Blended Finance and Female Entrepreneurs: Micro Evidence from Turkey*

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Abstract

We combine microdata from the Turkish credit registry with firm-level administrative tax records to trace the impacts of a large-scale blended finance program for female entrepreneurs. We find that participating banks durably increase lending to women—both in absolute terms and relative to male entrepreneurs. Banks lend more to pre-existing female borrowers, poach clients from other banks, and crowd in first-time borrowers. Compared with a matched control group, treated female entrepreneurs grow their operations significantly faster and are six percentage points less likely to default within three years after the start of the program. These effects are not spatially uniform as banks use the program strategically to increase market shares in districts where they lag their competitors.

JEL codes: D22, G21, G32, H81, J16, L26

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1 Introduction

Across much of the world, access to credit remains unevenly distributed across the firm population. While most large companies can borrow from banks and tap bond markets with relative ease, credit remains elusive for many smaller enterprises (Carpenter and Petersen, 2002; Beck et al., 2005). Small firms often lack collateral and cannot yet demonstrate a stable earnings track record. The resulting financial frictions make banks wary to lend (Jaffee and Russell, 1976; Stiglitz and Weiss, 1981). Credit-constrained firms then have to forgo investment opportunities and continue to operate at a smaller scale than they would in the absence of financial frictions.[1] This perpetuates resource misallocation and hurts aggregate productivity growth (Hsieh and Klenow, 2009).

To the extent that female entrepreneurs are especially likely to lack collateral, credit history and business connections, credit constraints may bind even more for them. Moreover, even when particular women-owned firms are *not* riskier than male-owned ones, banks may incorrectly perceive them to be, leading to statistical or taste-based discrimination of female loan applicants (Alesina et al., 2013; Demirgüç-Kunt et al., 2013; Brock and De Haas, 2022). As a result of such financial frictions, female-owned businesses remain strongly overrepresented in the left tail of the firm-size distribution in many countries.

Public policy has taken different approaches to make credit more accessible to small firms in general and to female entrepreneurs in particular (Demirgüç-Kunt et al., 2008). On one end of the spectrum lie measures to improve the overall functioning of credit markets. This includes strengthening creditor rights (La Porta et al., 1998) and collateral laws (Calomiris et al., 2017); introducing credit registries (Pagano and Jappelli, 1993); and allowing foreign banks to enter (Claessens and Laeven, 2004). These policies have made credit markets more competitive but did not necessarily benefit underserved segments. For example, foreign bank entry can lead to cream skimming and *less* credit for small firms (Detragiache et al., 2008).

[1] See Demirgüç-Kunt and Maksimovic (1998); Rajan and Zingales (1998); Aghion et al. (2007); Ayyagari et al. (2008); Beck et al. (2008)

Likewise, bank competition can hurt small businesses if it prevents the formation of durable lending relationships with banks (Petersen and Rajan, 1994).

On the other end of the spectrum lie policies that are both more targeted and interventionist, such as setting up state banks with a mandate to lend to specific industries or firm segments. In theory, state banks can improve welfare if private banks underprovide credit to socially desirable investments (Hainz and Hakenes, 2012; Jiménez et al., 2018). In practice the track record of state banks has been mixed at best (Panizza, 2021) as their lending tends to reflect political motivations and involves significant allocative inefficiencies.[2]

A third approach to make credit accessible to a broader set of firms is blended finance. In this approach, a public development bank or similar government institution provides lending facilities to commercial banks. These banks then lend these earmarked funds to small businesses, female entrepreneurs, or some other target segment (Arping et al., 2010; Gutierrez et al., 2011).[3] Blended finance facilities typically comprise a senior loan (with a use-of-proceeds clause) as well as credit guarantees and a technical assistance program to overcome banks' initial reluctance to lend to the targeted group.

Is blended finance a 'golden mean' to channel credit to underserved firms while avoiding the pitfalls of lending by state banks? Despite the billions in blended finance that are disbursed every year, empirical evidence on its effectiveness remains scarce.[4] A key impediment to rigorously evaluating these programs is a lack of sufficiently granular data. To address this gap, we combine several comprehensive firm-level data sets on a large-scale blended finance program for female entrepreneurs across the whole of Turkey. This "Women in Business" (WIB) program was rolled out across five Turkish banks during 2014–19. The program con-

[2]See Shleifer and Vishny (1994), La Porta et al. (2002), Sapienza (2004), Dinç (2005), Khwaja and Mian (2005), Carvalho (2014), and Bircan and Saka (2021).

[3]64% percent of all public development banks lend through private financial intermediaries to target firms (World Bank, 2018). Eslava and Freixas (2016) provide a theoretical discussion of how development banks can reduce credit underprovision through blended finance. In their model, development banks internalize both the full social value of projects and the aggregate benefits of screening.

[4]For example, an internal World Bank study concludes that the ability of credit lines to address credit shortages remains unproven (World Bank, 2005). Another evaluation of blended finance to SMEs (small and medium-sized enterprises) states that "it is unclear what impact these investments have at the firm level and there has been no attempt to assess impact through a systematic study" (World Bank, 2014).

sisted of credit lines that banks had to on-lend to female entrepreneurs. It also included a risk-mitigation mechanism (first loss risk cover) and technical assistance to banks.[5] These institutional features, typical of blended finance across the world, help to further our understanding of *how* blended finance may reduce financial frictions for targeted firms. More generally, they shed new light on whether and how the private sector can be leveraged to allocate public funding.

We aim to answer three questions about blended finance and the way in which private lenders allocate public funds. First, can blended finance cause a durable increase in bank credit to female entrepreneurs? Second, which types of women-owned businesses (if any) gain better access to credit? Third, what are the real-economic impacts (if any) at the level of firms in case blended finance eases credit constraints in a meaningful way? Answering these questions sheds light on the efficacy of this particular program but also on the mechanisms through which blended finance can loosen credit constraints more generally.

To trace the financial and real impacts of the program at the borrower and district level, we merge three micro data sets. We first access the Turkish credit registry. This registry suits our purposes particularly well because it covers the universe of loans (there is no minimum reporting threshold) and allows us to distinguish between business and consumer loans. The data enable us to track firms' borrowing activity over time and across lenders, and to gauge their risk profile based on credit history and past loan performance. The registry not only contains information about defaults on bank loans but also on obligations vis-à-vis suppliers. Crucially, the registry provides us with the gender of borrowers, a basic piece of information that is typically absent from credit registries.

