlights that the arrival of mobile broadband led to higher female labor force participation among skilled women and to a reduction in gender-biased social norms (Viollaz and Winkler 2022). In this study, I provide insights on how virtual platforms might provide online safe spaces for female entrepreneurs and increase their market exposure in conservative settings.

Focusing on social media, a growing literature has studied mental health, well-being, and political outcomes (Allcott, Braghieri, Eichmeyer, and Gentzkow 2020; Levy 2021; Zhuravskaya, Petrova, and Enikolopov 2020), mostly highlighting detrimental effects of social media. This study provides evidence on the economic benefits that social media can have on small businesses generally and on female entrepreneurs particularly, which helps explain their widespread use particularly for marketing purposes.

Finally, this study contributes to the literature on women's mobility, work, and access to opportunities. Recent empirical evidence highlights that social norms (Becker 2022; Bursztyn et al. 2020; Cheema et al. 2019; Goldin 1994; Jayachandran 2021), safety concerns (Ashraf et al. 2019; Borker 2021; Dean and Jayachandran 2019), familial preferences (Bernhardt, Field, Pande, and Rigol 2019; Lowe and McKelway 2021), and demands on women's time (Delecourt and Fitzpatrick 2021; Coen-Pirani, León, and Lugauer 2010; Talamas 2020) can form 'glass walls' that limit their mobility and access to opportunities outside the home. While many papers explore ways to lift constraints on women's mobility and participation, this project investigates the promise of digitalization in expanding female entrepreneurs' access *within* the constraints they face.

The rest of the paper proceeds as follows: section 2 discusses the Jordanian context and how virtual spaces are used by men and women within it; sections 3 to 6 describe the design, sample, main results, and heterogeneity analysis respectively; and section 7 concludes with policy implications.

2 Context

I conduct the study with low-income female entrepreneurs in Jordan. In this section, I provide information on the study context as relevant to the experimental design. To do so, I outline an overview on women's economic participation and digital access in Jordan, and I discuss how online spaces are used by male and female business owners.

2.1 Country Setting

Women's mobility and work: At 15%, Jordan has the world's third lowest female labor force participation rates (figure A.1). In contrast, men's labor force participation exceeds 60%, resulting in a striking gender gap in labor supply despite comparable education levels across men and women (figure A.2). With relatively high literacy rates, the underutilization of women's human capital entails substantial economic losses for them and their households (Ait Ali Slimane, Lundvall, Mohindra, Al Abbadi, Kurshitashvili, and Hisou 2020) and suggests the existence of untapped potential for growth among them.

Existing efforts to explain women's exclusion from the labor market have highlighted conservative social norms and the lack of flexible work opportunities as main contributors (Kaasolu, O'Brien, Hausmann, and Santos 2019). In a World Bank survey in urban areas of Jordan, 96% of Jordanians agreed that it is generally OK for women to work. However, this rate drops to 54% if women would have to leave their children with relatives, to 38% if women would have to work in mixed workplaces, and further to 26% if women would need return home from work after 5pm (Bank 2018). These rates are consistent with norms around women's work, as expressed in national surveys in Jordan. Over 80% of Jordanians believe that jobs should be reserved to men if they are scarce, and over 84% report that the children of a working mother suffer (World Value Survey, 2018). Reservations around women's work are accompanied by restrictive norms on their movement: 80% of men and more than 60% of women believe that women should not be allowed to travel alone. Given the lack of flexible employment in Jordan, as in many developing countries, informal home-based entrepreneurship has emerged as an economic lifeline for women to balance their financial needs with familial and societal constraints on their mobility and work.

Digital Access: It is also worth noting that Jordan, like many other countries with young populations, has a relatively high social media penetration rate. About 61% of Jordanians report using Facebook actively and 64% report using WhatsApp (figure A.4). Conditional on access to Internet, these usage rates reach 78% for Facebook and 81% for WhatsApp. Importantly, these usage rates exhibit smaller gender gaps when compared to economic participation rates, although women are slightly less likely to use Facebook, which allows broad exposure, and more likely to use WhatsApp, which requires knowing a user's phone number to contact her. While only suggestive, these figures imply that gender gaps in economic participation do not fully translate to differential usage of digital platforms.

2.2 Online Space Setting

Next, I document how online spaces are used by business owners in the Jordanian context. In principle, it is not clear that virtual spaces alleviate concerns on female entrepreneurs' visibility and

exposure to strangers. Norms that limit women's ability to work and interact with others might simply be mirrored online. If that's the case, digitalization might fail to increase market access.

To shed light on restrictions around women's visibility online, I document online practices for a subset of male and female users on Jordanian Facebook groups. Note that Jordan has dozens of national and region-specific Facebook trading groups across the country, each with a few hundreds to hundreds of thousands of members. Many of these groups are closed female-only groups: members are individually verified to be female users by group administrators before they are admitted into the group, and group administrators moderate content and monitor complaints[13]. On these groups, female users often post pictures of products and services they sell, most of which are oriented towards other women, consistent with existing research highlighting that women segregate into female-dominated industries (Ashraf et al. 2019). The popularity of these women-only groups suggests that online spaces do not relax preferences for gender segregation. Indeed, women try to create 'safe spaces' to interact and trade with each other online, a phenomenon also documented in Egypt (Kamel 2022) and Pakistan (Younas, Naseem, and Mustafa 2020).

Additionally, even when women post on public and mixed gender groups, they seem more likely than men to hide parts of their identity online. To shed light on this, I sample 30 popular public Facebook trading groups in Jordan and analyze more than 300 business-related posts by male and female users on them[14]. Figure 1 presents descriptive analysis from these and shows that male-looking users in the sample are significantly more likely than female users to use full names (75% for men vs. 56% for women) and identifying pictures (40% for men vs. 10% for women). Instead, female users are more likely to use pictures of objects such as flowers, pictures of prayers, or pictures of male relatives or children. Interestingly, both male and female users rarely use professional business names or pictures. Only 5% of female users use a business name for the profile they advertise from and only 15% use a business-related picture, compared to 10% and 20% of male users, respectively.

Together, these figures highlight two motivations for an intervention introducing online storefronts for female entrepreneurs. First, women choose not to reveal identifying information about themselves online, suggesting restrictions and costs around the visibility of female entrepreneurs even in online spaces. Second, women (and men) rarely use business names and pictures when marketing their businesses on Facebook. This suggests that there is scope for a market access intervention that helps women decouple businesses' market exposure from their owners' personal visibility in online spaces by using Facebook business pages. I elaborate on this design below.

[13] See figure A.5 in the appendix for a sample of women-only Facebook groups.

[14] Groups covered in the analysis include local or national public groups with words like 'trading' or 'business' in their title. They also had to have at least 1,000 members, 30 posts within the last 30 days, no restrictions on members' gender, and no restrictions on the type of product or service marketed on the groups. Among groups that satisfy this criteria, those that showed up first in the search were sampled, making this a convenience sample overall.

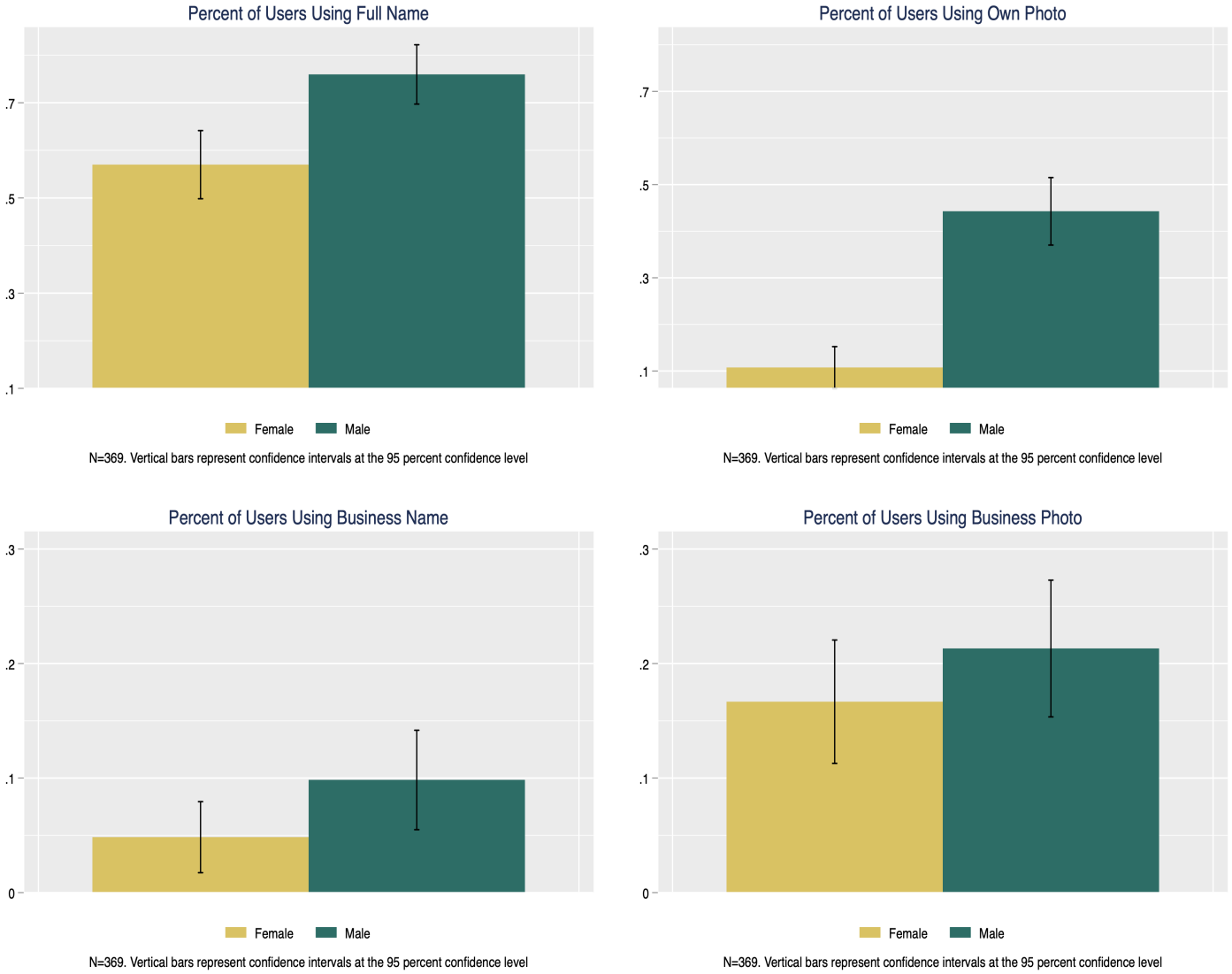


Figure 1: Practices from Public Groups

These figures are constructed from a convenience sample of more than 300 business-related posts across 30 mixed public Facebook trading groups.

3 Experimental Design

This section describes the study's design, outlined in figure 2, including an overview of the recruitment and eligibility criteria, onboarding process, and intervention details.

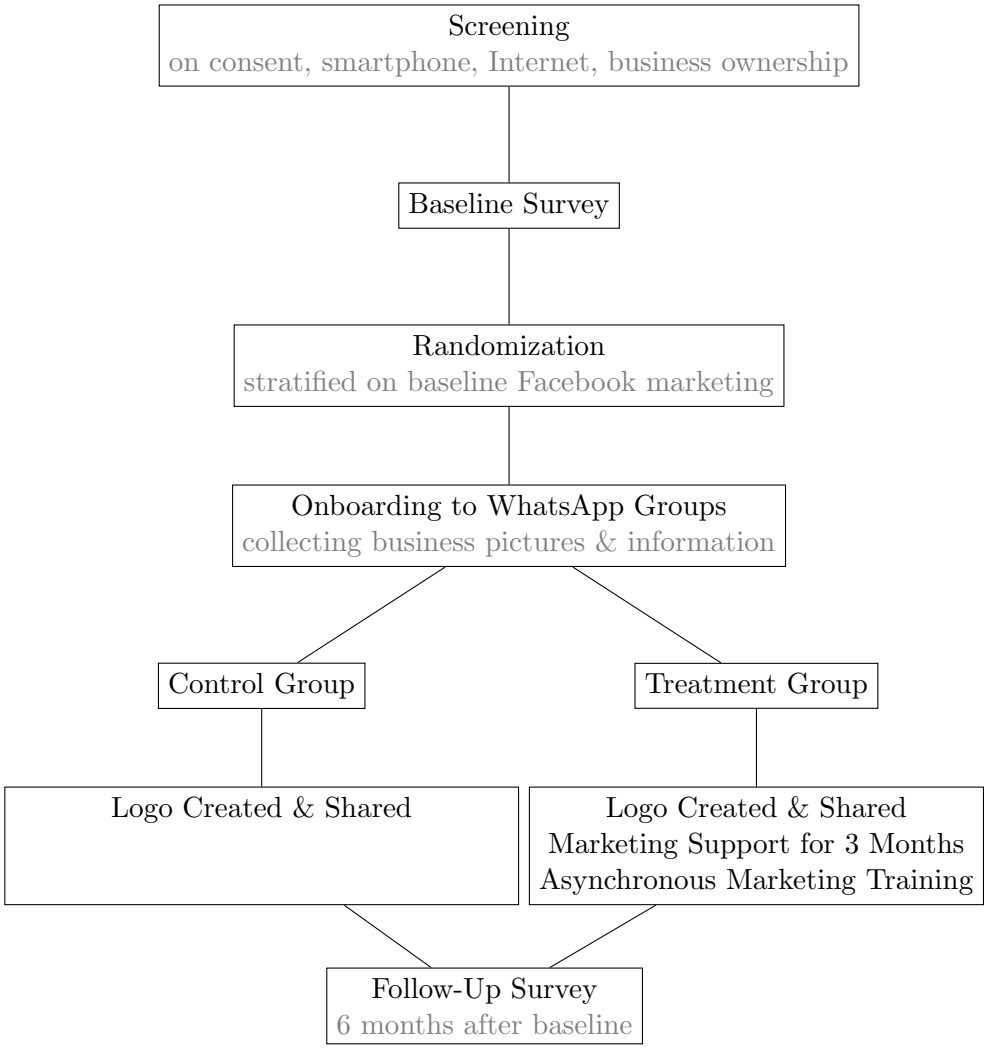


Figure 2: Experimental Design

3.1 Recruitment and Onboarding

The sampleframe consists of current and previous clients of Microfund For Women, one of the largest microfinance institutions (MFIs) in Jordan. The MFI provides eligible low-income individuals in Jordan with uncollateralized group and individual loans. As suggested by its name, the MFI particularly caters to women, which make up the majority of its clients, but does not specifically require borrowers to be women or to have a business.

To recruit participants, I randomly sampled potential study participants from the MFI's beneficiaries database, which included active and recent borrowers across Jordan. Surveyors called and informed participants that we are conducting a study on the impact of new technologies on

small businesses[15]. Among respondents who consented to participating in the survey, I screened on ownership of a smartphone, Internet access, ownership of a business, and interest in market access support. Eligible and interested respondents then filled the baseline survey and were randomized into either the treatment or the control group on Qualtrics, stratifying by whether participants reported marketing on Facebook at baseline (either through a Facebook page or their personal profiles). As the MFI operates at the national level, study participants covered different areas of Jordan.

Onboarding treatment and control groups: After the baseline survey, each participant was placed in a WhatsApp texting group with a logistical support team of 2-3 members. Through text messages and calls, the logistical support team asked each participant for the name of her business, if it has a name, a description of the business, and pictures of the goods and services that the business provides. Based on the business description and pictures, a business logo was then created and provided to treatment and control participants that responded to the prompt. Participants assigned to the treatment group were eligible to receive additional services through marketing support and online training, described below.

3.2 Bundled Treatment: Online Market Access

Participants in the treatment group were offered a bundled intervention aiming to set up public storefronts for them on Facebook. This intervention is motivated by aforementioned constraints on women's mobility and visibility online and offline, and accordingly has several objectives. The first is increasing business exposure by giving owners access to public Facebook pages, potentially increasing female entrepreneurs' market exposure from the safety and convenience of their homes. Public pages' accessibility to strangers is therefore key, as it contrasts with the limited exposure afforded through private and personal Facebook profiles and through WhatsApp groups that women market on otherwise. The second objective is conserving the business owner's privacy if desired by decoupling her business' exposure and her own visibility. As section 2.2 suggests, even in online spaces, women value privacy and take measures to limit the visibility of their full names and pictures. In this intervention, adopting a business name, logo, and page allows marketing the business widely without necessarily increasing the owner's privacy, potentially alleviating concerns from online exposure.

In addition to increasing exposure while conserving the owner's privacy if desired, the intervention's design aimed to alleviate logistical, financial, and informational constraints to technology adoption. The treatment accordingly bundled two interventions to maximize the first stage:

1- Marketing Outsourcing and Support: the support team created a Facebook business page for each treatment participant that did not have one, conditional on the participant confirming her continued interest in the service by sending pictures of her business and information about it. The support team then created a business logo and set up a business page on Facebook for reach participant that did not have one. Each page included information on the business' type, location, contact information, and whether a delivery service is offered - all of which were sent by the participants to the support team. For participants that already had a page, the support team reviewed the page

[15]I adopted phone surveys for the duration of the study given the difficulty of reaching women in-person in this context, the desire to recruit participants at the national level cost effectively, and lingering concerns about COVID-19 restrictions on in-person surveying in the early stages of this project. Respondents were familiar with phone surveys as the MFI has a research department that occasionally calls beneficiaries for market research and feedback on services. Participants were also familiar with non-financial support coming from the MFI, which has an academy arm that provides free in-person and online training to borrowers.

and offered the same service in updating it with a logo and business information. Appendix figure A.6 shows examples of created pages[16].

After page creation, business owners were made administrators on the created pages, allowing them to fully control and market them, and were encouraged to share the page within their social networks, WhatsApp groups, and on their Facebook personal profile. Participants that showed active engagement with the page received additional support. This included marketing outsourcing by publishing content on the pages' daily stories, wall, and on local and national Facebook trading groups. Finally, engaged pages were offered up to $20 in paid advertisement that the support team administered on behalf of interested participants.

Overall, the marketing support provided a service that falls between purely logistical support and complete outsourcing of digital marketing. As such, the intensity of the intervention depended on each participant's engagement, willingness to send the needed information to set up the page, and her ability to remain active on the page.

2-Virtual Training: In addition to the marketing support, I worked with the MFI's academy arm and several female social media influencers in Jordan to develop and shoot a digital marketing training. As with the support, the training aimed to expand businesses' market access without necessarily expanding the owner's visibility. To do so, we spent months curating local best practices that successful female influencers and businesses adopt on WhatsApp, Facebook, and Instagram. These practices were summarized through tutorials and animations in an asynchronous online training of 30 episodes of around 10 minutes each.