Second, we use exhaustive firm-level data drawn from fiscal receipts, which provide unique insights into domestic firm networks. These data are collected by the Ministry of Treasury and Finance for the purpose of calculating value added tax. They cover almost all buyer-supplier links in Turkey.

[5]Section 2 provides more details on the WIB program.

Third, we access administrative records from the same ministry. These records provide us with annual balance sheets and income statements for all businesses that pay corporate tax. As in the credit registry, we observe the gender of company owners so that we can also track women entrepreneurs who are not in the credit registry (that is, female non-borrowers). Because we identify all sub-borrowers under the blended finance program on the basis of their unique tax identification number, we can use this number to match entrepreneurial records across the three data sets.

In our econometric approach, we first check whether the five banks that participated in the blended finance program poses a selection problem that might affect our estimation. These five banks are slightly larger, when measured in terms of total assets, relative to other banks that did not participate in the program, but otherwise the two groups of banks are similar along many bank characteristics prior to the start of the program. We use a version of the synthetic difference-in-differences ("SDID") methodology recently proposed by Arkhangelsky et al. (2021) that allows for time staggered adoption of treatment to address potential issues that might arise from a non-random selection of banks participating in the program.[6] Results from this exercise confirm our descriptive evidence and main finding that the average effect of participating in the blended finance program on the participant banks is a strong increase in lending to female entrepreneurs.

To identify program effects on female entrepreneurs' access to credit and subsequent firm performance at a more granular level, we employ a two-way fixed effect model built around the staggered introduction of the program across five participating banks. We first aggregate our loan-level data up to panel data at the bank-district-quarter level, which allows us to track the medium- to long-term effects of blended finance. We then regress each bank's lending to female entrepreneurs (by all of its branches in a particular district) on an interaction term between a variable distinguishing between treatment and control banks and a timing

[6]SDID effectively makes the two-way fixed effect regression "local" (Arkhangelsky et al., 2021), by putting more weight, in our setting, on banks that did not participate in the program and that on average are similar in terms of their past to the participant banks, and on earlier time periods that are on average similar to those during which the program was active.

variable indicating whether a particular treatment bank had already started lending as part of the program. We saturate this model with a rich set of time-variant bank characteristics; bank-district pair fixed effects; and district-time fixed effects. Because standard two-way fixed effects estimators can return biased estimates when the treatment effect varies across units and time periods, we follow the "stacking" methodology of Gormley and Matsa (2011) and Cengiz et al. (2019). We conservatively allow all high-dimensional fixed effects and the bank-time controls to vary across treatment cohorts.

Using this empirical strategy, we first document that the program durably increased lending to female entrepreneurs—in absolute terms and relative to male-owned firms. Banks participating in the program raised their overall lending to female entrepreneurs by 34.8 percent more than control banks (on average across districts). They also increase the number of female business borrowers by 15.7 percent more. As a result, participating banks increase the portion of all business lending that they allocate to women by about 11 percent.

We track down all borrowers in the credit registry and show that participating banks not only expand lending to their pre-existing female borrowers but also actively poach clients from other banks. They also grant loans to first-time borrowers who so far had never borrowed from any bank. In fact, about 60 percent of the increased lending share to women is to borrowers new to the bank. First-time borrowers account for half of this effect, while clients poached from other banks account for the other half. The program therefore not only expanded lending to existing female borrowers that were still credit-constrained (intensive margin) but also crowded in many new entrepreneurs (extensive margin).

While the program stimulates banks to lend to new and slightly younger female entrepreneurs, this shift did not entail an increase in credit risk. This suggests that the program and the associated training components may have allowed banks to reach out to an underserved but deserving part of the entrepreneurial pool. One exception is the relatively strong increase in ex ante risk of first-time borrowers. Treated banks do take on more credit risk as they expand their lending to female entrepreneurs who had never borrowed from a bank before but had a blemished track record in terms of paying their suppliers. However, our findings show that these first-time borrowers went on to establish multiple banking relationships and increased their debt capacity in the two years after their first loan. This suggests that the program served as a gateway to durable financial inclusion for many female entrepreneurs who were previously underserved by the financial system.

We then assess whether program impacts are homogeneous across districts or instead spatially variegated. We find strong evidence for the latter, with a key role for individual banks' prior local market position in lending to female entrepreneurs. In particular, as a result of the blended finance program, treated banks shift the allocation of new lending more to female entrepreneurs in areas where they had a lower initial market share in this segment. They mainly do so by lending more to their existing female borrowers in these districts and by poaching clients from competitors. This shows that when blended finance programs use commercial banks to allocate public funds to specific target segments, local banking market characteristics determine which borrower types get credit (first).

Lastly, we investigate whether the improved access to credit by female entrepreneurs, due to the program, had positive effects on the enterprises they run. We match program firms with observably very similar control firms and use these matched pairs in a difference-in-differences setup to estimate the average program impact on treated firms. Our panel data on firm-to-firm networks allow us to track firms over time and to investigate the dynamic effects of the blended finance program. We would not have been able to do do with access to cross-sectional data only. We find that improved access to credit indeed helped firms to expand their operations significantly faster. Compared with a matched control group with credit access from banks that did not participate in the blended finance program, female borrowers of treated banks experience a 11.1 percent higher sales growth over a three-year horizon. They are also 6.1 percentage points less likely to default three years into the program, when compared with female entrepreneurs with access to credit from non-treated banks. Overall, our findings show how blended finance can alleviate information frictions when commercial banks initially find it difficult to serve specific unbanked firm populations.

We contribute to four strands of the literature. First, we provide novel evidence on the impacts of blended finance on firm-level activity. Earlier evidence from Argentina (Paravisini, 2008), France (Bach, 2014) and India (Banerjee and Duflo, 2014) shows how blended finance increased total borrowing of recipient firms, indicating that program loans did not substitute for other forms of credit and that targeted firms were indeed credit constrained. Moreover, the work on India and France also provides evidence of subsequent positive impacts on firm growth. Zia (2008) studies what happens when yarn producers in Pakistan lost access to subsidized export loans. Consistent with binding credit constraints, he finds that this led to a decline of exports by small, private firms but not by (unconstrained) larger, listed firms.

Our contribution is to combine highly granular data from a credit registry and from tax receipts to shed light on the mechanisms through which blended finance helps firms to grow. To the best of our knowledge, the firm-level and regional impacts of blended finance have not been studied at this level of detail before. First, we show how targeted lending not only helps existing bank clients to grow but can also crowd in hitherto financially excluded firms. Second, our analysis reveals important bank-level spatial variation in program impacts. Banks appear to use the program strategically to increase market shares in districts where they lag their competitors. They do so by lending more to existing clients and by poaching clients from other banks.

Second, our work falls within a broader literature investigating the extent to which credit constraints plague small businesses. A number of papers use observational data from across the world to show that smaller firms are more likely to be credit constrained than larger ones. As a consequence, financial development has a stronger positive effect on the growth of such small firms (Demirgüç-Kunt and Maksimovic, 1998; Demirguc-Kunt et al., 2005; Aghion et al., 2007; Ayyagari et al., 2008; Beck et al., 2008). Recent experimental evidence from Sri Lanka (De Mel et al., 2008) and Mexico (McKenzie and Woodruff, 2008) shows that also many microenterprises are financially constrained as they generate high returns on (randomly allocated) capital grants.

We contribute to this literature by analyzing whether and how blended finance can alleviate the credit constraints of small businesses. Our finding that blended finance does not only benefit existing borrowers but can also crowd in entrepreneurs that have never borrowed before, is of interest in light of recent macro-development models that highlight how financial frictions can hold back the entry of productive but poor would-be entrepreneurs (Buera et al., 2011, 2015).

Third, we contribute to the literature on public policies to improve credit access. Various papers focus on the impact of expanding the branch networks of financial intermediaries (Bruhn and Love, 2014; Brown et al., 2016; Agarwal et al., 2017; Carletti et al., 2021). A seminal contribution is Burgess and Pande (2005) who show that a large state-led bank branch expansion program in India reduced rural poverty through increased savings mobilization and credit provision. More recently, Agarwal et al. (2021) assess the impact of the geographic expansion of government-subsidized savings and credit cooperatives in Rwanda. In contrast, rather than studying the expansion of branch networks, we analyze whether governments can reduce firms' credit constraints by channelling more funding through existing branch networks and by training the banks that own these branches.

Fourth, we provide new insights into credit constraints as a brake on female entrepreneurship. While women own the majority of microenterprises in developing countries and emerging markets (Klapper and Parker, 2011) these firms tend to remain small and to underperform male-run enterprises (De Mel et al., 2008; Hardy and Kagy, 2018). A key question is whether this performance gap reflects differential access to credit (that is, supply-side constraints in the form of financial frictions)? On the one hand, there is evidence that women are financially more constrained than men, for example due to discriminatory laws (Naaraayanan, 2020)) or discriminatory lenders (Alesina et al., 2013; Brock and De Haas, 2022). Recent work on India shows how the removal of such barriers to female entrepreneurship can have sizeable positive impacts on aggregate total factor productivity and welfare as (previously sheltered) lower-productivity male-owned firms get replaced by more productive female-run ones (Chiplunkar and Goldberg, 2021). Similar evidence on the macro implications of barriers to female entrepreneurship, in particular financial frictions, exists for the U.S. (Morazzoni and Sy, 2022).

On the other hand, however, there is also evidence that the gender gap in the use of bank credit reflects demand differences. For example, women tend to select into smaller and less-capital intensive firms that require less credit (Demirgüç-Kunt et al., 2008; Aterido et al., 2013). This may reflect deep-rooted cultural norms (Giuliano, 2020) that lead women to forego entrepreneurial opportunities at odds with such norms (Field et al., 2010).

Our contribution here is to report on a large-scale blended finance program in a setting where cultural norms are likely holding back female entrepreneurs as well. Our findings suggest that even in such a setting, where multiple constraints may stymie female enterprise growth, improving the supply of credit can help women-owned businesses to expand.

The remainder of this paper is organized as follows. Section 2 provides more details about the WIB blended finance program. Sections 3 and 4 then describe our data and identification strategy to estimate the impact of blended finance on women entrepreneurs' access to credit. Section 4 provides the related empirical results. Next, Section 5 estimates the impact of the program on real outcomes using firm-to-firm network data. Section 6 concludes.

2 The Women in Business program

Launched in 2014, the Women in Business (WIB) program was a large-scale blended finance framework set up by the European Union, the EBRD, the Turkish Ministry of Labor and Social Security, and the Turkish employment agency İşkur. Its goal was to enable and stimulate Turkish banks to expand lending to women-owned small businesses, especially outside the metropolitan areas of İstanbul, Ankara, and İzmir. The program was developed in recognition of the large and persistent gender gap in financial access across Turkey. According to data for the 2021 Global Findex Database, for example, Turkish men are still more than twice as likely as Turkish women to borrow from a bank. While part of this gap reflects gender differences in the demand for financial services, supply-side constraints play an important role too. Recent evidence shows for example how gender-biased loan officers in Turkey tend to apply discriminatory lending requirements (Brock and De Haas, 2022). The blended finance program was designed to address such frictions, which continue to cause a mismatch between the financial products and lending conditions offered by banks and those demanded by female entrepreneurs.

Like most blended finance frameworks, the program comprised three components: credit lines to banks; a risk-mitigation mechanism in the form of a first loss risk cover; and technical assistance. The first component consisted of credit lines to five participating banks for a total of EUR 300 million. The banks had to on-lend these funds to women-owned small businesses.[7] Over 12,000 female entrepreneurs received part of this funding in the form of small-business loans. Participating banks also supplemented these credit lines with their own funding in order to expand lending further. A total of EUR 417 million had been disbursed to female-owned small businesses by the end of 2017.

Figure 1 shows the geographic footprint of the five participant banks at the district level using data on operational physical branches as of end-2014. Similar to most other banks that operate in Turkey, all five banks serve customers with physical branches spread throughout the country (there are no "local" banks in Turkey). Figure 2 shows the market share of participant banks as measured by their branch presence as of end-2014, indicating that where present, participant banks controlled anywhere between 20% to 60% of all branches within a district.