Table A.1 details the topics of different episodes and figure A.7 includes example screenshots from different episodes of the training. The curriculum covered basic, intermediate, and advanced social media marketing modules, with applications and tips on photography, editing pictures, content planning and writing, and paid advertising. The training concluded with a module on mental health and covered the challenges of dealing with online feedback when active on social media.

Throughout the training, an emphasis was placed on the importance of reaching new customers beyond one's immediate circles of friends and family, all while relying on one's social network for honest feedback and support. Additionally, the training aimed to address constraints women in conservative settings are particularly likely to face. For example, the training addressed privacy concerns women might have by explaining that online marketing does not always have to involve videos of the owner herself. Instead, informational videos can be produced by having a voice over a video of the business product. Additionally, the training highlighted local delivery and mobile money services that participants can use to complement their marketing outreach beyond their local community, without necessarily leaving their home.

The virtual training part of the intervention was launched 2-3 weeks after the marketing support part started. Usually, the support team waited for participants to send the required information to set up their business pages (pictures, business name, and business description) before sending them individualized training links. However, even if a participant did not send the required logistical support information after multiple follow-ups, the support team still sent her the links to watch the training at her convenience.

The training was hosted as private (unlisted) videos on Vimeo, limiting participants' exposure to

[16]While these pages are public, the pictures shade their names and contact information to preserve their privacy.

additional recommended content as is the case on platforms like Youtube. Additionally, the training episodes were embedded in Qualtrics, and an individualized Qualtrics link was sent to each participant as a WhatsApp text message. Hosting the videos on Qualtrics allowed tracking participants' progress and interactions with the training, which I report on below.

4 Sample Description

In this section, I provide a description of the sample, including an overview of participants' demographic information, gender norms, digital access, and business characteristics. These are summarized in table 1.

Demographics: The average participant is a 41 year old married woman with children. Education is relatively balanced in the sample, with close to a quarter of women having less than a high school degree, half having a high school degree, and another quarter having a college or advance vocational degree. These levels are comparable to the national average for Jordanian women, noting that women in the sample are 10 percentage points more likely to have a high school degree as opposed to no degree[17], compared to the national average.

Mobility and Gender Norms: Baseline data suggests limited mobility among study participants. For example, 41% of women said they would be unable to take weekly trips outside of their local neighborhood to attend a training or take business-related tasks; 44% reported that they would be unwilling to operate their business outside the house, even if rent were paid for; and the average woman reported leaving the house alone less than 7 times a month. These revealed mobility patterns are consistent with respondents' reported views around women's work. More than 70% of study participants agreed with a statement saying that if a mother works outside the home, her children suffer. This is slightly less agreement than the national average of 84% among Jordanian women, as measured in the World Value Survey (2018). Additionally, 44% of study participants reported believing that society judges a mother that works outside the home, and a third agreed that it would be better for women to stay at home to preserve their own value. Given that these interviews were conducted with women alone, these figures suggest that study participants themselves have views in favor of women staying at home and that they perceive society to hold even more conservative views.

Digital Practices: Consistent with high social media usage rates in Jordan, 85% of participants say that they use Facebook daily or weekly. The average participant estimates that 84% of her acquaintances use Facebook daily or weekly, suggesting common knowledge around the platform's high usage rates. Despite widespread acceptance around being on the platform, only 58% of women said they use their full names on Facebook, and only 11% said they use their real pictures. When participants were asked whether they would be willing to reveal their identity on a business page to increase perceived trustworthiness online, only 64% agreed to reveal their names, and only 31% said they would be willing to appear on the page to advertise it through informational videos. These preferences from the sample are consistent with practices adopted by female users in public trading groups on Facebook, as outlined in section 2.2. Indeed, women in the sample also seem to value their privacy in virtual spaces and to conceal parts of their identities online to protect it.

[17] At the national level, 37% of Jordanian women have less than a high school degree (26% in the sample), 36% have a high school degree (47% in the sample), and 27% have more than a high school degree (27% in the sample) (Arab Barometer, 2018-19 survey).

Table 1: Balance at Baseline by Treatment Assignment

	(1) Control Mean	(2) Control SD	(3) Treatment Difference	(4) N
Demographics				
Age	41.29	9.56	0.57	1122
Married	0.79	0.41	0.00	1122
Has children	0.90	0.31	-0.00	1122
Educ: less than high school	0.26	0.44	-0.01	1122
Educ: high school	0.47	0.50	0.00	1122
Mobility				
a- Times Out Last Month	6.90	7.70	0.57	1122
b- Can go to training weekly	0.59	0.49	0.00	1122
c- Willing to operate in shop if rent is covered	0.56	0.50	0.00	1122
Mobility Index (avg. z-scores of a-c)	-0.02	0.69	0.02	1122
Agrees with Statements				
If a mother works outside the home, children suffer	0.74	0.44	-0.00	1122
Society judges a mother that works outside the home	0.44	0.50	-0.01	1122
Better to work from home to conserve own value	0.34	0.48	-0.02	1122
Digital Practices (personal profile)				
FB: personally uses it daily/weekly	0.85	0.36	0.01	1112
% of your acquaintances using FB daily/weekly	83.56	21.08	1.83	972
FB: profile shows her real name	0.64	0.48	-0.01	1122
FB: profile picture shows her face	0.11	0.31	0.01	963
Digital Practices (business profile)				
Markets on FB	0.46	0.50	0.00	1119
Has FB business page	0.21	0.41	0.02	1122
Posts on FB groups	0.23	0.42	-0.00	982
FB page: willing to reveal name	0.67	0.47	-0.03	1122
FB page: willing to reveal picture	0.31	0.46	0.02	1054
Business Characteristics				
Home-based	0.79	0.41	-0.00	1122
Product (partially) made	0.43	0.50	-0.01	1122
Product bought & traded	0.28	0.45	-0.01	1122
Product is a service	0.17	0.38	-0.02	1122
Business is registered	0.10	0.31	-0.01	1103
Has partners or paid help	0.37	0.48	0.02	1122
Currently offers delivery	0.63	0.48	-0.01	1122
At least half of clients are friends/neighbors	0.68	0.47	-0.01	1122
Monthly profit (usd), 95p	141.46	152.87	-0.11	1122
F-test of joint significance (F-stat)				.57
Observations	563	563	1122	1122

Notes: * p≤0.1, ** p≤0.05, *** p≤0.01. Column (3) is the coefficient from a regression of the outcome on treatment assignment, holding strata fixed effects. Continous variables are winsorized at the 95th percentile (noted by 95p).

Business Characteristics: Finally, looking at business characteristics reveals that 80% of businesses are home-based. Businesses in the sample sell different products and services, with 44% of business owners selling a traded product that they make partially, such as prepared food or home-made accessories; 27% selling traded products without altering them such as clothes; and 15% providing a traded service such as a salon.

Importantly, only 10% of sampled businesses were registered at baseline, consistent with widespread informality in Jordan. Yet some businesses are likely more developed and formalized than others, with 37% of respondents reporting having a business partner or paid help, and more than half of participants reporting offering delivery services. Finally, businesses predominantly catered to owners' social networks, with 68% of respondents saying that at least half of their clients are members of their family, friends, or neighbors.

5 Main Effects: Impact of Online Market Access

In this section, I present the average treatment effects from the bundled market access intervention, including an overview of the empirical strategy, take-up, and effects on business outcomes and on women's work and values.

5.1 Empirical Strategy

As pre-specified, I follow a simple identification strategy of regressing outcomes on the bundled treatment assignment, controlling for baseline level of the outcome when available and for strata fixed effects. My preferred specification is:

$$Y_{is} = \alpha_0 + \alpha_1 \mathrm{T}_{is} + Y_{is}^0 + \delta X_{is} + \gamma_s + \epsilon_{is} \tag{1}$$

where i is a study participant belonging to strata s, T_{is} is the stratified intervention, Y_{is}^0 is the baseline level of the outcome when available, X_{is} is a vector of baseline controls selected by Belloni, Chernozhukov, and Hansen 2014's post double selection methodology, and γ_s reflects indicator variables for whether i belongs in strata s. Randomization was stratified by whether the respondent markets on Facebook at baseline (regardless of whether she marketed on her personal profile or a Facebook page). α_1 is the main coefficient of interest and reflects the effect of being assigned to the bundled intervention on outcome of interest Y_{is}. Note that I winsorize all continuous outcomes such as number of clients, revenues, and profits at the 95th percentile to reduce the effects of extreme values. I also impute any missing values in the Lasso-selected baseline control variables with the variable median and hold fixed effects for missing values. Most results are robust to randomization inference adjustment of p-values, also reported in the tables. Finally, table 1 confirms that the treatment assignment was successfully randomized and is balanced across baseline variables, with an F-stat from the F-test of joint significance equal to 0.57. The follow-up survey had limited attrition at 12%, also balanced across treatment and control arms. Table A.2 in the appendix confirms that treatment assignment is also balanced for the sample of participants found in the follow-up survey.

5.2 Take-Up and First Stage

The first two columns of table 2 show that the intervention had relatively high take-up. As a first step, 35% of the control group and 61% of the treatment group sent pictures of their business to the logistical support team (column 1). Recall that the control group sent their business pictures and information so that a logo is created for their business. As the support team was additionally tasked with creating pages for the treatment group, they were more likely to follow-up with them and obtain pictures of their business, resulting in more pictures obtained from the treatment group relative to the control group. After receiving the pictures and business information, the support staff created new business pages for treatment participants and invited them to become administrators (owners) on these. About 37% of the treatment group accepted the invitation and became admins on newly created pages as a result of the intervention, allowing them to market on these pages liberally (column (2)).

Table 2: Take-Up and First Stage

	Page Support		Online Training		Markets On	
	Sent Pictures (1)	Became Owner (2)	Opened Link (3)	Watched 1hr+ (4)	FB Page (5)	FB Groups (6)
Treatment	0.26***	0.37***	0.59***	0.16***	0.28***	0.12***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
RI p-values	0	0	0	0	0	0
Control Mean	.35	0	0	0	.22	.19
Obs	983	981	983	983	968	968

Notes: * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. All regressions have strata fixed effects and control for variables chosen using post-double-selection lasso procedures and baseline level of the outcome when available. RI p-values are from a randomization inference procedure that randomly permutes treatment assignment. Outcomes are defined as follows: outcomes (1) and (2) reflect study participants' engagement with the logistical support part of the bundled intervention, where (1) is a binary variable for whether the respondent sent the necessary pictures and information to set up a Facebook business page for her, and (2) is a binary variable for whether the respondent became an owner on the page by accepting the invitation to become an administrator. Outcomes (3) and (4) reflect participants' engagement with the online training part of the bundled intervention, where (3) is whether the respondent opened the training link at all, and (4) is whether she watched more than an hour of the training. Outcomes (5) and (6) reflect the first stage, where (5) is a binary variable for whether the respondent markets on a Facebook business page, and (6) is a binary varibale for whether the respondent markets on Facebook groups.

Columns (3) and (4) of table 2 show participants' engagement with the online asynchronous training. Tracking clicks on personalized links and time spent watching the training, column (3) suggests that 59% of women in the treatment group opened the training link. Engagements drops off quickly, however, with only 16% of the treatment group watching an hour or more of the training (column (4)). This is a significantly lower share than that of individuals engaged with the logistical

support, despite efforts to adapt the training to local practices, speech, and to include videos in short formats that individuals are used to seeing online.

Columns (5) and (6) highlight that the bundled intervention successfully increased online marketing practices. Treated participants were more than twice as likely than the control group to use Facebook pages for marketing their business (a 28 percentage points increase from a control mean of 22%), and reported a 63% increase in marketing on Facebook groups (up from a control mean of 19%).

Overall, the intervention had considerable take-up and led to a significant increase in the share of participants marketing on Facebook business pages and groups. While I cannot fully separate the effect of the logistical support vs. training arms, given that these were not cross-randomized, we can reasonably expect that effects would be driven by the logistical intervention given relatively low completion rates for the online training.

5.3 Business Outcomes

In table 3, I examine whether higher online market access translates to better business outcomes. This might not be the case if, for example, businesses have production-side constraints that keep them from taking advantage of higher demand, or if businesses are not market-constrained.

Results in table 3 suggest that the intervention had positive and significant effects on businesses. On the extensive margin, online market access increased business survival rate by 7 percentage points (randomization inference p-value=0.02), a 9.3% increase from a control mean of 75% (column (1)).

These effects are particularly noteworthy given relatively high closure rates, which might reflect relatively harsh conditions for small businesses in the aftermath of COVID-19 (the intervention was conducted in the second half of 2022).

Next, I investigate effects on revenues and profits. Since the treatment has a significant effect on business survival rate, looking at surviving businesses' outcomes should be interpreted descriptively rather than causally, as the surviving businesses sample combines both the treatment effect and selection into operating a business. I follow the literature standard for a causal interpretation of the treatment effects and look at the combined extensive and intensive margins by imputing zeros for closed businesses' outcomes. I additionally report descriptive results conditional on business survival in table A.7 of the appendix.

Another threat to measurement of business outcomes is the long tail of outcomes such as revenues and profits. To deal with this, I winsorize continuous outcomes at the 95th percentile in the main tables. I also report inverse hyperbolic sine transformations to address outliers in table A.5, noting that recent evidence has cautioned against such transformations when the outcome variables are frequently observed at zero, as is the case here (Mullahy and Norton 2022).

Looking at the entire sample (table 3), I find that treated business owners reported 1.68 more distinct clients over the last month (p-value=0.05), an increase of 19% from the control mean of 8.64 distinct clients. Consistently, treated owners reported more than $11 increase in weekly revenue (p-value=0.05), a 19% increase from a control mean of $60 weekly. Monthly revenue also increased by $28, up from a control mean of $214, but results are not significant at conventional levels (p-value=0.11). Effects on monthly profits are positive but also noisy and insignificant at conventional levels: they increase by $9, up from a control mean of $98 (p-value=0.24).

Table 3: Business Outcomes

	Business Performance						Client Composition					
	Business Survival	Total Clients	Revenue Last Week	Revenue Last Month	Profit Last month	Performance Index (1)-(5)	Sells to Strangers	Online Clients	Store credit value	Store credit clients	Store credit Percent	Offers delivery
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment	0.07***	1.68**	11.26*	27.82	9.15	0.13**	0.08***	0.76***	-1.25	-0.56*	-2.45	0.05*
	(0.03)	(0.80)	(5.85)	(16.95)	(8.32)	(0.05)	(0.03)	(0.23)	(4.37)	(0.34)	(1.66)	(0.03)
RI p-values	.02	.05	.05	.11	.24	.02	0	0	.77	.04	.11	.06
Control Mean	.75	8.64	60.11	213.53	98.41	-.06	.31	1.38	37.81	3.6	20.66	.31
Obs	983	985	961	952	947	985	914	985	960	913	957	915

Notes: This table estimates specification (1) in the paper. Outcomes (2) to (12) are coded as zero for closed businesses; table A.7 reports on the outcomes conditional on business survival. * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. All regressions have strata fixed effects and control for variables chosen using post-double-selection lasso procedures and baseline level of the outcome when available. RI p-values are from a randomization inference procedure that randomly permutes treatment assignment. Business performance outcomes are defined as follows: (1) is a binary variable for whether the business is still active; (2) is the distinct number of clients who made a purchase last month; (3) and (4) are revenue in USD last week and last month, respectively, winsorized at the 95th percentile; (5) is profit in USD last month, winsorized at the 95th percentile; and (6) is a business performance index that averages the z-scores from outcomes (1) to (5). Client composition outcomes are defined as follows: (7) is a binary variable for whether the respondent reports that at least some of her clients are not a part of her family or friends; (8) is the number of distinct clients who made a purchase last month and who made the order via online channels such as Facebook or Instagram; (9) is the value in USD of last month's sales made on store credit, winsorized at the 95th percentile; (10) is the number of distinct clients that currently owe store credit; (11) is the reported percent of last month's revenue coming through store credit; and (12) is a binary variable for whether the respondent offers delivery services. Outcomes in USD assume a conversion rate of 1.41 USD for 1 JD

Given concerns on multiple hypotheses testing, I follow Kling et al. 2007 and construct a business index averaging the z-scores of business survival and performance outcomes. The index exhibits an increase of 0.13 standard deviations (p-value=0.02) as a result of the intervention. As table A.5 shows, the results are qualitatively similar when using inverse hyperbolic sine transformations, but effects on weekly revenues become insignificant at conventional levels (p-value=0.16). Additionally, table A.7 reveals that most of these effects are coming from business survival rates: conditional on business survival, the treatment is associated with positive but statistically insignificant increases in business revenues and profits.

Higher business survival for the treatment group is consistent with recent evidence suggesting that female microentrepreneurs are particularly likely to face market access constraints, which are often underestimated in standard enterprise surveys (Hardy et al. 2022). Results are also promising, especially when compared to existing evidence on growth-targeting policies among microenterprises. For example, an experiment in Sri Lanka randomizing (male-owned) enterprises' access to wage subsidies for a worker over a 6-month period found significant effects on business survival, but not on sales and profits during the subsidy period or after it (De Mel et al. 2019).

Next, I look at whether the intervention impacted client type. I start by looking at the effects at the sample level in columns (7)-(12) of table 3. Broadly, we see an increase in the likelihood of selling to strangers, the number of online clients, and the likelihood of offering delivery services. This composition effect, however, might be coming mechanically from business survival, since closed businesses have no clients at all. Similarly, we see a decrease in informal practices usually adopted with customers within business owners' social networks, such as selling on store credit. These effects might also be mechanical, since closed businesses have no sales.

In table A.7, I reports on these outcomes among the sample of operating businesses, which reflects both the treatment effects and selection into business survival. While we expect that businesses induced by the intervention to stay open are more negatively selected, compared to those that stayed open in the control group, we still see an enhancement in business outcomes conditional on survival. While noisy, the likelihood of selling to strangers among surviving businesses is 5 percentage points higher in the treatment group (p-value=0.15). Additionally, treated business owners reach 41% more online clients (an increase of 0.71 clients coming from online platform over a month period, up from a control mean of 1.81). Also conditional on survival, treated business owners still report a lower share of store credit out of revenue and a smaller number of store credit clients, compared to their counterparts in the control group. Qualitatively, women complain about their neighbors, friends, and family members borrowing from them through store credit requests, or informal 'buy now pay later' requests. Such informal practices could become a form of 'kin tax' (Jakiela and Ozier 2016) limiting the growth of businesses (Squires 2018). Access to online markets offered by the intervention seems to have increased sales to new clients found online, shifting the composition of customers that women sell to away from social network members who might ask for store credit. Finally, among surviving businesses, we see that the treatment group is only 2 percentage points (SE=0.03) more likely to offer delivery services than the control group (42% of which offer delivery). The small difference suggests that improvements in business outcomes might be coming particularly from women who were already offering delivery services. Qualitatively, women do not report constraints on their ability to offer delivery services, even if they themselves rarely leave the home. Most women report that a male

relative or neighbor can deliver their goods for them.