Figure 3 plots the distribution of female-owned small businesses that benefited from the program. The recipient businesses are not exclusively concentrated in the main cities but are instead spread across most districts. There is nevertheless a skew towards the economically

[7]Four of these banks are commercial non-state banks whereas the fifth is a state lender.

more developed parts of the country in the west and the south. Importantly, because of different negotiation dynamics, not all banks received the program-related funding at the same time. Banks therefore started to disburse WIB sub-loans at different dates. The vertical dashed red lines in Figure 4 indicate when each of the five banks started to lend as part of the program. As discussed in Section 4, this staggered roll-out is part of our identification strategy.

Second, the program contained a EUR 29.4 million first loss risk cover that guaranteed up to 10% of each participating bank's sub-loan portfolio. As such, the cover acted as a temporary incentive for banks to lend to an underserved borrower segment and, in doing so, to learn about women-run businesses' true risk profiles.

Third, the program involved a technical assistance program of consultancy services to help banks to expand lending to women-owned small businesses. Commercial banks may lack the experience to analyze the credit risk of these targeted borrowers and to lend to them profitably. Consultants helped participating bank(s) to enter new market segments (or scale up their existing activity) while managing risks and profitability (Tahir et al., 2021). The aim was to durably change banks' lending practices so that they continue to lend to female-owned enterprises on a fully commercial basis even after having repaid the public credit lines. The technical assistance started with an in-depth analysis of each participating bank's approach to lending to female entrepreneurs. These baseline studies resulted in tailored consultancy packages. Examples include classroom training programs on gender-responsive sales and communication; online training modules for bank staff on gender awareness; and the optimization of Management Information Systems to gather, monitor, and analyze gender-disaggregated lending data. The technical assistance component explicitly focused on the sustainability of the program's impact after it ended. For example, banks received training-of-trainers modules to durably anchor attitudes regarding lending to female entrepreneurs.

Turkey's Women in Business program is far from unique. In fact, a multitude of public development banks have introduced, or are in the process of introducing, similar programs in a wide range of countries. Prominent examples include the International Finance Corporation's (IFC) USD 1.45 billion Women Entrepreneurs Opportunity Facility (rolled out across 33 countries in cooperation with Goldman Sachs) as well as its Banking on Women Programme (USD 3 billion); the African Development Bank's Affirmative Finance Action for Women in Africa (over USD 1.3 billion); the European Investment Bank's SheInvest Program (EUR 2 billion); and the Inter-American Development Bank's Women Entrepreneurship Banking Programme (USD 800 million in 12 countries). In addition, the Women Entrepreneurs Finance Initiative (We-Fi), funded by 14 governments, aims to mobilize over USD 1 billion to be distributed in the form of various types of financial products for women entrepreneurs and women-owned businesses.

3 Empirical strategy

3.1 Data

We use three main data sets for our empirical analysis. The first data set is the national credit registry, which provides loan-level data from all credit institutions in Turkey. The data set contains detailed information on each commercial loan granted to both *capital companies* and *non-capital companies* (or *personal companies*) by all types of banks (including state-owned, private, and foreign) on a monthly basis.[8] There is no minimum threshold for loan size, which is crucial to study borrowing by entrepreneurs and small firms.

We retain all commercial loans granted between January 2014 and March 2020 to personal companies in the data set, which uniquely includes information on gender for this subset of borrowers (by definition, gender is missing for capital companies, since we do not observe

[8] The Turkish Commercial Code classifies companies into two main groups: "capital companies" and "non-capital companies". A capital company is characterised by limited liability, owned by multiple shareholders, and most commonly incorporated as a joint stock company (JSC) or limited liability company (LLC). In contrast, shareholders in a non-capital company have unlimited liability for the company's debts and undertakings. Non-capital companies are typically owned by a single shareholder, who are often self-employed as individual manufacturers, shop-keepers, merchants, tradesmen, craftsmen, or artisans, and incorporated as self-proprietorships. Hence, they are often referred to as "personal companies".

the gender of their shareholders).

The credit registry also provides unique information on whether, and if so when, a firm issued a commercial check, to another firm, that subsequently bounced. Commercial checks are used by especially smaller Turkish companies to pay suppliers. If they bounce, the issuing company is subject to a judicial fine (and a loss of reputation with existing and potential suppliers). The credit registry records all instances of bounced checks and banks have access to this information at the time of a loan application. Banks can therefore assess the *ex ante* riskiness of borrowers by not just checking companies' past defaults on loans but also their inability to meet obligations vis-a-vis customers and suppliers. Using this wealth of information from the credit registry, we construct various time-varying borrower characteristics, such as each individual's relationship history with his/her bank, whether or not they are a first-time borrower, and their loan and check repayment history.

The second data set includes information on domestic firm networks, collected originally by the Ministry of Treasury and Finance for the purposes of calculating and collecting value added tax (VAT). These VAT data cover all domestic firm-to-firm transactions whenever the total transaction value exceeds 5,000 Turkish Liras (around USD 1,600 in 2016) in a given year. This low threshold means that we observe the vast majority of buyer-supplier links in Turkey.

Our third data set contains administrative tax records from the Ministry of Treasury and Finance. It provides company-level balance sheets and income statements at the annual frequency for the universe of businesses liable to pay corporate tax. Since our focus is on small-scale female-owned firms, we retain the tax records of all personal companies. Uniquely, we are able to observe the gender of company owners in this data set, which allows us to track women entrepreneurs who are not necessarily in the credit registry (that is, entrepreneurs without access to credit). The inclusion of tax identification numbers allows us to match the records of entrepreneurs across the three data sets and track them over time.

3.2 Addressing selection into the program

Our main identification strategy exploits the staggered roll-out of the blended finance program and the pre-existing structure of banking markets at the district level. An advantage of such a difference-in-differences setup is that it does not require explicit assumptions on how units select into treatment but instead relies on parallel trends assumptions (Ghanem et al., 2022). Although the dates at which the five banks join the program are quasi-random (due to the different negotiation dynamics and internal bureaucratic checks that each bank had to clear with the main lender), it is important to check whether these five banks differ from other banks prior to the start of the program, at least in terms of their observable characteristics.

Table 1 shows the average values for selected bank characteristics at the national level as of end-2014 for banks that participated in the program ("treated banks") and for banks that did not ("control banks"). The five banks that participated in the blended finance program have, on average, slightly more assets when compared with control banks. As such, they tend to have a higher market share in lending to corporates. However, treated banks look remarkably similar to control banks otherwise, as both groups of banks have comparable levels of liquidity, profitability, non-performing loans, loan-loss reserves, and capital ratios, on average. Despite their greater market shares in lending to corporates, treated banks' market shares in lending to small businesses and entrepreneurs are not much larger than those of control banks. Most importantly, both groups of banks have similar shares of lending to women within that segment.

Although treated banks looked similar to control banks along most dimensions before the program began, this does not guarantee that they were on "parallel trends". Given the small number of banks involved in the program, we employ a synthetic control method to reweigh banks to match treated banks' pre-program trends with control banks' pre-program trends. Specifically, we employ a version of the synthetic difference-in-differences approach of Arkhangelsky et al. (2021) that allows for time staggered adoption of units selecting into treatment and estimate:

$$y_{bt} = \alpha + \beta_1 WIB_b * Post_{bt} + \gamma_b + \delta_t + \epsilon_{bt} \quad (1)$$

where y_{bt} is total lending to female entrepreneurs nationwide by bank b in quarter t. WIB_b indicates the five banks that participated in the blended finance program, $Post_{bt}$ equals 1 from the first quarter when a participant bank starts lending as part of the program onward, and 0 otherwise. β_1 gives us the average treatment effect on the treated (ATT); in other words, the effect on lending to female entrepreneurs for banks that participated in the program. Standard errors are calculated using the "placebo method" as considered in the literature on synthetic controls (Abadie et al., 2010). The main idea of this method is to replace the participant banks with different banks that did not participate and use these placebo predictions to estimate the variance.

This methodology helps weaken the reliance on the stricter parallel trends assumption typically required in a difference-in-differences setting and addresses pretesting concerns. In practice, it finds one set of weights that align pre-program trends in the outcome of untreated banks with those for the treated banks, and another set of weights that align pre-program time periods with post-program ones (Arkhangelsky et al., 2021). These weights are then used in a basic two-way fixed-effects regression to estimate the average causal effect of program participation.[9] In the next section, we will present the results of this methodology first and then turn to our main identification strategy, which utilises variation at the bank-district-time level.

Table 2 presents summary statistics on lending to female entrepreneurs that are aggregated to the bank-branch-quarter level for our sample period of 2014q1-2020q1 based on the credit registry data. Treated banks' district-level lending to female entrepreneurs was comparable on average to that of control banks (Panel A). Over the sample period, they served

[9] In comparison, standard difference-in-differences would estimate the effect of program participation without time or unit weights.

a slightly lower number of female business borrowers when compared with control banks (Panel B). The share of female entrepreneurs in treated banks' portfolios—both in terms of total credit volume and number of all entrepreneurs with access to credit—was comparable to that of control banks (Panels C and D).

3.3 Identification

We exploit the staggered implementation of the blended finance program by each of the five participating banks to identify the effect of the program on access to credit for female entrepreneurs. We aggregate our raw loan level data to the bank-district-time level and estimate the following baseline specification:

$$y_{bdt} = \alpha + \beta_1 WIB_{bd} * Post_{bt} + \beta_2 x_{bt} + \gamma_{bd} + \delta_{dt} + \epsilon_{bdt} \tag{2}$$

where y_{bdt} is total lending to female entrepreneurs by bank b by all of its branches located in district d in quarter t.[10] WIB_{bd} equals 1 for all branches of the five participant banks, and 0 otherwise. As earlier, $Post_{bt}$ equals 1 from the first quarter when a participant bank starts lending as part of the program onward, and 0 otherwise. We control for time-variant bank characteristics in x_{bt}, including liquidity, capital, non-performing loans (NPLs), market share in corporate credit, and total assets, all in logs, and profitability ratios as % of total assets. Bank-district pair fixed effects γ_{bd} control for unobserved and time-invariant factors that might correlate with credit access for women and location-specific bank characteristics. District-time fixed effects δ_{dt} capture time-varying shocks common to all borrowers in a district, such as changes in local economic conditions.

Our main coefficient of interest, β_1, captures the average change in total lending to female entrepreneurs in a district by treated banks following their program start date when compared with lending by control banks. The key identification assumption in this setting

[10] Banks typically serve a district from a single branch except in the most densely populated areas. We assume that potential borrowers in a district have access to all branches within a district.

is that the timing of the program roll-out by participating banks is unrelated to aggregate credit demand by female entrepreneurs due to unobserved factors. A threat to identification would arise if participating banks increase lending to women as part of the blended finance program at a time of increased loan demand specifically by women borrowers. This can arise, for instance, if participating banks have a large branch presence in districts experiencing a positive local economic shock where they also serve many women borrowers.

We carry out the following tests to check the validity of this identifying assumption. First, we test whether the geographic footprint of participating banks' branches differs in any meaningful way from that of the non-participating banks in terms of a district's prevalence of women entrepreneurs in 2014. Second, we test whether women entrepreneurs experience higher sales growth in the year before a bank joins the blended finance program in districts where the bank has a greater physical presence. Third, we estimate Equation (2) with the share of lending to female entrepreneurs in total local lending to all entrepreneurs as a dependent variable. If participating banks primarily serve localities that receive a positive economic shock, then this shock should affect female and male entrepreneurs similarly. As shown in Figure 4, each participating bank starts lending to women entrepreneurs as part of the program in a different quarter sometime between the second quarter of 2015 and the first quarter of 2017. Several recent studies show that in research designs where units start to receive the treatment at different times, the standard two-way fixed effects (TWFE) estimator returns biased estimates when the treatment effect varies across units and time periods (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2020; Cengiz et al., 2019; Borusyak et al., 2021; De Chaisemartin and d'Haultfoeuille, 2020). These studies also introduce event study estimators and suggest new methods to aggregate the average treatment effect on the treated (ATT) across units.