5.4 Female Empowerment

Next, I examine how improvements in businesses' performance impact the owners. First, I investigate whether better business performance due to online market access leads women to substitute away from in-person or formal employment. As table 4 shows, the intervention has economically and statistically insignificant impacts on participants' likelihood of working outside the home (column (1)) and on being employed (not shown). Similarly, on average, the intervention has no effect on the number of hours spent working on the business or on the number of hour spent on chores every week. In general, the intervention seems to have negligible impacts on women's labor supply.

Financial outcomes are noisy when looking at the entire sample. Treated participants report spending around 4.71 more dollars a month on their personal needs and consumption, but the effects are insignificant at conventional levels (p-value=0.28). Treated respondents were also 3 percentage points less likely to report having loans (randomization inference p-value=0.11).

Finally, treated women also reported a 0.21 points increase in locus of control (p-value=0.07), which is defined as a score from 1 to 10 of how much the respondent feels she has control over her life, up from a control mean of 7.52 (a 3% increase). Reassuringly, despite increasing their ability to make income from home, the intervention did not reinforce conservative views around women's work. If anything, the intervention led to a 5 percentage points decrease in the share of women who agree with conservative statements such as 'women's value is better preserved if they stay at home', down from a control mean of 40%. The share of participants agreeing with other conservative statements such as 'if a mother works outside the home, her children suffer' and 'if a woman works, her husband must be unable to provide' also decreases, but the effects are noisy and insignificant when summarized with an index.

Table 4: Empowerment Outcomes

	Work Outcomes			Financial & Personal Agency				Agreement with Conservative Norms				
	Works outside home	Hours on business	Hours on chores	Spending on self	Has Savings	Has Loans	Locus of Control	Women better home	Children suffer	Husband can't provide	Reserve Jobs to Men	Norms Index 8-11
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment	0.01	0.02	-0.16	4.71	0.02	-0.03*	0.21	-0.05*	-0.05	-0.03	0.01	-0.11
	(0.02)	(0.21)	(0.18)	(3.88)	(0.02)	(0.02)	(0.13)	(0.03)	(0.03)	(0.03)	(0.03)	(0.08)
RI p-values	.63	.94	.43	.28	.27	.11	.07	.09	.16	.51	.65	.2
Control Mean	.2	3.89	4.69	51.92	.1	.93	7.52	.4	.77	.55	.59	2.22
Obs	983	971	985	985	945	944	828	952	956	952	952	969

Notes: This table estimates specification (1) in the paper. * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. All regressions have strata fixed effects and control for variables chosen using lasso.

6 Heterogeneous Treatment Effects

It is not clear whether digital market access can substitute for in-person exposure among low-mobility women. Although these might be more market-constrained, they might also have limited capital, time, skills, or aspirations. If that's the case, there might not be a significant share of productive but market-constrained women for the intervention to impact.

To shed light on this tension, I first present heterogeneity in treatment effects by women's mobility levels. Second, I present consistent heterogeneous treatment effects as predicted using machine learning algorithms, following Chernozhukov et al. 2018. Finally, I present results by whether a business is home-based, which is a pre-specified measure of business owners' mobility and market exposure.

6.1 Heterogeneity by Baseline Mobility

I create an index for respondents' physical mobility using mobility variables collected from the baseline survey. Following Kling et al. 2007, the index averages the standardized values of baseline mobility variables. These variables are summarized in table 1 and consist of: (1) Ability to take weekly trips alone for business-related reasons; (2) Willingness to operate the business outside the home if rent is covered; and (3) The number of times the respondent went out alone last month.

6.1.1 Differences across high vs. low-mobility women:

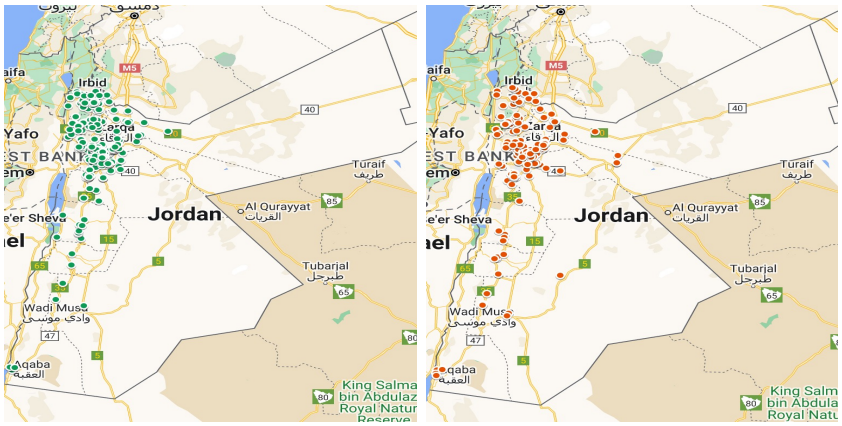
In table 5, I document how high vs. low mobility women differ in demographics and business outcomes, defining high and low mobility as above vs. below median mobility index. As one might expect, high and low mobility women have significant differences in their demographics, values, digital practices, and business characteristics. These differences are not necessarily confounders for mobility, but underlying reasons for it.

For example, high mobility women are significantly less likely than low mobility women to live in rural areas, in clan communities, to be married, to have children, and to have a working husband. They are also more likely to have a high school degree and to have ever been employed, and they overall have significantly higher household incomes than low-mobility women. High mobility women also less likely to think that the children of a woman that works outside the home suffer and that society judges working mothers.

Interestingly, there are little differences in high and low mobility women's use and perception of Facebook, but high mobility women are 9 percentage points more likely to use profile pictures that show their faces on Facebook. They are also more likely to use Facebook to market their business and to display their personal names and pictures on their online business page.

Also note that high and low mobility women differ in how they operate their businesses. High mobility women are 17 percentage points less likely to operate their business from home. They are also more likely to offer a service (e.g. a salon) as opposed to trading products. High mobility women's businesses also have more formalized practices: they are more likely to register their business and to offer delivery services, and they are less likely to sell exclusively to friends and neighbors and to sell on store credit. Overall, high mobility women have significantly higher business profits than their counterparts. Finally, figure 3 presents two maps showing that the approximate distribution of high vs. low mobility women across the country is comparable.

Figure 3: Locations with High (a) vs. Low (b) Mobility



(a) (b)

6.1.2 Empirical Strategy:

Following the main estimating equation, my preferred specification to investigate heterogeneity is:

$$Y_{is} = \beta_0 + \beta_1 \mathrm{T}_{is} + \beta_2 \mathrm{T}_{is} \times \mathrm{HighMobility}_{is} + \beta_3 \mathrm{HighMobility}_{is} + Y_{is}^0 + \delta X_{is} + \sigma_s + \varepsilon_{is} \qquad (2)$$

where i is a study participant belonging to strata s, T_{is} is the stratified intervention, and $\mathrm{HighMobility}_{is}$ is a binary variable for above median mobility index at baseline. Y_{is}^0 is the baseline level of the outcome, when available, X_{is} is a vector of controls chosen by Belloni et al. 2014's post-double selection Lasso method, and γ_s reflects indicator variables for whether i belongs in strata s. Coefficients of interest are β_1, which is the effect of the intervention on low-mobility women; $\beta_1 + \beta_2$, which is the effect of the intervention among high-mobility women; and β_2, which reflects the difference in effects between high and low mobility women. Following the main specification, I also winsorize all continuous outcomes such as number of clients, revenues, and profits at the 95th percentile to reduce the effects of extreme values. I also impute any missing values in the chosen control variables with the variable median and holding fixed effects for missing values. Finally, tables A.3 and A.4 in the appendix show that baseline variables are balanced across the treatment and control groups within the subsamples of women with below and with above median mobility index.

Table 5: Baseline Differences Across Above vs. Below Median Mobility Women

	(1) Below Mobility	(2) Above Mobility	(3) Difference	(4) N
Demographics				
Lives in rural area	0.34	0.22	−0.12***	1122
Lives around clan community	0.66	0.52	−0.14***	1122
Age	40.20	43.03	2.83***	1122
Married	0.84	0.74	−0.10***	1122
Has children	0.92	0.87	−0.05***	1122
Educ: less than high school	0.26	0.24	-0.02	1122
Educ: high school	0.50	0.44	−0.06**	1122
Educ: more than high school	0.23	0.29	0.06**	1122
Currently employed (in addition to business)	0.09	0.08	-0.00	1102
Ever employed	0.30	0.41	0.11***	1122
Husband works (if married)	0.66	0.60	−0.06**	1084
HH income (usd), 95p	678.37	780.95	102.58***	1122
HH debt and rent (usd), 95p	443.90	494.03	50.13***	1100
Agrees with Statements				
If a mother works outside the home, children suffer	0.79	0.68	−0.12***	1122
Society judges a mother that works outside the home	0.50	0.36	−0.13***	1122
Better to work from home to conserve own value	0.38	0.29	−0.10***	1122
Digital Practices, Personal				
FB: personally uses it daily/weekly	0.84	0.86	0.02	1112
% of your acquaintances using FB daily/weekly	83.71	85.07	1.36	972
FB: profile shows her real name	0.61	0.65	0.04	1122
FB: profile picture shows her face	0.07	0.16	0.09***	963
Digital Practices, Business				
Markets on FB	0.42	0.48	0.06**	1119
Has FB business page	0.19	0.25	0.06**	1122
Posts on FB groups	0.21	0.24	0.03	982
FB page: willing to reveal name	0.58	0.71	0.13***	1122
FB page: willing to reveal picture	0.22	0.42	0.19***	1054
Business Characteristics				
Home-based	0.87	0.70	−0.17***	1122
Product (partially) made	0.45	0.41	-0.04	1122
Product bought & traded	0.32	0.23	−0.09***	1122
Product is a service	0.11	0.21	0.10***	1122
Business is registered	0.06	0.14	0.08***	1103
Has partners or paid help	0.35	0.40	0.05*	1122
Currently offers delivery	0.57	0.67	0.10***	1122
At least half of clients are friends/neighbors	0.71	0.65	−0.07**	1122
At least half of clients ask for store credit	0.30	0.20	−0.09***	1122
Monthly profit (usd), 95p	115.24	167.16	51.93***	1122
Observations	567	555	1122	

Notes: * p≤0.1, ** p≤0.05, *** p≤0.01. Column (3) is the coefficient from a regression of the outcome on a binary variable for above median mobility index, holding strata fixed effects. Mobility index is defined as the average of z-scores from mobility variables (a)-(c) in table 1. Continous variables are winsorized at the 95th percentile (noted by 95p).

Table 6: Take-Up and First Stage

	Page Support		Online Training		Markets On	
	Sent Pictures (1)	Became Owner (2)	Opened Link (3)	Watched 1hr+ (4)	FB Page (5)	FB Groups (6)
β_1: Treatment ($\times$ Low Mobility)	0.26***	0.39***	0.59***	0.14***	0.30***	0.14***
	(0.04)	(0.03)	(0.03)	(0.02)	(0.04)	(0.04)
β_2: Treatment $\times$ High Mobility	0.00	-0.03	-0.01	0.04	-0.04	-0.04
	(0.06)	(0.04)	(0.04)	(0.03)	(0.05)	(0.05)
High Mobility	0.00	0.01*	0.00	-0.00	0.05	0.03
	(0.04)	(0.01)	(0.00)	(0.00)	(0.03)	(0.03)
$\beta_1 + \beta_2$ (High Mobility Effect)	0.26***	0.36***	0.58***	0.18***	0.26***	0.10***
$\beta_1 + \beta_2 = 0$ (*p-value*)	0.00	0.00	0.00	0.00	0.00	0.01
RI p-values β_1	0	0	0	0	0	0
RI p-values β_2	.96	.58	.9	.21	.51	.4
Low Mobility Control Mean	.34	0	0	0	.17	.16
High Mobility Control Mean	.35	0	0	0	.27	.21
Obs	983	981	983	983	968	968

Notes: High Mobility refers to a binary variable for above median mobility index, which averages the z-scores from mobility variables (a)-(c) in table 1. * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. All regressions have strata fixed effects and control for variables chosen using post-double-selection lasso procedures and baseline level of the outcome when available. RI p-values are from a randomization inference procedure that randomly permutes treatment assignment. Outcomes are defined as follows: outcomes (1) and (2) reflect study participants' engagement with the logistical support part of the bundled intervention, where (1) is a binary variable for whether the respondent sent the necessary pictures and information to set up a Facebook business page for her, and (2) is a binary variable for whether the respondent became an owner on the page by accepting the invitation to become an administrator. Outcomes (3) and (4) reflect participants' engagement with the online training part of the bundled intervention, where (3) is whether the respondent opened the training link at all, and (4) is whether she watched more than an hour of the training. Outcomes (5) and (6) reflect the first stage, where (5) is a binary variable for whether the respondent markets on a Facebook business page, and (6) is a binary varibale for whether the respondent markets on Facebook groups.

6.1.3 Results

Take-Up and First Stage: Table 6 suggests that there is little difference in take-up rates across women with high vs. low mobility. Participants are equally likely to engage with the logistical support intervention by providing the needed pictures and information and by accepting an invitation to become owners on a newly created business page on Facebook. They are also equally likely to click on the online training program link and to spend more than an hour watching it. Consistently, there was little difference in the intervention's first stage effects: impacts on Facebook marketing on business pages and on groups are similar across women with high vs. low mobility. The results suggest that conditional on selection into the service, high and low mobility women did not have significantly different beliefs about its efficacy; they also did not have differential willingness or ability to engage with it.

Business Performance: Despite comparable take-up rates, table 7 suggests that the intervention had significantly different impacts for women with high vs. low mobility. Looking at coefficient β_1, which reflects the intervention's effect on low-mobility women, we see a 12 percentage points increase in business survival rates (p-value<0.01). In contrast, the intervention had no impact on high mobility women's business survival rates ($\beta_1 + \beta_2 = 0.02$, p-value=0.63).

This pattern is reflected in other business performance outcomes, where effects are mostly concentrated among low-mobility women and muted among high-mobility women. Six months after the intervention, low-mobility women in the treatment group reported 2.7 more distinct clients in the month before surveying, $23 more in revenue last week, $57 more in revenue last month, and $24 more in profits last month - all effects significant at the 95% confidence level. Additionally, a Business Performance Index that averages the z-score of these business performance variables increased by 0.24 standard deviations (p-value<0.01) for low-mobility women; effects are again muted for high-mobility women. These effects are economically and statistically significant whether looking at the entire sample or the sample of surviving businesses, and whether winsorizing continuous outcomes or applying an inverse sine transformation to them.

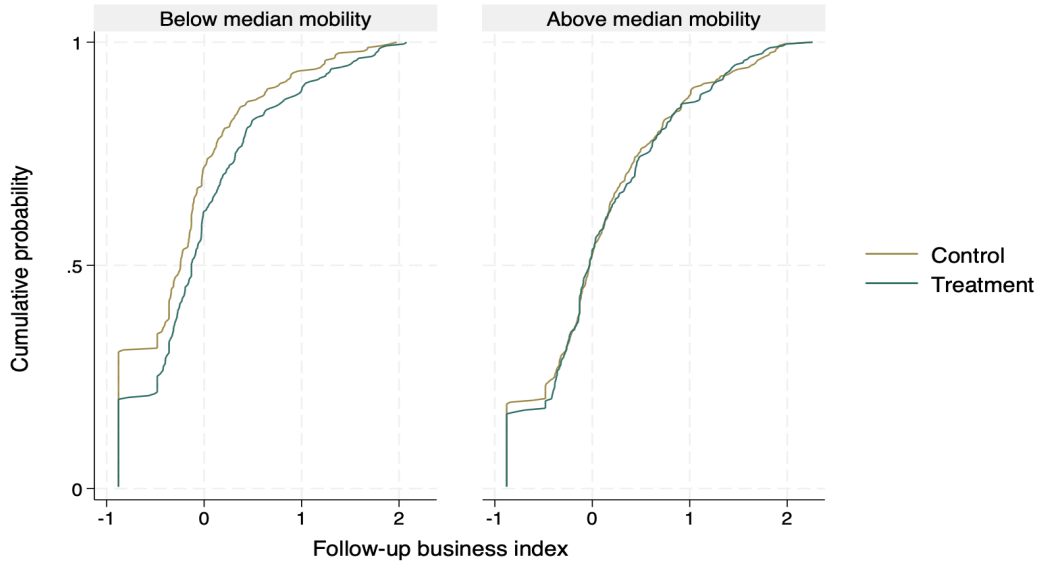
To understand whether these changes are driven by subsets of the sample, I plot the business index for the treatment and control groups across women with high vs. low mobility. As figure 4 panel (a) shows, treated low-mobility women exhibit a shift in the distribution of the business index out to the right, indicating higher business performance outcomes compared to their counterparts in the control group.

Table 7: Business Outcomes

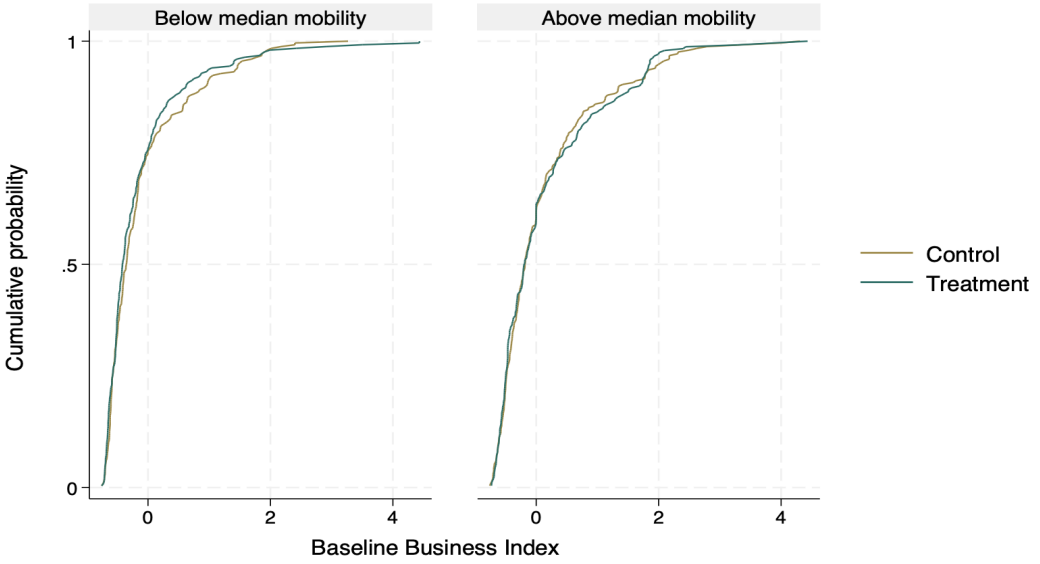
	Business Performance						Client Composition					
	Business Survival	Total Clients	Revenue Last Week	Revenue Last Month	Profit Last month	Performance Index (1)-(5)	Sells to Strangers	Online Clients	Store credit value	Store credit clients	Store credit Percent	Offers delivery
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
β_1: Treatment ($\times$ Low Mobility)	0.12***	2.69**	22.96***	56.70**	24.00**	0.24***	0.14***	0.82***	0.77	-0.55	-3.45	0.10**
	(0.04)	(1.09)	(7.86)	(22.88)	(10.98)	(0.07)	(0.04)	(0.29)	(6.21)	(0.47)	(2.38)	(0.04)
β_2: Treatment $\times$ High Mobility	-0.10**	-2.05	-23.38**	-57.78*	-29.66*	-0.22**	-0.12**	-0.11	-4.10	-0.04	2.03	-0.10*
	(0.05)	(1.60)	(11.66)	(33.71)	(16.68)	(0.10)	(0.06)	(0.47)	(8.70)	(0.67)	(3.30)	(0.06)
High Mobility	0.09**	1.02	20.80**	48.97**	24.76**	0.20***	0.08*	0.34	0.20	0.13	0.26	0.08**
	(0.04)	(1.09)	(8.17)	(23.37)	(11.83)	(0.07)	(0.04)	(0.30)	(6.15)	(0.51)	(2.40)	(0.04)
$\beta_1 + \beta_2$ (High Mobility Effect)	0.02	0.64	-0.43	-1.08	-5.66	0.02	0.02	0.71*	-3.33	-0.58	-1.42	0.01
$\beta_1 + \beta_2 = 0$ (*p-value*)	0.63	0.59	0.96	0.97	0.65	0.78	0.65	0.05	0.59	0.23	0.54	0.89
RI p-values β_1	0	.03	0	.02	.05	0	0	0	.94	.2	.16	.01
RI p-values β_2	.05	.23	.06	.12	.08	.02	.05	.82	.62	.96	.54	.09
Low Mobility Control Mean	.69	7.23	43.41	164.33	72.51	-.24	.24	1	36.05	3.43	21.03	.27
High Mobility Control Mean	.8	10.05	76.75	262.52	124.2	.11	.37	1.75	39.56	3.77	20.28	.34
Obs	983	985	961	952	947	985	914	985	960	913	957	915

Notes: This table estimates specification (2) in the paper. Outcomes (2) to (12) are coded as zero for closed businesses; table A.8 reports on the outcomes conditional on business survival. High Mobility refers to a binary variable for above median mobility index, which averages the z-scores from mobility variables (a)-(c) in table 1. * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. All regressions have strata fixed effects and control for variables chosen using post-double-selection lasso procedures and baseline level of the outcome when available. RI p-values are from a randomization inference procedure that randomly permutes treatment assignment. Business performance outcomes are defined as follows: (1) is a binary variable for whether the business is still active; (2) is the distinct number of clients who made a purchase last month; (3) and (4) are revenue in USD last week and last month, respectively, winsorized at the 95th percentile; (5) is profit in USD last month, winsorized at the 95th percentile; and (6) is a business performance index that averages the z-scores from outcomes (1) to (5). Client composition outcomes are defined as follows: (7) is a binary variable for whether the respondent reports that at least some of her clients are not a part of her family or friends; (8) is the number of distinct clients who made a purchase last month and who made the order via online channels such as Facebook or Instagram; (9) is the value in USD of last month's sales made on store credit, winsorized at the 95th percentile; (10) is the number of distinct clients that currently owe store credit; (11) is the reported percent of last month's revenue coming through store credit; and (12) is a binary variable for whether the respondent offers delivery services. Outcomes in USD assume a conversion rate of 1.41 USD for 1 JD

For high-mobility women, in contrast, the treatment and control performance distribution are indistinguishable. Panel (b) of figure 4 reassuringly shows that the business index had comparable distributions across treatment and control groups for both low and high mobility women at baseline. Differences seen in the follow-up survey therefore do not seem to be driven by sizable imbalances at baseline.



(a) In Follow-Up



(b) At baseline

Figure 4: Business Index by Treatment & Mobility, at baseline & follow-up

Consistently, treatment effects also seem to increase with lower mobility levels. In figure 5, I further split the mobility index and show treatment effects across mobility quartiles. Results suggest that the intervention's impact is higher at lower mobility quartiles.

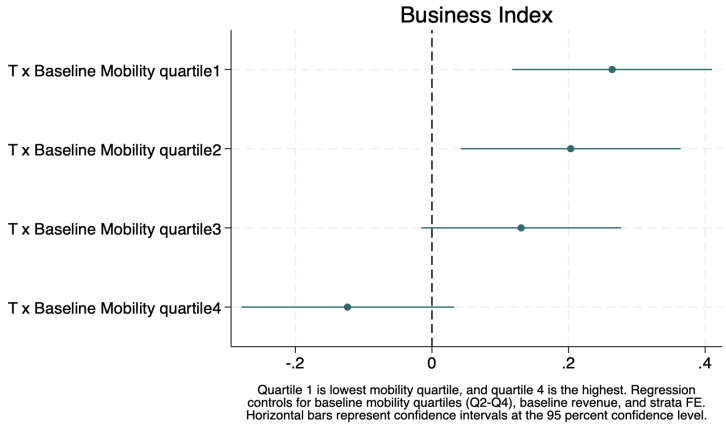


Figure 5: Treatment Effects across Mobility Quartiles

Client Composition: Consistent with the main results, improvements in business performance seem to be driven by changes in client composition. Columns (7) to (12) of table 7 also show significant increases in the likelihood of selling to strangers, in the number of distinct online clients, and in the likelihood of offering delivery services. As these effects might be mechanically driven by business survival, I also look at effects conditional on having an operational business in table A.8. Overall, results shows that even among surviving businesses, low-mobility women are 11 percentage points more likely to sell to strangers (p-value=0.02), as opposed to selling to their social networks of friends, family, and neighbors. They also report a 0.69 increase in the number of online clients (p-value=0.05), up from a base of 1 in the control group. Low mobility women also see a significant decrease in the number of store credit clients and the share of store credit out of revenue, indicating less demands for favors from newly acquired clients. In contrast, the intervention had economically and statistically insignificant impacts on high mobility women (as reflected by the sum and p-value of $\beta_1 + \beta_2$). These effects are economically and statistically comparable when conditioning on business survival (table A.8).

Work Outcomes: As in the main results, table 8 shows that the intervention has insignificant impacts on women's work outside the home. If anything, low-mobility women are 3 percentage points more likely to work outside the home, but the results are noisy (randomization inference p-value=0.26). Low-mobility women also spend an additional half an hour on their business per week (p-value=0.05) and report spending \$9.24 more on their own consumption and needs per month (p-value=0.08), almost double the sample average of \$4.71 per month.

High-mobility women, on the other hand, spend 0.49 less hours on their business (p-value=0.02), indicating potential substitution from the business owner to the support team. High-mobility women also witness negligible increases in consumption, but are significantly less likely to report having loans. This is accompanied with a significant increase in locus of control among treated high mobility women, compared to their counterparts in the control group.

Finally, effects on values and agreement with conservative gender views do not seem to consistently differ across high and low mobility women. Overall, the intervention seems to increase business survival and revenue for low-mobility women without reinforcing conservative gender norms among them. High-mobility women, on the other hand, might substitute away hours of work on business when they get the support and in turn exhibit higher locus of control.

Table 8: Empowerment Outcomes

	Work Outcomes			Financial & Personal Agency				Agreement with Conservative Norms				
	Works outside home	Hours on business	Hours on chores	Spending on self	Has Savings	Has Loans	Locus of Control	Women better home	Children suffer	Husband can't provide	Reserve Jobs to Men	Norms Index 8-11
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
β_1: Treatment (Low Mobility)	0.03	0.51*	-0.24	9.24*	0.04	-0.01	-0.04	-0.02	-0.06	-0.01	0.03	-0.05
	(0.03)	(0.28)	(0.26)	(4.95)	(0.03)	(0.02)	(0.19)	(0.04)	(0.04)	(0.04)	(0.04)	(0.11)
β_2: Treatment × High Mobility	-0.03	-1.00**	0.15	-8.85	-0.03	-0.04	0.54**	-0.05	0.03	-0.03	-0.04	-0.12
	(0.04)	(0.41)	(0.36)	(7.66)	(0.04)	(0.04)	(0.26)	(0.06)	(0.06)	(0.06)	(0.06)	(0.16)
High Mobility	0.07**	0.58*	-0.28	17.60***	0.04	-0.01	-0.07	0.01	-0.07*	0.00	-0.02	-0.03
	(0.03)	(0.31)	(0.25)	(5.53)	(0.03)	(0.02)	(0.19)	(0.04)	(0.04)	(0.04)	(0.04)	(0.11)
$\beta_1 + \beta_2$ (High Mobility Effect)	-0.01	-0.49	-0.08	0.40	0.01	-0.05*	0.50***	-0.08*	-0.03	-0.04	-0.01	-0.17
$\beta_1 + \beta_2 = 0$ (*p-value*)	0.84	0.11	0.73	0.95	0.74	0.06	0.01	0.07	0.47	0.35	0.83	0.13
RI p-values β_1	.26	.05	.34	.08	.19	.62	.76	.55	.14	.84	.52	.67
RI p-values β_2	.42	.02	.66	.28	.5	.29	.03	.42	.55	.56	.58	.41
Low Mobility Control Mean	.12	3.28	4.9	41.04	.08	.92	7.47	.41	.81	.56	.6	2.3
High Mobility Control Mean	.29	4.5	4.48	62.81	.12	.93	7.57	.4	.72	.54	.57	2.14
Obs	983	971	985	985	945	944	828	952	956	952	952	969

Notes: This table estimates specification (2) in the paper. High Mobility refers to a binary variable for above median mobility index, which averages the z-scores from mobility variables (a)-(c) in table 1. * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. All regressions have strata fixed effects and control for variables chosen using post-double-selection lasso procedures. RI p-values are from a randomization inference procedure that randomly permutes treatment assignment. Outcomes are defined as follows: (1) is a binary variable for whether the respondent has a job or a business that she operates outside the home; (2) and (3) are the average number of hours that the respondent spends per day on her business and on household chores, respectively; (4) is the amount of money in USD that the respondent spent on her personal needs and consumption per month; (5) and (6) are binary variables for whether the respondent has any savings and any loans, respectively; and (7) is respondent's answer to the question: on a scale of 1-10, how much control do you have over your life?. Finally, the third panel reflects whether the respondent agrees with each of the following statements: (9) women's value is better-preserved at home; (10) if a woman works outside the home, her children suffer; (11) if a woman works, her husband must be unable to provide; (11) when jobs are scarce, they should be reserved to men. (12) is an index that averages the z-scores from outcomes 8-11.

6.1.4 Machine Learning Predictions and Pre-Registration

Next, I use generic machine learning inference to explore heterogeneity in treatment effects transparently. I follow Chernozhukov et al. 2018 to test whether treatment effects are heterogeneous at the sample level and to examine which variables drive any heterogeneity. To look at the combined effect at the intensive and extensive margins, I look at the business index as an outcome. The index averages the z-scores from business survival, number of clients, revenues, and profits.

Figure 6 shows the average treatment effect (β_1) and the sample heterogeneous treatment effect (β_2), as predicted using Chernozhukov et al. 2018's generic machine learning inference. While noisy, given limited sample and power, the sample-level heterogeneous treatment effect appears to be four times bigger than the average treatment effect. Furthermore, following Chernozhukov et al. 2018, I split the sample into 5 groups of participants least to most affected by the treatment. I find that the group least affected by the intervention, G1, has a null treatment effect, while the group most affected by the intervention, G5, has a significant treatment effect of 0.25 standard deviations (figure 7), more than twice the average treatment effect. While relatively noisy, I take these effects to suggest considerable heterogeneity in the sample, and proceed to explore sources for it.

To do so, I follow Chernozhukov et al. 2018 and compare the characteristics of participants least affected by the intervention (group G1) to the characteristics of groups most affected by it (G5). Testing baseline variables reflecting demographics, digital literacy, business characteristics, mobility, and norms, I find that baseline mobility and business performance significantly predict treatment effects. As shown in figure 8, groups least affected by the intervention had the highest mobility, while those with the highest treatment effects had the lowest mobility. Additionally, I find that treatment effects are highest among businesses with fixed business assets at baseline and businesses with above median baseline revenue. Both of these variables reflect higher business quality at baseline, consistent with higher skill, aspirations, or capacity. This heterogeneity is not surprising, and is consistent with evidence on higher returns to resources among 'gung-ho' (Banerjee et al. 2019) and high ability (Hussam et al. 2022) entrepreneurs.

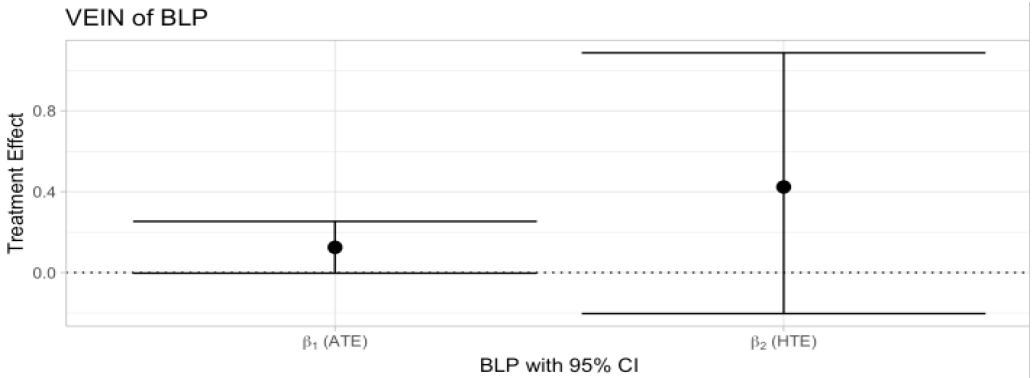


Figure 6: Average and Heterogeneous Treatment Effects (Chernozhukov et al. 2018)

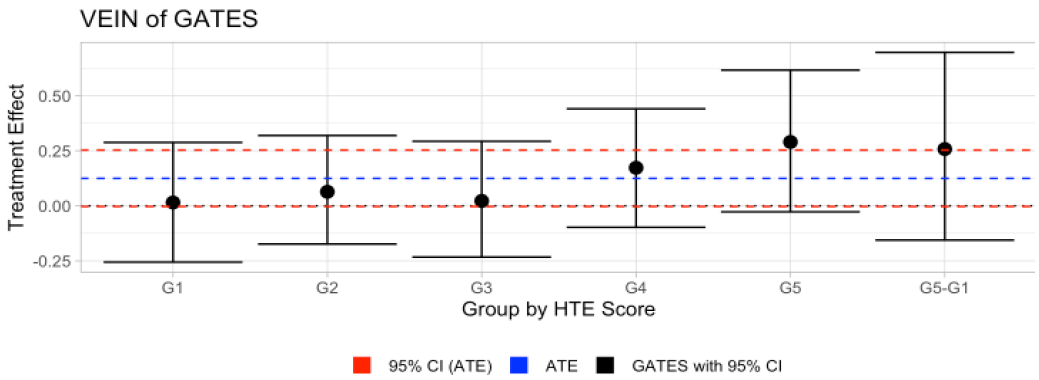


Figure 7: Treatment Effects Across Groups Least (G1) vs. Most (G5) affected

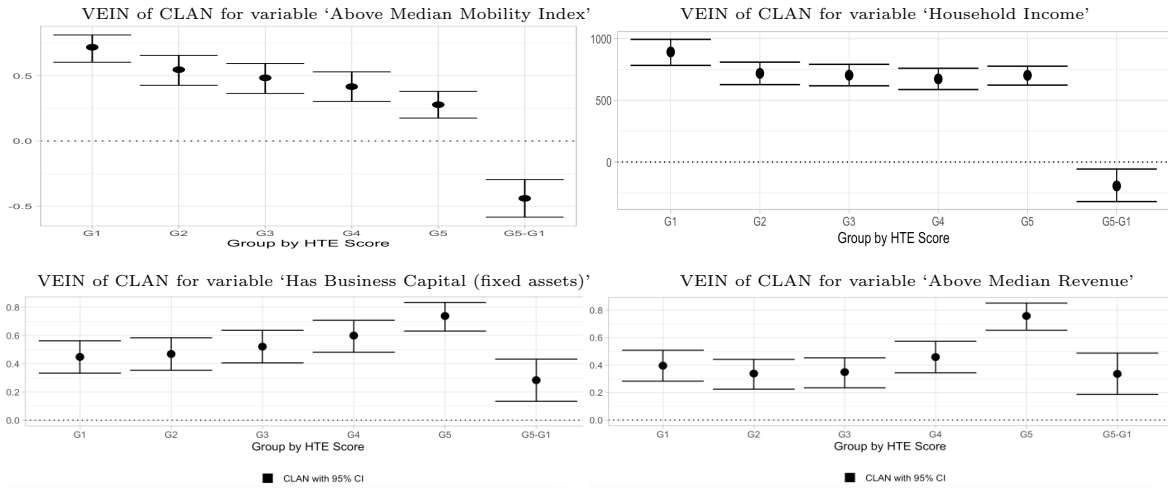


Figure 8: Averages of baseline variables across groups least (G1) vs. most (G5) affected

Pre-Registration: Finally, I explore heterogeneous treatment effects by pre-specified variables. Particularly, following Chernozhukov et al. 2018, I plot how pre-specified variables vary across the 5 groups least (G1) vs. most (G5) affected by the treatment. Pre-specified heterogeneity dimensions include schooling, business type, Facebook marketing activity at baseline, and whether a business is home-based. As figure 9 shows, none of these seem to significantly predict treatment effects for the business performance index.