We follow the "stacking" methodology suggested by Cengiz et al. (2019) to tackle the problems that can potentially arise from estimating Equation (2) with the conventional two-way fixed effects estimator.[11] Specifically, for each quarter(-year) that a participant bank joins the program, we construct a cohort of treated and untreated bank-district pairs using the four quarters before and the eight quarters after a bank's program joining date. In each cohort, a treated bank is the participant bank and untreated banks are those that never participated in the blended finance program. We redefine the quarters around the program joining date as relative time indicators, $t \in [-4, 8]$, and then pool the data across all five cohorts to estimate the average treatment effect. We allow bank-district fixed effects, district-time fixed effects, and bank-time controls in Equation (2) to vary by cohort (by interacting each with cohort fixed effects), which is a more conservative approach than including the fixed effects on their own (Gormley and Matsa, 2011). To account for potential correlation in lending to female entrepreneurs across districts and time within a bank, we cluster the standard errors at the bank level.[12]

4 Blended finance and female entrepreneurs' access to credit

4.1 Bank-level analysis

As explained in Section 3.2, the roll-out of the blended finance program proceeded in a staggered fashion: the five participating banks introduced the program at different points in time (Figure 4). Figure 5 provides some first visual evidence of the impact of the program on bank lending. For each of the five participating banks we normalize the quarter in which it introduced the program to *t=0* (indicated by the vertical dotted line). We then plot as an auburn line the change (in percentage points) in the share of these banks' total corporate loan portfolio that is allocated to female entrepreneurs. Likewise, the blue line shows the development of the share of female corporate lending among the control group of never-treated Turkish banks. It is noteworthy that there is no time trend in the gender allocation

[11] The same methodology was earlier applied by Gormley and Matsa (2011) in the finance literature.

[12] Clustering alternatively at the level of bank branches or districts leads to more conservative estimates of the variance (unreported).

of corporate lending among control banks. In contrast, we find a clear and persistent increase of 1 percentage point (equivalent to an increase of 11%) in the share of lending to female entrepreneurs by treated banks.

This simple visualisation does not take into account that treated banks may have been on a different time trend regarding lending to female entrepreneurs and it compares treated banks to all other banks in the country. To control for common time trends more precisely and get as close as possible to a comparison of similar banks, we present the results of the synthetic DID estimation in Table 3. This estimation procedure compares treated banks to a weighted average of control banks that are similar in terms of lending to women entrepreneurs before a treated bank joins the program. We find that the estimated average treatment effect on treated banks is positive and statistically significant for both the volume of credit extended to female entrepreneurs, the number of female entrepreneurs who have access to credit, and the share of women in the total loan portfolio (panels A-C, column 1).

Specifically, the SDID estimate suggests that the share of female entrepreneurs in total lending to small businesses was 1.9 percentage points higher for treated banks after their participation in the program when compared with a synthetically created control bank that had a similar trend of lending to women before the program. Columns (2)-(5) present SDID estimates by type of female clients. The effect is stronger for poached borrowers than for repeat borrowers, and it is strongest – at 3.8 percentage points – for first-time borrowers.

The results from the synthetic DID estimation give us confidence that, in the absence of program participation, treated banks were unlikely to be subject to shocks that might shift their risk preferences or capacity for lending to women differently from control banks. Indeed, Abadie et al. (2010) show that a primary reason to use a synthetic control method is to account for the effect of unobservable factors that have an impact on the common time trend in the treatment and control groups.

4.2 District-level analysis

We now proceed with the estimation of average treatment effects using the "stacking" methodology for Equation (2). We estimate the effect of the blended finance program on the (log) total amount of lending to female entrepreneurs as well as the (log) total number of unique female business borrowers. Table 4 shows that after the start of the blended finance program, treated banks increase their lending to female entrepreneurs—on average and across districts—by 34.8% more than never-treated control banks (Panel A, column 1). At the same time, they increase the (log) number of female business borrowers by 15.7% more than control banks. These impacts are large, significant at the 1% statistical level, and based on regressions saturated with the full battery of bank-level controls as well as bank-district fixed effects and district-quarter fixed effects (all interacted further with cohort fixed effects).

The event-study plots in Figure 6 reveal how these estimated treatment effects vary over time. We exclude the quarter before a bank enters the program as our reference period. Reassuringly, trends in the outcome variables appear parallel in the pre-treatment period, reducing worries that treatment and control banks would have displayed different lending patterns in the absence of the program. Moreover, the magnitude of the quarterly treatment effects closely matches the baseline TWFE estimates of Table 4. The treatment effects appear to be persistent over time as well, at least within the two-year treatment horizon for which we have data available.

An important follow-up question is where treated banks source the female entrepreneurs they start lending to once they enter the blended finance program? Three distinct—though not mutually exclusive—mechanisms are possible, each with very different implications for local entrepreneurs. First, banks can simply start to lend more to their existing female clients. This could further relax the credit constraints of these repeat borrowers (and possibly affect their performance, something we investigate in Section 5). This scenario would, however, not involve the crowding in of female entrepreneurs that previously could not access credit. Second, banks can poach existing borrowers from other banks. In this case, inter-bank competition will increase and loan terms may improve for those borrowers who switch lenders. Yet, the total number of female borrowers will not increase in this scenario either. Third, banks may start to lend to first-time borrowers: female entrepreneurs who have never taken out a business loan before. Only in this scenario does the pool of female business borrowers deepen as a result of the direct lending intervention.

Because we have access to time-series information on the complete universe of Turkish business borrowers, we can disentangle these potential mechanisms and quantify their relative importance. To do so, we use the credit registry to classify each bank's borrowers as either repeat borrowers or new ones. Repeat borrowers received at least one loan during the treatment period and had also received at least one loan from the same bank in the pre-treatment period (the latter starts in 2006 when the credit registry was introduced). In contrast, new borrowers are those who received at least one loan from a treated bank during the treatment period but had never borrowed from that bank before. We further divide these new borrowers into new-to-bank borrowers and first-time borrowers. While new-to-bank borrowers never borrowed from that particular bank in the pre-treatment period, they *did* borrow from one or several other banks in the past. In contrast, first-time borrowers not only borrow for the first time from a particular treatment bank but had never borrowed from *any* bank in the past.[13] These are therefore new entrants into the credit market.