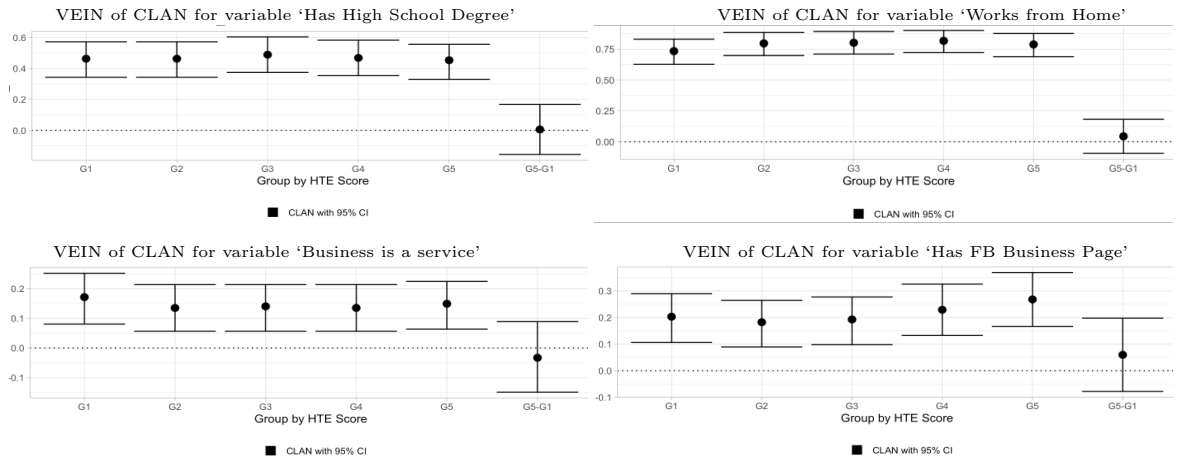


Figure 9: Averages of baseline variables across groups least (G1) vs. most (G5) affected

Note that I had pre-specified interest in heterogeneity by whether a business is home-based, assuming that home-based businesses are a proxy for low mobility and business exposure at baseline. However, 80% of the sample turned out to have home-based businesses, limiting the power to detect differences across the subsamples of businesses based at home vs. not. Additionally, having a business outside the home turned out to be more correlated with business revenue and profits than with mobility. For example, the correlation between having a home-based business and an index for baseline mobility is -0.28, while its correlation with an index for baseline profits and revenue is -0.43, suggesting that having a business outside the home reflects both the owners' mobility constraints but also their entrepreneurial ability and aspirations. In section A.7 of the appendix, I still report tables testing heterogeneity in the first stage effects and business outcomes by pre-specified variables, including having a home-based businesses. Most of these effects do not vary significantly by the pre-specified variables.

6.2 Heterogeneity by Baseline Mobility and Business Performance

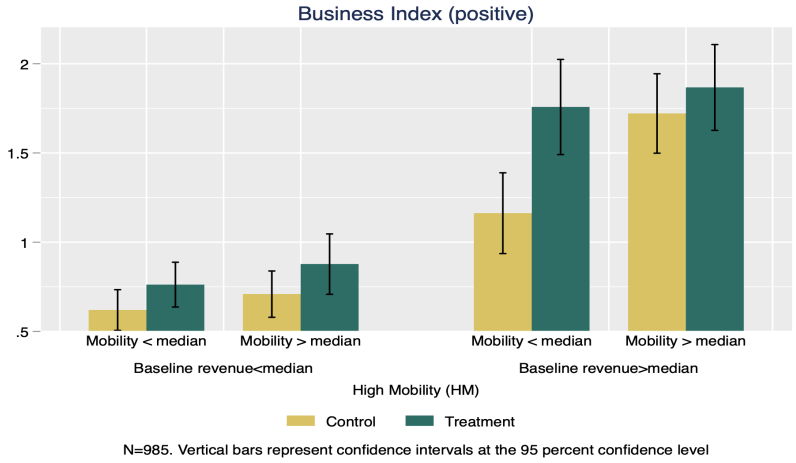
As descriptive table 5 shows, low-mobility have a worse business performance than high-mobility women at baseline. They are less likely to have registered businesses, paid help, customers outside their social networks, and have lower profits overall. The intervention's higher impact on low mobility women therefore seems to stands in contrast with existing evidence from the training and entrepreneurship literature suggesting that the impact of growth-oriented interventions are usually highest among high ability (Hussam et al. 2022) or 'gung-ho' entrepreneurs (Banerjee et al. 2019).

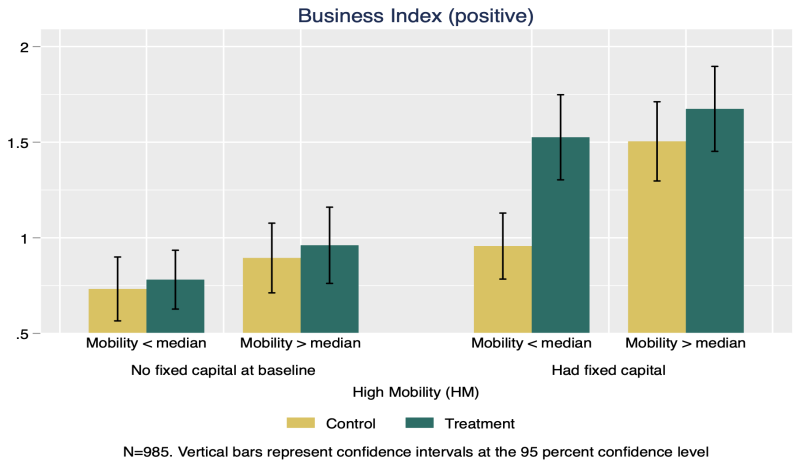
To understand whether results are consistent with existing findings, I examine effects across baseline mobility and business quality measures. To measure business quality, I rely on several baseline variables. First, I rely on whether the business had an above median business revenue at baseline, and

on whether the business had fixed assets at baseline. These variables are consistent with how baseline ability or business quality is proxied in the literature and are two variables that significantly predicted heterogeneous treatment effects following Chernozhukov et al. 2018's methodology.

Second, I develop a measure of business quality by rating business pictures collected at baseline from both the treatment and control group. The pictures' rating were given by members of the logistical support team at baseline and were based on the overall appeal of the product or service as pictured, as opposed to underlying product quality (which is hard to evaluate from pictures). Figure A.8 shows examples of pictures of the same type of products with above vs. below median quality score. The benefit of this measure is that it is more likely to reflect business owners' skills than baseline revenue would, as revenues are also a function of access to resources or existing networks. As discussed in section 5.2, however, the support team was more likely to follow-up with the treatment group for pictures. This resulted in an imbalance in the number of pictures collected from the treatment vs. the control group. If anything, however, this imbalance makes it more likely the case that treatment participants with pictures are more negatively selected than control group participants with pictures. Indeed, this is confirmed by a lower average rating among treatment participants' business pictures, compared to the control group's business picture ratings.

Across the three business quality measures, I find that treatment effects are highest for women with below median mobility yet relatively good business productivity at baseline. This is the case whether productivity is measured by having above median revenue, fixed capital, or above median picture ratings at baseline (figure 10). Together, these results suggest that mobility constraints and skills are not necessarily correlated at the individual level among female entrepreneurs. Many women have an underlying talent that can benefit from wider market exposure, and digitalization might afford them this exposure if its take-up and usage are well-supported.





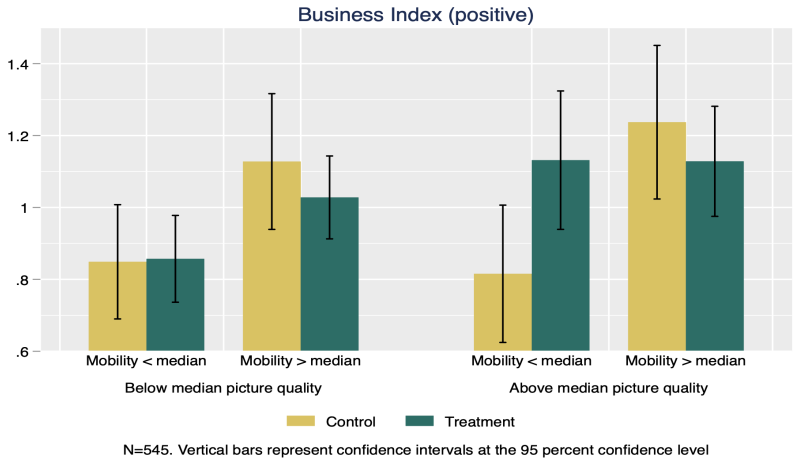


Figure 10: Heterogeneity by Mobility and Business Quality Measures

7 Conclusion

As social media usage rates escalate in developing countries, it is increasingly important to understand how these accessible technologies impact the livelihoods of people around the world. While social media platforms' use for marketing has been associated with individuals and firms in relatively rich countries, diverse qualitative work highlights that low-income women in conservative contexts use them to maintain their livelihoods. In this paper, I provide causal evidence on the impact of social media on aspiring and existing female entrepreneurs in Jordan, a relatively conservative country.

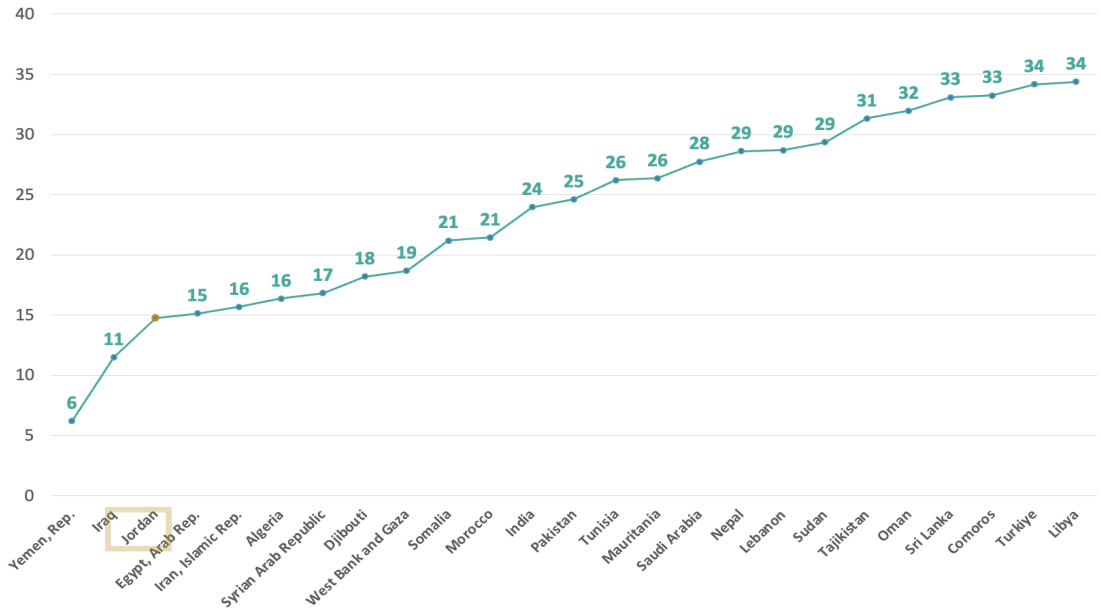
First, I investigate whether virtual market access can meaningfully increase female entrepreneurs' productivity, with a focus on women with limited mobility. Though online qualitative work, I find that female entrepreneurs marketing on Facebook often choose to conceal parts of their identities: they hide their names, pictures, and post in closed female-only trading groups. These practices suggest that gender norms around women's visibility and mixing are mirrored online, but that women find ways to work within these by creating 'safe spaces' to operate and trade with each other. Next, in an experiment, I give Jordanian female microentrepreneurs access to online storefronts through business pages on Facebook, marketing outsourcing, and digital marketing training. The bundled intervention aims to increase businesses' market access without increasing their owners' personal visibility. I find that within 6 months of support, treated participants were more likely to have a surviving business after 6 months of support and reported higher revenues, more online and diverse clients, and less informal practices with customers through store credit. Looking at heterogeneous treatment effects, I find that the effects are higher among mobility-constrained women, and particularly those with relatively high skills among them.

While this study takes place in a conservative setting, mobility constraints are faced by women across the cultural and economic spectrum. In the US, for example, women created half of new businesses in 2023 for the third year in a row, up from 29% in 2019 just before the COVID-19 outbreak. Surveys have highlighted the need for flexibility as the number one reason for starting a business, shedding light on entrepreneurship's central role in providing alternative employment for mobility-constrained women. In such contexts, social media might provide higher market exposure more flexibly, therefore lowering the cost of entry for new businesses.

Finally, when considering policy implications from the presented results, several issues have to be taken into considerations. First, while the experiment shows a positive impact of market access outsourcing, we cannot rule out displacement effects without a clustered randomized control trial. Indeed, although respondents are located in different places across the country, it is possible that some of the gains in the treatment group came at the expense of businesses in the control group. Still, the results suggest potentially better matching across firms and customers as high productivity entrepreneurs increase their market exposure. Additionally, the results have important distributional effects, with higher revenues going to low-mobility women. Second, while the intervention is not cost effective for the average participant given noisy estimates on profits, targeting low mobility and high quality entrepreneurs could be. Finally, the results highlight the increasingly important role that technology companies can play in supporting marginalized communities. Features like 'Pages You May Like' on Facebook, for example, provide advertisement to business pages free of charge. Expanding these services in conservative countries might be particularly helpful to low-mobility female entrepreneurs.

A Appendix

A.1 Country Context



Source: World Bank Gender Data Portal, 2022

Figure A.1: This figure plots the world's 25 lowest female labor force participation rates, marking rates of Arab countries in yellow.

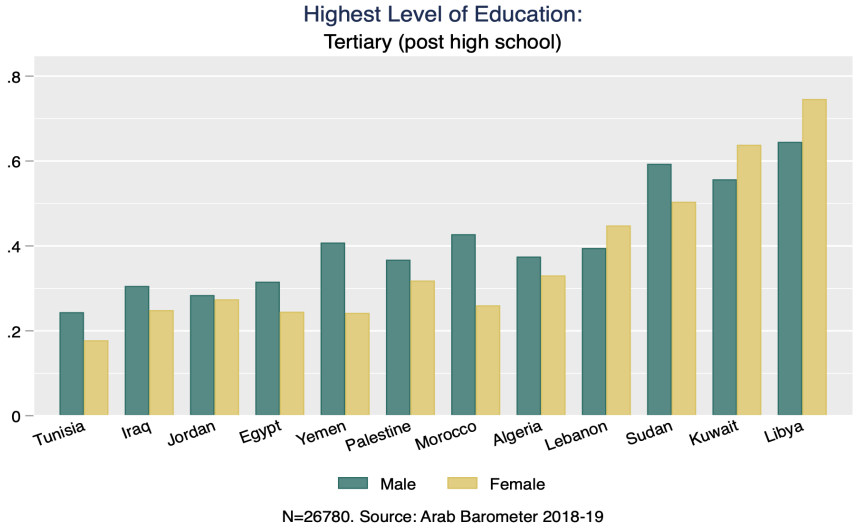


Figure A.2: This figure plots the percentage of people who list tertiary education (post high school, including college and vocational training) when asked about their highest level of education in the 2018-19 Arab Barometer survey.

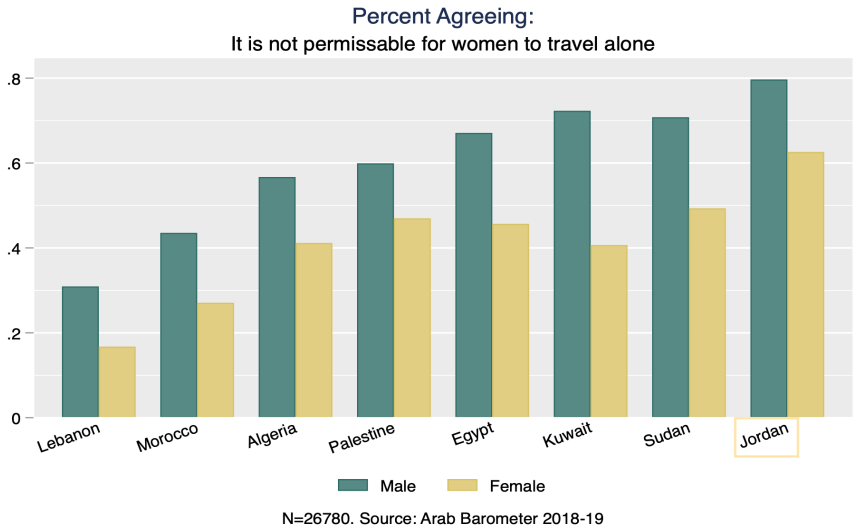


Figure A.3: This figure plots the percentage of people by country who agree with a statement saying that it would *not* be acceptable for a woman to travel alone. It includes all countries in the Arab barometer that answered this question in the 2018-19 round.

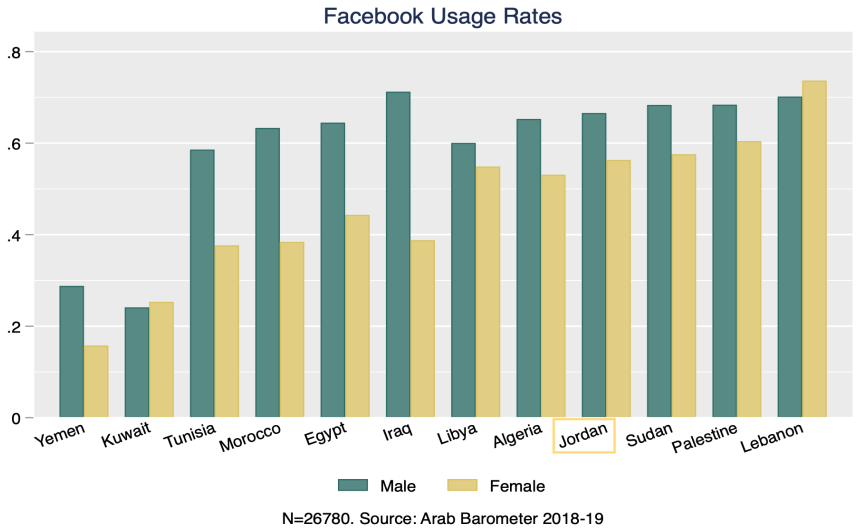


Figure A.4: This figure plots the percentage of people who list Facebook when asked what social media platforms that they use in the 2018-19 Arab Barometer survey. If respondents do not use the Internet, they are coded as not using Facebook.

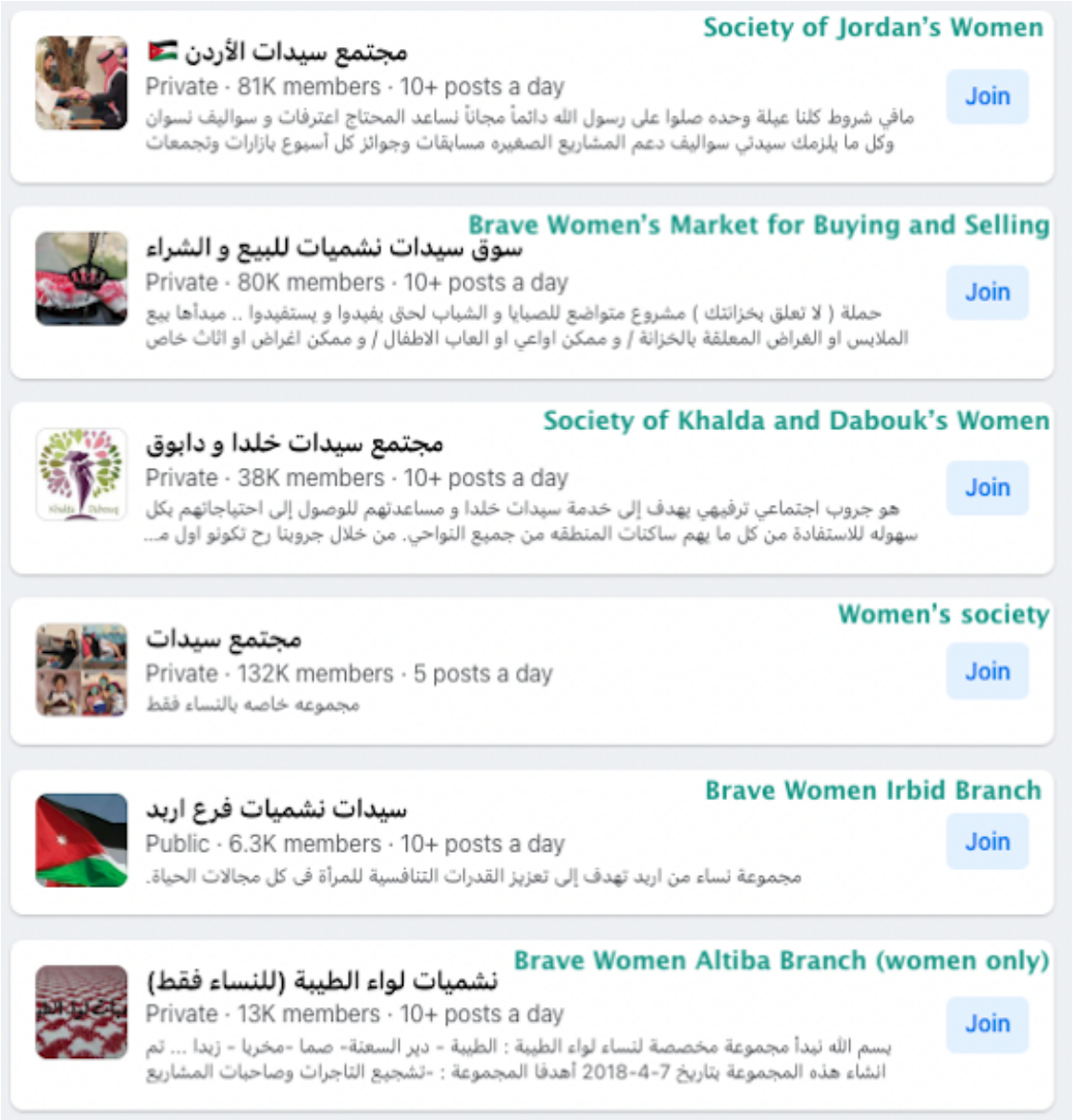


Figure A.5: Examples of women-only groups in Jordan, with thousands of members in each

A.2 Marketing Support Intervention

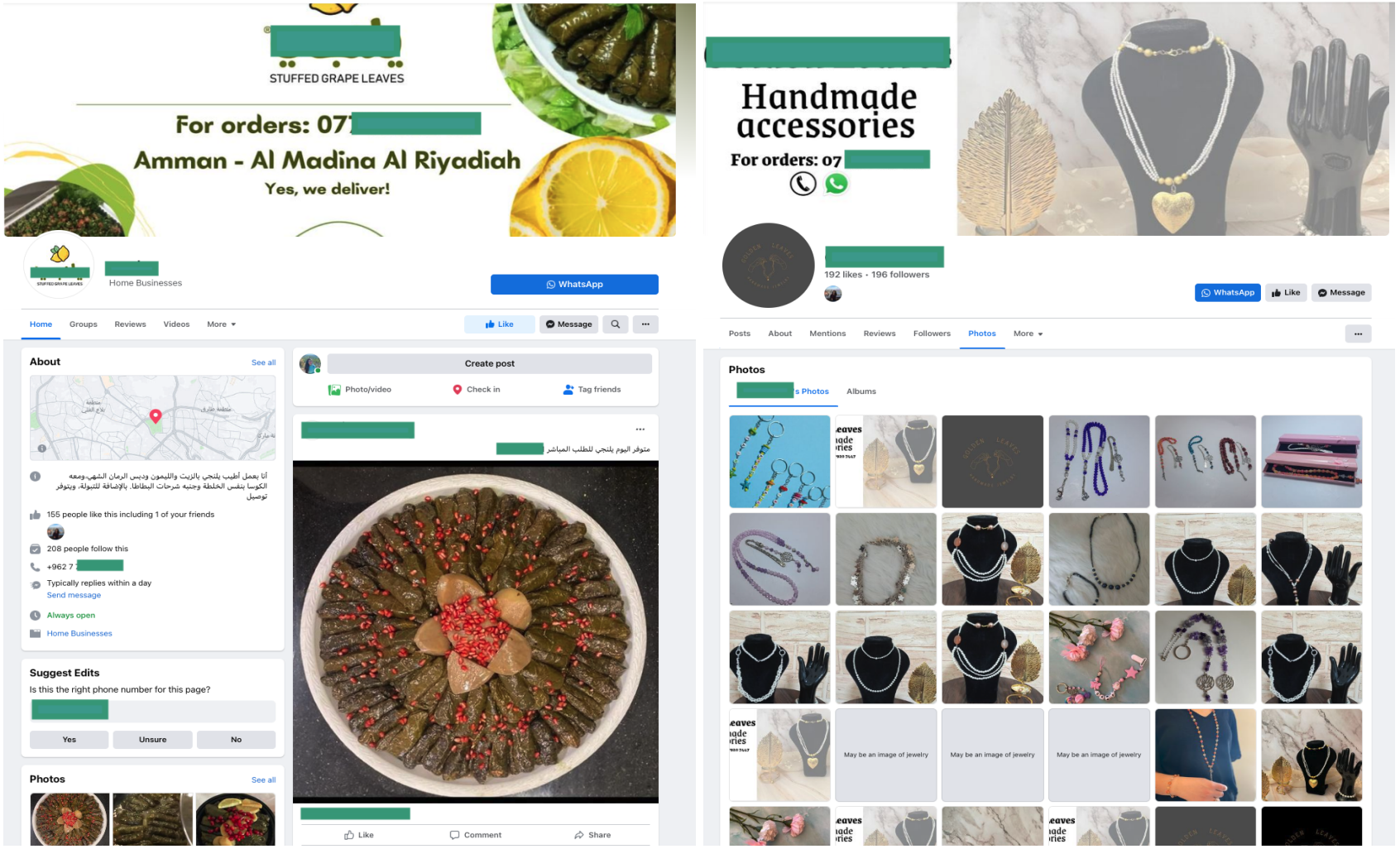


Figure A.6: Two Examples of Created Pages

A.3 Marketing Training Intervention

Table A.1: Marketing Training Content

Level	Episode	Content
Level 1	1	Why is digital marketing important, and what are the main differences between digital and traditional marketing?
	2	How can you use the Internet to increase your audience reach and your revenue from home?
	3	Quick tips: creative ideas and digital marketing best practices
	4	How do you start business accounts on Facebook, Instagram, and WhatsApp?
	5	How do you determine your target audience?
	6	How do you determine the goals from your digital marketing strategy? And what are the different types of content that help you reach your goals?
	7	Quick tips: examples of creative content of different types
	8	How can you take a nice picture from your own phone?
	9	Learn how to use a free app to edit pictures on your phone
	10	Success story: using social media marketing from one of our own clients
	11	What is the importance of influencer marketing, and how can you benefit from it?
	12	How do you deal with online customers, their questions, and their feedback?
	13	Four pieces of advice on content creation and management
Level 2	14	Checklist: does your business page have these components?
	15	Using WhatsApp and Facebook groups to reach wider customers
	16	How do you protect your data and privacy on social media?
	17	Building a successful content plan
	18	Creative writing: how do you write content that touches customers and increases their trust and interest in your products?
	19	Why is it important to publish videos on your page? What is a reel and how can we use it to grow our reach?
	20	Review: a free app to edit videos professionally on your phone
	21	Inspiring examples from women who stood out in their creative content
	22	Success story using social media marketing from one of our own clients
	23	Tips and tricks to increase interactions on your content and page
Level 3	24	Analyzing your audience and content success: reading and analyzing data from the Facebook dashboard
	25	Success story: interview with Alaa Hamdan who reached more than 1 million followers on Instagram
	26	Facebook marketplace: an overview
	27	Graphic design using Canva
	28	Paid digital advertising on Facebook
	29	Paid digital advertising on Instagram
	30	Mental health and avoiding negativity in a virtual world



Figure A.7: Screenshots from Online Marketing Training

A.4 Balance: Analysis Sample, Low and High Mobility Samples

Table A.2: Balance at Baseline by Treatment Assignment (Analysis Sample)

	(1) Control Mean	(2) Control SD	(3) Treatment Difference	(4) N
Demographics				
Age	41.71	9.51	0.65	983
Married	0.80	0.40	-0.01	983
Has children	0.89	0.31	0.01	983
Educ: less than high school	0.27	0.44	-0.03	983
Educ: high school	0.46	0.50	0.02	983
Mobility				
a- Times Out Last Month	6.83	7.67	0.71	983
b- Can go to training weekly	0.59	0.49	-0.00	983
c- Willing to operate in shop if rent is covered	0.56	0.50	0.00	983
Mobility Index (avg. z-scores of a-c)	-0.03	0.69	0.02	983
Agrees with Statements				
If a mother works outside the home, children suffer	0.74	0.44	-0.01	983
Society judges a mother that works outside the home	0.43	0.50	-0.01	983
Better to work from home to conserve own value	0.35	0.48	-0.03	983
Digital Practices (personal profile)				
FB: personally uses it daily/weekly	0.84	0.37	0.03	975
% of your acquaintances using FB daily/weekly	83.52	21.09	1.87	970
FB: profile shows her real name	0.63	0.48	-0.01	983
FB: profile picture shows her face	0.10	0.30	0.03	851
Digital Practices (business profile)				
Markets on FB	0.47	0.50	0.00	983
Has FB business page	0.22	0.42	0.01	983
Posts on FB groups	0.23	0.42	-0.00	980
FB page: willing to reveal name	0.67	0.47	-0.04	983
FB page: willing to reveal picture	0.31	0.46	0.02	924
Business Characteristics				
Home-based	0.79	0.41	-0.01	983
Product (partially) made	0.44	0.50	0.00	983
Product bought & traded	0.28	0.45	-0.01	983
Product is a service	0.16	0.37	-0.02	983
Business is registered	0.11	0.31	-0.01	969
Has partners or paid help	0.37	0.48	0.01	983
Currently offers delivery	0.61	0.49	0.01	983
At least half of clients are friends/neighbors	0.68	0.47	-0.00	983
Monthly profit (usd), 95p	141.40	152.80	0.42	983
Observations	495	495	983	

Notes: * p≤0.1, ** p≤0.05, *** p≤0.01. Column (3) is the coefficient from a regression of the outcome on treatment assignment, holding strata fixed effects. Continous variables are winsorized at the 95th percentile (noted by 95p).

Table A.3: Balance at Baseline by Treatment Assignment: Low Mobility Sample

	(1) Control Mean	(2) Control SD	(3) Treatment Difference	(4) N
Demographics				
Age	40.10	9.37	0.11	567
Married	0.82	0.38	0.03	567
Has children	0.91	0.28	0.01	567
Educ: less than high school	0.26	0.44	-0.01	567
Educ: high school	0.50	0.50	0.01	567
HH income (usd), 95p	680.79	331.01	-2.32	567
Mobility				
a- Times Out Last Month	3.47	3.41	-0.06	567
b- Can go to training weekly	0.24	0.43	0.03	567
c- Willing to operate in shop if rent is covered	0.25	0.44	0.00	567
Mobility Index (avg. z-scores of a-c)	-0.61	0.36	0.02	567
Mobility Index Above Median	0.00	0.00	0.00	567
Agrees with Statements				
If a mother works outside the home, children suffer	0.78	0.41	0.02	567
Society judges a mother that works outside the home	0.51	0.50	-0.02	567
Better to work from home to conserve own value	0.39	0.49	-0.00	567
Digital Practices (personal profile)				
FB: personally uses it daily/weekly	0.83	0.38	0.03	565
% of your acquaintances using FB daily/weekly	84.86	21.46	-2.25	494
FB: profile shows her real name	0.63	0.48	-0.04	567
FB: profile picture shows her face	0.06	0.24	0.01	484
Digital Practices (business profile)				
Markets on FB	0.43	0.50	0.00	566
Has FB business page	0.18	0.38	0.04	567
Posts on FB groups	0.20	0.40	0.01	495
FB page: willing to reveal name	0.60	0.49	-0.02	567
FB page: willing to reveal voice	0.56	0.50	-0.05	536
FB page: willing to reveal picture	0.22	0.42	-0.00	536
Business Characteristics				
Home-based	0.88	0.33	-0.01	567
Product (partially) made	0.47	0.50	-0.04	567
Product bought & traded	0.31	0.47	0.02	567
Product is a service	0.12	0.32	-0.02	567
Business is registered	0.06	0.25	-0.00	567
Has partners or paid help	0.34	0.47	0.02	567
Currently offers delivery	0.60	0.49	-0.06	567
At least half of clients are friends/neighbors	0.71	0.45	0.00	567
Monthly profit (usd), 95p	118.81	135.47	-6.55	567
Observations	280	280	567	

Notes: * p≤0.1, ** p≤0.05, *** p≤0.01. Column (4) is the coefficient from a regression of the outcome on treatment assignment, holding strata fixed effects. Continous variables are winsorized at the 95th percentile (noted by 95p).

Table A.4: Balance at Baseline by Treatment Assignment: High Mobility Sample

	(1) Control Mean	(2) Control SD	(3) Treatment Difference	(4) N
Demographics				
Age	42.46	9.62	1.13	555
Married	0.76	0.43	-0.03	555
Has children	0.88	0.33	-0.02	555
Educ: less than high school	0.25	0.43	-0.02	555
Educ: high school	0.44	0.50	-0.00	555
HH income (usd), 95p	776.17	388.16	12.87	555
Mobility				
a- Times Out Last Month	10.29	9.14	1.46*	555
b- Can go to training weekly	0.94	0.23	-0.01	555
c- Willing to operate in shop if rent is covered	0.87	0.34	0.02	555
Mobility Index (avg. z-scores of a-c)	0.56	0.37	0.05	555
Mobility Index Above Median	1.00	0.00	0.00	555
Agrees with Statements				
If a mother works outside the home, children suffer	0.69	0.46	-0.04	555
Society judges a mother that works outside the home	0.36	0.48	-0.00	555
Better to work from home to conserve own value	0.30	0.46	-0.04	555
Digital Practices (personal profile)				
FB: personally uses it daily/weekly	0.86	0.35	-0.01	547
% of your acquaintances using FB daily/weekly	82.25	20.66	6.02***	478
FB: profile shows her real name	0.64	0.48	0.02	555
FB: profile picture shows her face	0.15	0.35	0.02	479
Digital Practices (business profile)				
Markets on FB	0.49	0.50	-0.00	553
Has FB business page	0.25	0.43	0.01	555
Posts on FB groups	0.26	0.44	-0.01	487
FB page: willing to reveal name	0.73	0.44	-0.04	555
FB page: willing to reveal voice	0.71	0.45	0.04	518
FB page: willing to reveal picture	0.40	0.49	0.04	518
Business Characteristics				
Home-based	0.70	0.46	-0.00	555
Product (partially) made	0.40	0.49	0.02	555
Product bought & traded	0.25	0.43	-0.03	555
Product is a service	0.22	0.42	-0.02	555
Business is registered	0.14	0.35	-0.01	536
Has partners or paid help	0.39	0.49	0.01	555
Currently offers delivery	0.65	0.48	0.05	555
At least half of clients are friends/neighbors	0.66	0.48	-0.02	555
Monthly profit (usd), 95p	163.88	165.54	8.04	555
Observations	283	283	555	

Notes: * p≤0.1, ** p≤0.05, *** p≤0.01. Column (4) is the coefficient from a regression of the outcome on treatment assignment, holding strata fixed effects. Continous variables are winsorized at the 95th percentile (noted by 95p).