Columns 2 and 3 of Table 4 show that the introduction of the blended finance program led participating banks to lend more to both repeat and new borrowers. In fact, the impact on lending to new borrowers was especially large in terms of the amount of lending (Panel A) but less so in terms of the number of new borrowers (Panel B). This indicates that while the program led to an expansion of treated banks' lending to female entrepreneurs at the intensive margin (repeat borrowers), it also expanded these banks' portfolio at the extensive margin by crowding in new clients. Columns 4 and 5 of Table 4 estimate separate impacts for new-to-bank borrowers and first-time borrowers. The results show that the program

[13] The credit registry goes back to 2003, so we check each borrower's history going back to this year to determine if they are a first-time borrower or not.

impacted lending to both types of new clients to a similar extent.

In sum, Table 4 reveals how, due to the blended finance program, banks expanded their lending to female businesses—both in terms of loan volume and in terms of borrower numbers—at the intensive as well as the extensive margins. In Table 5, we now investigate whether there was also a measurable effect on the amount of lending to women relative to male entrepreneurs. That is, did the program lead to a change in the gender allocation of total entrepreneurial lending, as suggested earlier by Figure 5?

Column 1 of Table 5 shows that, across treated banks and districts, and as a result of the program, treated banks increased the portion of all business lending allocated to women by 1 percentage point on average (Panel A). This is in line with the effect size suggested by Figure 5. It is also an economically meaningful effect (an increase of 11%), given that treated banks allocated only around 9% of their total lending to female entrepreneurs in 2014.

Columns 2 to 5 show that this increase in the portion of lending allocated to women entrepreneurs is mainly driven by lending to new borrowers (0.7 percentage points), especially first-time borrowers that had never before borrowed from any bank (0.3 percentage points, column 5). That is, while absolute amounts of lending increased across all borrower types (Table 4), the shift in the gender allocation was strongest for new borrowers that were crowded into the credit market for the first time. These borrowers accounted for 30% of the increase in the share of female entrepreneurs in lending to all entrepreneurs, while new-to-bank borrowers accounted for a further 30%.

Similarly, column 1 in Panel B shows that treated banks increase the share of female borrowers among all entrepreneurs with access to credit by 0.9 percentage points. This increase is again mainly driven by new borrowers, especially first-time borrowers who account for 44% (=0.004/0.009) of this effect. Figure 7 displays the related dynamic treatment effects on the share of lending allocated to female businesses (top chart) and the share of female businesses among all borrowers (bottom chart) as event-study plots. We again find no pre-trends but sustained treatment effects of a similar magnitude as in Figure 5 and Table 5.

4.3 District-level heterogeneity

Existing models of strategic information acquisition in credit markets suggest that banks acquire proprietary information both to soften lending competition and to extend their market share (Hauswald and Marquez, 2006). Our context of lending to female entrepreneurs is an interesting setting to examine where treated banks invest differently in information acquisition. On the one hand, credit to small businesses crucially relies on firm-specific subjective intelligence collected by loan officers during the origination process and as part of long-term lending relationships (Agarwal and Hauswald, 2010). On the other hand, banks may consider female entrepreneurs more opaque than male entrepreneurs given the historical gap in access to credit between men and women, which may make it more costly for banks to acquire and process information about female entrepreneurs.

In this sub-section, we analyze whether the positive effect of the blended finance program on lending to female entrepreneurs is homogeneous across districts or instead spatially variegated. We build on our main specification in Equation 2 and introduce an interaction term, $WIB_{bd} * Post_{bt} * Market\ Share_{bd}$, where $Market\ Share_{bd}$ captures the pre-treatment (i.e. end-2014) market share of lending to women for each bank in the relevant district. We define these local bank-level market shares by using either lending volumes or number of female borrowers in alternative specifications.

Table 6 shows the results of this exercise when the dependent variable is (log) total loan volume to female entrepreneurs (Panels A and B) or (log) number of female entrepreneurs (Panels C and D). Our results are broadly similar regardless of the definition of market share. We find that after the start of the program, treated banks increase lending to women by 23 to 29% more than never-treated control banks in districts where they have a relatively low pre-program market share of 10%, compared with 13 to 19% in districts where they already had a market share of 20% (Panels A and B, column 1). Similarly, the number of female entrepreneurs they reached after the start of the program was 15-17% higher in districts where they had an initial market share of 10%, compared with 9-10% in districts where they had a market share of 20% (Panels C and D, column 1).

Our market share measures are based on credit to female entrepreneurs only. This masks the possibility that banks have different strategic incentives when it comes to their market position for lending to male entrepreneurs. If it is costly to invest in information acquisition (or to offer products) differentiated by borrower gender, then banks' lending to female entrepreneurs might mimic their lending to male entrepreneurs. To account for this possibility, Table 7 shows results from estimating Equation (2) with our interaction term when the dependent variable is the share of all business lending allocated to female entrepreneurs.

We find that after the start of the blended finance program, treated banks increase the portion of all business lending allocated to women by 0.9-1.15 percentage points in districts where they initially had lower market shares, and only marginally by around 0.3 percentage points in districts where they initially had high market shares, when compared with never-treated control banks (Panels A and B, column 1). This shows that treated banks tilt their loan portfolios towards greater inclusion of women only in districts where they were lagging the market in lending to female entrepreneurs. They have done so especially by increasing lending to their repeat borrowers and by poaching other banks' customers (columns 2-4).

These results suggest that treated banks used the program strategically to invest in information acquisition and to increase their market shares only in locations where they were initially lagging their competitors. However, the evidence does not suggest that banks focused their information acquisition on certain types of borrowers in these locations. Instead, the program seems to have led banks to acquire further information on both borrowers already in the credit system, who are presumably easier to assess given their credit history, and first-time borrowers without a credit history. Our findings therefore suggest that treated banks increased their risk appetite and reached first-time borrowers in districts where they were lagging their competitors.