A.5 Market Access Effects: Inverse Hyperbolic Sine Outcomes

Table A.5: Business Outcomes

	Business Performance						Client Composition					
	Business Survival	Total Clients	asinh Revenue Week	asinh Revenue Month	asinh Profit Month	Performance Index (1)-(5)	Sells to Strangers	asinh Online Clients	asinh SC Value	asinh SC clients	Store credit Percent	Offers delivery
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment	0.07***	0.22**	0.21	0.20	0.24	0.09**	0.08***	0.23***	-0.34*	-0.06	-2.45	0.05*
	(0.03)	(0.10)	(0.15)	(0.17)	(0.15)	(0.04)	(0.03)	(0.06)	(0.19)	(0.08)	(1.66)	(0.03)
RI p-values	.03	.02	.18	.24	.11	.06	0	0	.05	.33	.11	.05
Control Mean	.75	1.67	2.36	3.56	2.96	-.04	.31	.47	2.19	1	20.66	.31
Obs	983	985	946	936	934	1119	914	985	594	913	957	915

Notes: This table estimates specification (1) in the paper. Outcomes (2) to (12) are coded as zero for closed businesses; table A.7 reports on the outcomes conditional on business survival. * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. All regressions have strata fixed effects and control for variables chosen using post-double-selection lasso procedures and baseline level of the outcome when available. RI p-values are from a randomization inference procedure that randomly permutes treatment assignment. Business performance outcomes are defined as follows: (1) is a binary variable for whether the business is still active; (2) is the distinct number of clients who made a purchase last month; (3) and (4) are revenue in USD last week and last month, respectively, winsorized at the 95th percentile; (5) is profit in USD last month, winsorized at the 95th percentile; and (6) is a business performance index that averages the z-scores from outcomes (1) to (5). Client composition outcomes are defined as follows: (7) is a binary variable for whether the respondent reports that at least some of her clients are not a part of her family or friends; (8) is the number of distinct clients who made a purchase last month and who made the order via online channels such as Facebook or Instagram; (9) is the value in USD of last month's sales made on store credit, winsorized at the 95th percentile; (10) is the number of distinct clients that currently owe store credit; (11) is the reported percent of last month's revenue coming through store credit; and (12) is a binary variable for whether the respondent offers delivery services. Outcomes in USD assume a conversion rate of 1.41 USD for 1 JD

Table A.6: Business Outcomes

	Business Performance						Client Composition					
	Business Survival	Total Clients	asinh Revenue Week	asinh Revenue Month	asinh Profit Month	Performance Index (1)-(5)	Sells to Strangers	asinh Online Clients	asinh SC Value	asinh SC clients	Store credit Percent	Offers delivery
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
β_1: Treatment (× Low Mobility)	0.11***	0.42***	0.52**	0.49**	0.46**	0.18***	0.14***	0.28***	-0.29	-0.06	-3.45	0.10**
	(0.04)	(0.14)	(0.21)	(0.24)	(0.21)	(0.06)	(0.04)	(0.08)	(0.26)	(0.11)	(2.38)	(0.04)
β_2: Treatment × High Mobility	-0.10*	-0.39**	-0.61**	-0.59*	-0.44	-0.18**	-0.13**	-0.10	-0.10	0.01	2.04	-0.09
	(0.05)	(0.20)	(0.30)	(0.33)	(0.30)	(0.09)	(0.06)	(0.13)	(0.38)	(0.15)	(3.30)	(0.06)
High Mobility	0.09**	0.34**	0.65***	0.57**	0.47**	0.17***	0.07*	0.13	0.13	0.02	0.27	0.08**
	(0.04)	(0.14)	(0.21)	(0.24)	(0.22)	(0.06)	(0.04)	(0.08)	(0.27)	(0.11)	(2.41)	(0.04)
$\beta_1 + \beta_2$ (High Mobility Effect)	0.02	0.03	-0.10	-0.10	0.02	-0.01	0.01	0.18*	-0.39	-0.06	-1.41	0.01
$\beta_1 + \beta_2 = 0$ (*p-value*)	0.56	0.85	0.65	0.67	0.94	0.92	0.78	0.07	0.16	0.60	0.54	0.83
RI p-values β_1	0	0	.01	.06	.04	.01	0	0	.32	.5	.16	.01
RI p-values β_2	.04	.05	.01	.06	.14	.03	.05	.55	.87	.94	.54	.1
Low Mobility Control Mean	.69	1.43	1.86	3.06	2.54	-.18	.24	.35	2.04	.97	21.03	.27
High Mobility Control Mean	.8	1.91	2.86	4.06	3.39	.1	.37	.59	2.36	1.02	20.28	.34
Obs	983	985	946	936	934	1119	914	985	594	913	957	915

Notes: This table estimates specification (2) in the paper. Outcomes (2) to (12) are coded as zero for closed businesses; table A.8 reports on the outcomes conditional on business survival. High Mobility refers to a binary variable for above median mobility index, which averages the z-scores from mobility variables (a)-(c) in table 1. * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. All regressions have strata fixed effects and control for variables chosen using post-double-selection lasso procedures and baseline level of the outcome when available. RI p-values are from a randomization inference procedure that randomly permutes treatment assignment. Business performance outcomes are defined as follows: (1) is a binary variable for whether the business is still active; (2) is the distinct number of clients who made a purchase last month; (3) and (4) are revenue in USD last week and last month, respectively, winsorized at the 95th percentile; (5) is profit in USD last month, winsorized at the 95th percentile; and (6) is a business performance index that averages the z-scores from outcomes (1) to (5). Client composition outcomes are defined as follows: (7) is a binary variable for whether the respondent reports that at least some of her clients are not a part of her family or friends; (8) is the number of distinct clients who made a purchase last month and who made the order via online channels such as Facebook or Instagram; (9) is the value in USD of last month's sales made on store credit, winsorized at the 95th percentile; (10) is the number of distinct clients that currently owe store credit; (11) is the reported percent of last month's revenue coming through store credit; and (12) is a binary variable for whether the respondent offers delivery services. Outcomes in USD assume a conversion rate of 1.41 USD for 1 JD

A.6 Market Access Effects: Conditional on Business Survival

Table A.7: Business Outcomes

	Business Performance						Client Composition					
	Business Survival	Total Clients	Revenue Last Week	Revenue Last Month	Profit Last month	Performance Index (1)-(5)	Sells to Strangers	Online Clients	Store credit value	Store credit clients	Store credit share	Offers delivery
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treatment	0.07***	1.24	6.86	17.06	3.89	0.05	0.06*	0.73**	-3.74	-0.94**	-4.54**	0.02
	(0.03)	(0.97)	(7.20)	(20.19)	(10.15)	(0.05)	(0.04)	(0.29)	(5.41)	(0.41)	(1.90)	(0.03)
RI p-values	.02	.22	.32	.36	.76	.41	.07	0	.49	.01	0	.68
Control Mean	.75	11.54	81.21	288.47	133.53	.3	.43	1.85	51.08	4.94	27.91	.42
Obs	983	762	740	731	726	762	693	762	739	692	736	694

Notes: This table estimates specification (1) in the paper. Outcomes (2) to (12) condition on business survival in this table, while table 3 shows the outcomes for the entire sample (coding client composition outcomes as zero for closed businesses). * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. All regressions have strata fixed effects and control for variables chosen using post-double-selection lasso procedures and baseline level of the outcome when available. RI p-values are from a randomization inference procedure that randomly permutes treatment assignment. Outcomes are defined as follows: (1) is a binary variable for whether the business is still active; (2) is the distinct number of clients who made a purchase last month; (3) and (4) are revenue in USD last week and last month, respectively, winsorized at the 95th percentile; (5) is profit in USD last month, winsorized at the 95th percentile; and (6) is a business performance index that averages the z-scores from outcomes (1) to (5); (7) is a binary variable for whether the respondent reports that at least some of her clients are not a part of her family or friends; (8) is the number of distinct clients who made a purchase last month and who made the order via online channels such as Facebook or Instagram; (9) is the value in USD of last month's sales made on store credit, winsorized at the 95th percentile; (10) is the number of distinct clients that currently owe store credit; (11) is the reported percent of last month's revenue coming through store credit; and (12) is a binary variable for whether the respondent offers delivery services. Outcomes in USD assume a conversion rate of 1.41 USD for 1 JD.

Table A.8: Business Outcomes

	Business Performance						Client Composition					
	Business Survival	Total Clients	Revenue Last Week	Revenue Last Month	Profit Last month	Performance Index (1)-(5)	Sells to Strangers	Online Clients	Store credit value	Store credit clients	Store credit share	Offers delivery
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
β_1: Treatment ($\times$ Low Mobility)	0.12***	1.82	20.03**	41.43	15.42	0.11	0.12**	0.69*	-2.55	-1.10*	-7.08**	0.05
	(0.04)	(1.36)	(10.11)	(28.15)	(13.71)	(0.07)	(0.05)	(0.37)	(7.90)	(0.59)	(2.76)	(0.05)
β_2: Treatment $\times$ High Mobility	-0.10**	-1.18	-24.85*	-46.38	-21.68	-0.12	-0.12*	0.09	-2.51	0.31	4.81	-0.07
	(0.05)	(1.93)	(14.32)	(40.50)	(20.14)	(0.10)	(0.07)	(0.59)	(10.74)	(0.81)	(3.76)	(0.07)
High Mobility	0.09**	-0.17	17.51*	28.15	16.25	0.09	0.03	0.14	-2.46	0.00	-2.87	0.04
	(0.04)	(1.39)	(10.46)	(28.36)	(14.52)	(0.07)	(0.05)	(0.38)	(7.81)	(0.65)	(2.81)	(0.05)
$\beta_1 + \beta_2$ (High Mobility Effect)	0.01	0.64	-4.82	-4.95	-6.26	-0.01	0.01	0.78*	-5.06	-0.79	-2.27	-0.02
$\beta_1 + \beta_2 = 0$ (*p-value*)	0.65	0.64	0.64	0.86	0.67	0.88	0.91	0.08	0.49	0.17	0.38	0.70
RI p-values β_1	0	.2	.05	.17	.24	.16	.01	.05	.8	.07	0	.28
RI p-values β_2	.05	.62	.12	.25	.26	.21	.09	.89	.77	.71	.19	.23
Low Mobility Control Mean	.69	10.53	63.66	241.02	106.97	.17	.37	1.45	52.87	5.11	30.85	.41
High Mobility Control Mean	.8	12.4	96.13	328.83	156.06	.42	.47	2.19	49.55	4.79	25.4	.43
Obs	983	762	740	731	726	762	693	762	739	692	736	694

Notes: This table estimates specification (2) in the paper. Outcomes (2) to (12) condition on business survival in this table, while table 7 the outcomes for the entire sample, coding client composition outcomes as zero for closed businesses. High Mobility refers to a binary variable for above median mobility index, which averages the z-scores from mobility variables (a)-(c) in table 1. * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. All regressions have strata fixed effects and control for variables chosen using post-double-selection lasso procedures and baseline level of the outcome when available. RI p-values are from a randomization inference procedure that randomly permutes treatment assignment. Outcomes are defined as follows: (1) is a binary variable for whether the business is still active; (2) is the distinct number of clients who made a purchase last month; (3) and (4) are revenue in USD last week and last month, respectively, winsorized at the 95th percentile; (5) is profit in USD last month, winsorized at the 95th percentile; and (6) is a business performance index that averages the z-scores from outcomes (1) to (5); (7) is a binary variable for whether the respondent reports that at least some of her clients are not a part of her family or friends; (8) is the number of distinct clients who made a purchase last month and who made the order via online channels such as Facebook or Instagram; (9) is the value in USD of last month's sales made on store credit, winsorized at the 95th percentile; (10) is the number of distinct clients that currently owe store credit; (11) is the reported percent of last month's revenue coming through store credit; and (12) is a binary variable for whether the respondent offers delivery services. Outcomes in USD assume a conversion rate of 1.41 USD for 1 JD.

A.7 Heterogeneity by Pre-Registered Variables

Table A.9: Take-Up and First Stage

	Page Support		Online Training		Markets On	
	Sent Pictures (1)	Became Owner (2)	Opened Link (3)	Watched 1hr+ (4)	FB Page (5)	FB Groups (6)
β_1: Treatment ($\times$ Home-Based)	0.48***	0.38***	0.62***	0.15***	0.26***	0.11***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
β_2: Treatment $\times$ Outside Home	-0.03	-0.08*	-0.02	-0.04	-0.12**	-0.03
	(0.05)	(0.05)	(0.05)	(0.03)	(0.06)	(0.06)
Outside Home	-0.03***	0.01	-0.00	-0.01	0.06*	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)
$\beta_1 + \beta_2$ (Outside Home Effect)	0.45***	0.30***	0.60***	0.12***	0.14***	0.08
$\beta_1 + \beta_2 = 0$ (*p-value*)	0.00	0.00	0.00	0.00	0.01	0.11
RI p-values β_1	0	0	0	0	0	0
RI p-values β_2	.63	.23	.71	.27	.06	.64
Low Mobility Control Mean	0	0	0	0	.16	.15
High Mobility Control Mean	0	0	0	0	.32	.2
Obs	1122	1122	1122	1122	1122	1122

Notes: * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. All regressions have strata fixed effects and control for variables chosen using post-double-selection lasso procedures. RI p-values are from a randomization inference procedure that randomly permutes treatment assignment. Outcomes are defined as follows: outcomes (1) and (2) reflect study participants' engagement with the logistical support part of the bundled intervention, where (1) is a binary variable for whether the respondent sent the necessary pictures and information to set up a Facebook business page for her, and (2) is a binary variable for whether the respondent became an owner on the page by accepting the invitation to become an administrator. Outcomes (3) and (4) reflect participants' engagement with the online training part of the bundled intervention, where (3) is whether the respondent opened the training link at all, and (4) is whether she watched more than an hour of the training. Outcomes (5) and (6) reflect the first stage, where (5) is ab inary variable for whether the respondent markets on a Facebook business page, and (6) is a binary varibale for whether the respondent markets on Facebook groups.

Table A.10: Business Outcomes

	Business Performance						Client Composition					
	Business Survival	Total Clients	Revenue Last Week	Revenue Last Month	Profit Last month	Performance Index (1)-(5)	Sells to Strangers	Online Clients	Store credit value	Store credit clients	Store credit share	Offers delivery
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
β_1: Treatment (× Home-Based)	0.08**	1.97**	3.95	19.71	10.29	0.12**	0.09***	0.70***	-2.39	-0.33	-1.76	0.08**
	(0.03)	(0.79)	(6.20)	(17.59)	(8.57)	(0.05)	(0.03)	(0.24)	(4.52)	(0.34)	(1.90)	(0.03)
β_2: Treatment × Outside Home	-0.06	-1.79	34.96**	35.04	-7.75	0.05	-0.08	0.24	2.04	-1.16	-3.35	-0.11
	(0.05)	(2.51)	(16.51)	(50.40)	(25.30)	(0.14)	(0.07)	(0.67)	(12.87)	(0.99)	(3.93)	(0.07)
Outside Home	0.05	5.85***	-8.27	1.39	-0.15	0.08	0.03	-0.06	15.76	2.51***	3.58	0.03
	(0.04)	(1.86)	(11.94)	(36.58)	(18.91)	(0.11)	(0.06)	(0.45)	(9.60)	(0.75)	(2.86)	(0.06)
$\beta_1 + \beta_2$ (Outside Home Effect)	0.02	0.18	38.91**	54.74	2.54	0.17	0.01	0.94	-0.35	-1.48	-5.11	-0.03
$\beta_1 + \beta_2 = 0$ (*p-value*)	0.68	0.94	0.01	0.25	0.91	0.21	0.83	0.13	0.98	0.11	0.14	0.58
RI p-values β_1	.02	0	.52	.18	.18	.03	0	0	.57	.24	.34	.02
RI p-values β_2	.24	.53	.05	.44	.74	.68	.34	.79	.9	.28	.41	.15
Home-Based Control Mean	.72	6.6	52.49	170.48	80.07	-.2	.26	1.11	31.37	2.88	19.66	.32
Outside Home Control Mean	.86	16.34	90.23	379.26	169.69	.45	.48	2.37	63.23	6.21	24.51	.27
Obs	965	985	961	952	947	985	914	985	960	913	957	915

Notes: This table estimates specification (2) in the paper. * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. All regressions have strata fixed effects and control for variables chosen using post-double-selection lasso procedures and baseline level of the outcome when available. RI p-values are from a randomization inference procedure that randomly permutes treatment assignment. Outcomes are defined as follows: (1) is a binary variable for whether the business is still active; (2) is the distinct number of clients who made a purchase last month; (3) and (4) are revenue in USD last week and last month, respectively, winsorized at the 95th percentile; (5) is profit in USD last month, winsorized at the 95th percentile; and (6) is a business performance index that averages the z-scores from outcomes (1) to (5); (7) is a binary variable for whether the respondent reports that at least some of her clients are not a part of her family or friends; (8) is the number of distinct clients who made a purchase last month and who made the order via online channels such as Facebook or Instagram; (9) is the value in USD of last month's sales made on store credit, winsorized at the 95th percentile; (10) is the number of distinct clients that currently owe store credit; (11) is the reported percent of last month's revenue coming through store credit; and (12) is a binary variable for whether the respondent offers delivery services. All client composition outcomes condition on business survival; table **??** in the appendix shows the outcomes for the entire sample, coding client composition outcomes as zero for closed businesses. Outcomes in USD assume a conversion rate of 1.41 USD for 1 JD.

Table A.11: Take-Up and First Stage

	Page Support		Online Training		Markets On	
	Sent Pictures (1)	Became Owner (2)	Opened Link (3)	Watched 1hr+ (4)	FB Page (5)	FB Groups (6)
β_1: Treatment (× No Page)	0.41***	0.41***	0.66***	0.11***	0.28***	0.13***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.03)	(0.03)
β_2: Treatment × Has Business Page	0.34***	-0.22***	-0.23***	0.19***	-0.09	-0.15*
	(0.05)	(0.04)	(0.05)	(0.05)	(0.07)	(0.08)
Has Business Page	-0.01	0.03	-0.03	-0.01	0.36***	0.24***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.07)	(0.07)
$\beta_1 + \beta_2$ (Has Business Page Effect)	0.75***	0.18***	0.43***	0.30***	0.19***	-0.02
$\beta_1 + \beta_2 = 0$ (*p-value*)	0.00	0.00	0.00	0.00	0.01	0.81
RI p-values β_1	0	0	0	0	0	0
RI p-values β_2	0	0	0	0	.22	.11
No Page Control Mean	0	0	0	0	.15	.13
Has Business Page Control Mean	0	0	0	0	.68	.51
Obs	1117	1117	1117	1117	966	966

Notes: * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. All regressions have strata fixed effects and control for variables chosen using post-double-selection lasso procedures and baseline level of the outcome when available. RI p-values are from a randomization inference procedure that randomly permutes treatment assignment. Outcomes are defined as follows: outcomes (1) and (2) reflect study participants' engagement with the logistical support part of the bundled intervention, where (1) is a binary variable for whether the respondent sent the necessary pictures and information to set up a Facebook business page for her, and (2) is a binary variable for whether the respondent became an owner on the page by accepting the invitation to become an administrator. Outcomes (3) and (4) reflect participants' engagement with the online training part of the bundled intervention, where (3) is whether the respondent opened the training link at all, and (4) is whether she watched more than an hour of the training. Outcomes (5) and (6) reflect the first stage, where (5) is a binary variable for whether the respondent markets on a Facebook business page, and (6) is a binary varibale for whether the respondent markets on Facebook groups.

Table A.12: Business Outcomes

	Business Performance						Client Composition					
	Business Survival	Total Clients	Revenue Last Week	Revenue Last Month	Profit Last month	Performance Index (1)-(5)	Sells to Strangers	Online Clients	Store credit value	Store credit clients	Store credit share	Offers delivery
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
β_1: Treatment (× No Page)	0.04	0.82	10.78*	30.60*	9.90	0.11*	0.08**	0.71***	-0.77	-0.44	-2.44	0.05
	(0.03)	(0.87)	(6.36)	(18.50)	(8.99)	(0.06)	(0.03)	(0.24)	(4.92)	(0.38)	(1.88)	(0.03)
β_2: Treatment × Has Business Page	0.09	3.88*	-0.78	-42.38	-13.99	0.05	-0.08	-0.16	-8.09	-0.82	0.17	-0.05
	(0.06)	(2.15)	(17.46)	(49.72)	(24.12)	(0.14)	(0.08)	(0.79)	(12.29)	(0.88)	(4.08)	(0.08)
Has Business Page	0.04	-0.59	11.43	68.04*	22.77	0.12	0.21***	1.22*	6.23	0.48	-0.91	0.15**
	(0.05)	(1.49)	(14.22)	(39.78)	(18.61)	(0.11)	(0.07)	(0.64)	(10.78)	(0.78)	(3.57)	(0.06)
$\beta_1 + \beta_2$ (Has Business Page Effect)	0.14***	4.70**	10.01	-11.78	-4.09	0.16	-0.00	0.56	-8.87	-1.26	-2.27	0.00
$\beta_1 + \beta_2 = 0$ (*p-value*)	0.01	0.02	0.54	0.80	0.85	0.20	0.97	0.46	0.43	0.11	0.53	0.96
RI p-values β_1	.13	.43	.09	.1	.29	.06	.01	0	.82	.2	.13	.13
RI p-values β_2	.08	.07	.92	.37	.63	.69	.26	.81	.47	.34	.98	.49
No Page Control Mean	.74	8.62	56.93	195.48	91.83	-.1	.26	1.04	37.89	3.68	21.58	.28
Has Business Page Control Mean	.8	8.9	81.18	327.08	140.22	.17	.59	3.43	37.86	3.14	15.21	.5
Obs	981	983	959	950	945	983	912	983	958	911	955	913

Notes: This table estimates specification (2) in the paper. * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. All regressions have strata fixed effects and control for variables chosen using post-double-selection lasso procedures and baseline level of the outcome when available. RI p-values are from a randomization inference procedure that randomly permutes treatment assignment. Outcomes are defined as follows: (1) is a binary variable for whether the business is still active; (2) is the distinct number of clients who made a purchase last month; (3) and (4) are revenue in USD last week and last month, respectively, winsorized at the 95th percentile; (5) is profit in USD last month, winsorized at the 95th percentile; and (6) is a business performance index that averages the z-scores from outcomes (1) to (5); (7) is a binary variable for whether the respondent reports that at least some of her clients are not a part of her family or friends; (8) is the number of distinct clients who made a purchase last month and who made the order via online channels such as Facebook or Instagram; (9) is the value in USD of last month's sales made on store credit, winsorized at the 95th percentile; (10) is the number of distinct clients that currently owe store credit; (11) is the reported percent of last month's revenue coming through store credit; and (12) is a binary variable for whether the respondent offers delivery services. All client composition outcomes condition on business survival; table **??** in the appendix shows the outcomes for the entire sample, coding client composition outcomes as zero for closed businesses. Outcomes in USD assume a conversion rate of 1.41 USD for 1 JD.

Table A.13: Take-Up and First Stage

	Page Support		Online Training		Markets On	
	Sent Pictures (1)	Became Owner (2)	Opened Link (3)	Watched 1hr+ (4)	FB Page (5)	FB Groups (6)
β_1: Treatment ($\times$ Clan Community)	0.45***	0.36***	0.66***	0.11***	0.29***	0.11***
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
β_2: Treatment $\times$ Non-Clan	0.05	0.01	-0.09**	0.09***	-0.01	0.01
	(0.04)	(0.04)	(0.04)	(0.03)	(0.05)	(0.05)
Non-Clan	-0.01	0.01**	0.00	-0.01	0.00	-0.03
	(0.01)	(0.01)	(0.00)	(0.00)	(0.03)	(0.03)
$\beta_1 + \beta_2$ (Non-Clan Effect)	0.50***	0.37***	0.56***	0.20***	0.27***	0.12***
$\beta_1 + \beta_2 = 0$ (*p-value*)	0.00	0.00	0.00	0.00	0.00	0.00
RI p-values β_1	0	0	0	0	0	0
RI p-values β_2	.37	.73	.1	0	.8	.88
Clan Community Control Mean	0	0	0	0	.2	.18
Non-Clan Control Mean	0	0	0	0	.25	.19
Obs	1119	1117	1119	1119	968	968

Notes: * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. All regressions have strata fixed effects and control for variables chosen using post-double-selection lasso procedures and baseline level of the outcome when available. RI p-values are from a randomization inference procedure that randomly permutes treatment assignment. Outcomes are defined as follows: outcomes (1) and (2) reflect study participants' engagement with the logistical support part of the bundled intervention, where (1) is a binary variable for whether the respondent sent the necessary pictures and information to set up a Facebook business page for her, and (2) is a binary variable for whether the respondent became an owner on the page by accepting the invitation to become an administrator. Outcomes (3) and (4) reflect participants' engagement with the online training part of the bundled intervention, where (3) is whether the respondent opened the training link at all, and (4) is whether she watched more than an hour of the training. Outcomes (5) and (6) reflect the first stage, where (5) is a binary variable for whether the respondent markets on a Facebook business page, and (6) is a binary varibale for whether the respondent markets on Facebook groups.

Table A.14: Business Outcomes

	Business Performance						Client Composition					
	Business Survival	Total Clients	Revenue Last Week	Revenue Last Month	Profit Last month	Performance Index (1)-(5)	Sells to Strangers	Online Clients	Store credit value	Store credit clients	Store credit share	Offers delivery
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
β_1: Treatment ($\times$ Clan Community)	0.07**	1.45	12.86*	39.48*	15.14	0.14**	0.06	0.53*	-2.66	-0.33	-1.55	0.02
	(0.03)	(1.08)	(7.39)	(21.76)	(10.60)	(0.06)	(0.04)	(0.30)	(5.88)	(0.46)	(2.29)	(0.04)
β_2: Treatment $\times$ Non-Clan	-0.02	0.31	-3.50	-29.92	-15.88	-0.02	0.05	0.52	1.68	-0.60	-2.18	0.07
	(0.05)	(1.62)	(12.14)	(34.86)	(17.33)	(0.11)	(0.06)	(0.48)	(8.77)	(0.68)	(3.28)	(0.06)
Non-Clan	-0.01	-1.02	3.47	14.75	9.33	-0.00	-0.01	-0.57*	-2.75	0.29	-0.53	-0.02
	(0.04)	(1.11)	(8.59)	(24.88)	(12.68)	(0.08)	(0.04)	(0.31)	(6.34)	(0.51)	(2.39)	(0.04)
$\beta_1 + \beta_2$ (Non-Clan Effect)	0.06	1.76	9.36	9.56	-0.73	0.12	0.10**	1.05***	-0.98	-0.93*	-3.73	0.09**
$\beta_1 + \beta_2 = 0$ (*p-value*)	0.16	0.14	0.33	0.73	0.96	0.16	0.02	0.00	0.88	0.06	0.11	0.03
RI p-values β_1	.03	.21	.05	.06	.17	.04	.14	.12	.6	.44	.48	.59
RI p-values β_2	.66	.85	.68	.38	.36	.81	.45	.21	.79	.31	.45	.19
Clan Community Control Mean	.75	8.94	57.79	203.36	91.54	-.08	.3	1.49	40.29	3.68	21.87	.31
Non-Clan Control Mean	.75	8.23	63.43	227.77	108.14	-.04	.32	1.22	34.3	3.48	18.92	.31
Obs	983	985	961	952	947	985	914	985	960	913	957	915

Notes: This table estimates specification (2) in the paper. * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. All regressions have strata fixed effects and control for variables chosen using post-double-selection lasso procedures and baseline level of the outcome when available. RI p-values are from a randomization inference procedure that randomly permutes treatment assignment. Outcomes are defined as follows: (1) is a binary variable for whether the business is still active; (2) is the distinct number of clients who made a purchase last month; (3) and (4) are revenue in USD last week and last month, respectively, winsorized at the 95th percentile; (5) is profit in USD last month, winsorized at the 95th percentile; and (6) is a business performance index that averages the z-scores from outcomes (1) to (5); (7) is a binary variable for whether the respondent reports that at least some of her clients are not a part of her family or friends; (8) is the number of distinct clients who made a purchase last month and who made the order via online channels such as Facebook or Instagram; (9) is the value in USD of last month's sales made on store credit, winsorized at the 95th percentile; (10) is the number of distinct clients that currently owe store credit; (11) is the reported percent of last month's revenue coming through store credit; and (12) is a binary variable for whether the respondent offers delivery services. All client composition outcomes condition on business survival; table **??** in the appendix shows the outcomes for the entire sample, coding client composition outcomes as zero for closed businesses. Outcomes in USD assume a conversion rate of 1.41 USD for 1 JD.

Table A.15: Take-Up and First Stage

	Page Support		Online Training		Markets On	
	Sent Pictures (1)	Became Owner (2)	Opened Link (3)	Watched 1hr+ (4)	FB Page (5)	FB Groups (6)
β_1: Treatment (× No High School)	0.45***	0.41***	0.65***	0.12***	0.28***	0.09**
	(0.04)	(0.04)	(0.04)	(0.03)	(0.05)	(0.04)
β_2: Treatment × Has High School	0.03	-0.05	-0.05	0.03	0.00	0.03
	(0.05)	(0.05)	(0.05)	(0.03)	(0.06)	(0.05)
Has High School	-0.03***	0.01	0.01*	-0.01**	0.06*	0.04
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)
$\beta_1 + \beta_2$ (Has High School Effect)	0.48***	0.35***	0.61***	0.15***	0.28***	0.13***
$\beta_1 + \beta_2 = 0$ (*p-value*)	0.00	0.00	0.00	0.00	0.00	0.00
RI p-values β_1	0	0	0	0	0	.02
RI p-values β_2	.63	.32	.53	.31	.92	.5
No High School Control Mean	0	0	0	0	.1	.11
Has High School Control Mean	0	0	0	0	.26	.21
Obs	1119	1117	1119	1119	968	968

Notes: * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. All regressions have strata fixed effects and control for variables chosen using post-double-selection lasso procedures and baseline level of the outcome when available. RI p-values are from a randomization inference procedure that randomly permutes treatment assignment. Outcomes are defined as follows: outcomes (1) and (2) reflect study participants' engagement with the logistical support part of the bundled intervention, where (1) is a binary variable for whether the respondent sent the necessary pictures and information to set up a Facebook business page for her, and (2) is a binary variable for whether the respondent became an owner on the page by accepting the invitation to become an administrator. Outcomes (3) and (4) reflect participants' engagement with the online training part of the bundled intervention, where (3) is whether the respondent opened the training link at all, and (4) is whether she watched more than an hour of the training. Outcomes (5) and (6) reflect the first stage, where (5) is a binary variable for whether the respondent markets on a Facebook business page, and (6) is a binary varibale for whether the respondent markets on Facebook groups.

Table A.16: Business Outcomes

	Business Performance						Client Composition					
	Business Survival	Total Clients	Revenue Last Week	Revenue Last Month	Profit Last month	Performance Index (1)-(5)	Sells to Strangers	Online Clients	Store credit value	Store credit clients	Store credit share	Offers delivery
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
β_1: Treatment (× No High School)	-0.00	2.58	17.98	51.70	8.88	0.13	0.04	0.75**	15.91*	-0.17	-3.57	0.01
	(0.05)	(1.70)	(11.92)	(35.71)	(16.90)	(0.11)	(0.06)	(0.36)	(9.57)	(0.61)	(3.49)	(0.05)
β_2: Treatment × Has High School	0.09	-1.31	-8.68	-32.88	-0.39	-0.01	0.06	-0.01	-23.84**	-0.55	1.54	0.05
	(0.06)	(1.93)	(13.69)	(40.58)	(19.61)	(0.12)	(0.07)	(0.46)	(10.77)	(0.73)	(3.97)	(0.06)
Has High School	-0.07*	-0.12	-3.00	12.52	2.17	-0.02	-0.06	0.64**	3.00	0.21	-2.49	0.07*
	(0.04)	(1.25)	(9.85)	(27.89)	(14.06)	(0.09)	(0.05)	(0.28)	(7.13)	(0.57)	(2.96)	(0.04)
$\beta_1 + \beta_2$ (Has High School Effect)	0.09***	1.26	9.30	18.82	8.49	0.13**	0.09***	0.74**	-7.94	-0.72*	-2.03	0.06*
$\beta_1 + \beta_2 = 0$ (*p-value*)	0.00	0.16	0.17	0.33	0.38	0.03	0.01	0.01	0.10	0.07	0.28	0.06
RI p-values β_1	.95	.16	.14	.17	.55	.22	.56	.06	.12	.8	.4	.8
RI p-values β_2	.08	.54	.52	.4	.97	.97	.45	.98	.03	.54	.72	.36
No High School Control Mean	.77	8.37	59.55	186.63	82.57	-.1	.3	.55	39.81	3.97	24.75	.23
Has High School Control Mean	.74	8.74	60.32	223.28	104.06	-.05	.31	1.68	37.09	3.46	19.21	.33
Obs	983	985	961	952	947	985	914	985	960	913	957	915

Notes: This table estimates specification (2) in the paper. * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors in parentheses. All regressions have strata fixed effects and control for variables chosen using post-double-selection lasso procedures and baseline level of the outcome when available. RI p-values are from a randomization inference procedure that randomly permutes treatment assignment. Outcomes are defined as follows: (1) is a binary variable for whether the business is still active; (2) is the distinct number of clients who made a purchase last month; (3) and (4) are revenue in USD last week and last month, respectively, winsorized at the 95th percentile; (5) is profit in USD last month, winsorized at the 95th percentile; and (6) is a business performance index that averages the z-scores from outcomes (1) to (5); (7) is a binary variable for whether the respondent reports that at least some of her clients are not a part of her family or friends; (8) is the number of distinct clients who made a purchase last month and who made the order via online channels such as Facebook or Instagram; (9) is the value in USD of last month's sales made on store credit, winsorized at the 95th percentile; (10) is the number of distinct clients that currently owe store credit; (11) is the reported percent of last month's revenue coming through store credit; and (12) is a binary variable for whether the respondent offers delivery services. All client composition outcomes condition on business survival; table **??** in the appendix shows the outcomes for the entire sample, coding client composition outcomes as zero for closed businesses. Outcomes in USD assume a conversion rate of 1.41 USD for 1 JD.

A.8 Heterogeneity by Mobility and Quality

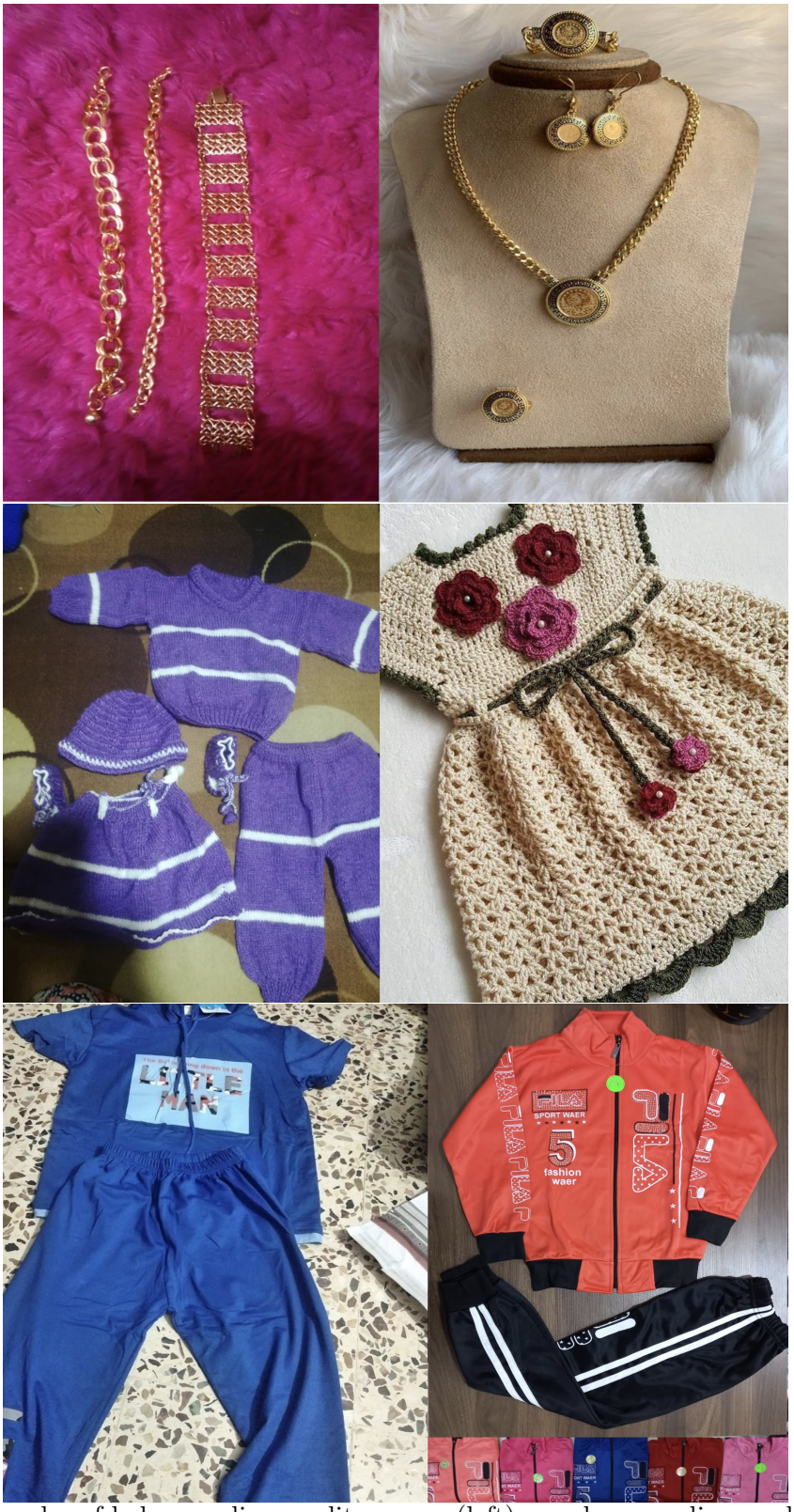


Figure A.8: Examples of below median quality scores (left) vs. above median quality score (right)

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