4.4 First-time borrowers analysis

How do female entrepreneurs that gain first-time access to credit due to the blended finance program fare in the long run? Do they stay with their original / parent banks, which enabled them to take out their first loan, or do they switch to competitor banks in search of better credit terms? To answer these questions, we focus on a sample of first-time borrowers who enter the financial system through treated banks following each of the five banks' entry into the program. We compare these women to similar first-time female business borrowers that enter the financial system through control banks in cross-sectional regressions. Specifically, we estimate:

$$y_{i(b)dz} = \beta * \textit{First-time WiB borrower}_{i(b)dz} + FE_{bd} + FE_{dz} + \epsilon_{i(b)dz} \tag{3}$$

where $y_{i(b)dz}$ captures the ex-post outcomes of first-time female business borrower i who obtained her first-ever loan from a bank b in district d in quarter z.[14] $\textit{First-time WiB borrower}_{i(b)dz}$ is an indicator that equals 1 if the borrower obtained her first-ever loan from a treated bank, and 0 if she obtained it from a control bank. We include bank-district fixed effects to capture any local unobserved heterogeneity in the characteristics of first-time borrowers that individual banks may be targeting regardless of time. We further include district-quarter dummies to account for unobservable characteristics of all first-time borrowers entering the system in a certain locality and time period (e.g. to control for local supply shocks that might affect all female entrepreneurs similarly). Identification then comes from comparing first-time female business borrowers who enter the system via treated vs. control banks in the same district and quarter.

To understand ex-post performance, we focus on outcomes in the eight quarters following female business borrowers' entry into the system (shown in columns 1 to 6 of Table 8). We define *New banking relationship*, which equals 1 if the female entrepreneur goes on to establish

[14] Note that each female business borrower i who enters the financial system does so only through one bank b.

a new banking relationship within the eight quarters after she joins the system through her parent bank, and 0 if she does not take out a loan from a new bank. We find that women who enter the financial system with a treated bank following the program are 17.7 percentage points more likely than women who enter the system with a control bank to establish at least one new banking relationship in the future (column 1). We do not find any evidence that they are more likely to switch from their parent banks to their new banks completely (column 2), meaning that any new banking relationship helps them to increase their debt capacity (and potentially improve on their original credit terms from their parent bank). When we define $y_{i(b)dz}$ to be the *Loans from parent bank* and *Loans from new banks* in columns (3) and (4), respectively, of Table 8, we find that first-time borrowers of treated banks go on to obtain an extra quarter of a loan, on average, from a new bank when compared with female entrepreneurs who get a first-time loan from a control bank. These findings suggest that blended finance helps banks to reach a certain type of female business borrowers and serve as a "gateway" for durable financial inclusion.

In the final two columns of Table 8, we check the ex-post riskiness of first-time female business borrowers. We define *Check default*, which equals 1 if a borrower fails to meet the obligations of any commercial checks that she writes to her suppliers, and 0 otherwise, over the eight quarters since she first took out a business loan. Similarly, we define *Loan default*, which equals 1 if a borrower defaults on any of her loan obligations. In each case, we do not find any evidence that first-time treated borrowers differ in any statistically significant way from first-time control borrowers.

Our results from the previous sub-section indicated that treated banks were potentially increasing their risk exposure to reach women who were previously under-served by the financial system. The results in this sub-section show that lending to these women do not necessarily translate into greater ex-post risk. Hence, our findings suggest that the program may have helped banks to overcome the imperfect observability of borrower quality in the check registry and reach customers who could signal their soft information.[15]

5 The impact of blended finance on real outcomes

Consider the following cross-sectional regression:

$$y_{idt} = \alpha + \beta_1 WIB_{idt} + \beta_2 x_{idt} + \gamma_t + \epsilon_{idt} \tag{4}$$

where y_{idt} is an outcome (e.g. firm survival, change in sales) for entrepreneur i located in district d who took out a loan in year t. Changes in outcomes are defined as the (log) difference between the year in which a loan was issued (t) and the following three years: $t+1$, $t+2$, $t+3$. x_{idt} is a set of firm or entrepreneur characteristics including total assets (in logs), entrepreneur age (in logs), and ratios of total liabilities, bank loans, current assets, tangible fixed assets and net sales to total assets, all measured in 2014. γ_t captures year dummies for loan cohorts.

We define $WIB_{idt} = 1$ as female entrepreneurs who have access to a loan during the sample period from a treated bank. The control group, $WIB_{idt} = 0$, consists of all female entrepreneurs who have access to a loan during the sample period only from a never-treated bank (i.e. such entrepreneurs did not have access to a loan from a treated bank during the sample period).

We use matching to ensure that female entrepreneurs who are in the control group were similar to those who borrowed from a treated bank before the blended finance program began. Specifically, we select a control group of companies using a combination of exact and propensity score matching, subject to the restriction on their access to credit mentioned

[15] This contrasts with recent findings from Bosnia & Herzogovina (Augsburg et al., 2015), where loan officers from a microfinance institution were asked to identify a group of slightly more-risky-than-usual loan applicants and to lend to a random subset of half of these. Loan quality among these marginal clients was significantly lower than among inframarginal clients receiving credit at the same time. This suggests that loan officers were already lending at the right risk-return margin or that they were unable to profitably expand the lending frontier without receiving proper training (which was, in contrast, an integral part of the program).

above. We ensure that controls are matched exactly on province and loan year, while we calculate propensity scores based on asset size, entrepreneur age, total liabilities, tangibility, dummies indicating ex-ante cheque and credit defaults, and squared terms of these characteristics, all measured in 2014. We also include changes between 2013 and 2014 (or $x_{t-1} - x_{t-2}$) in assets in the matching procedure; this helps ensure that matched controls are on similar growth paths as treated companies. We impose common support and retain a single control firm for each treated female entrepreneur with a propensity score in a 10% bandwidth.

Table 8 shows estimates when the control group consists of female entrepreneurs who had access to credit from a never-treated bank during the sample period. Relative to this comparison group, female entrepreneurs with a loan from a treated bank are more likely to survive by 1.5 percentage points a year from their initial loan, but this survival probability climbs to 4.1 percentage points two years in, and to 6.1 percentage points three years in (column 1). Likewise, the program has a small impact on sales (column 2), a negligible impact on customer numbers (column 3), and again a small impact on suppliers (column 4) in the short term. But these effects grow in size over time. Female entrepreneurs borrowing from a treated bank increase sales by 11.1%, customers by 8.1%, suppliers by 7.1%, and total purchases from suppliers by 12.9% three years from the initial time of their loan, when compared with women who have access to credit from a never-treated bank.

6 Conclusion

Blended finance via commercial banks has grown in popularity in recent years to alleviate financial frictions faced by particular segments of society and make access to credit more equal. In this paper, we evaluated a large-scale blended finance program aimed at increasing financial access for female entrepreneurs in Turkey. Drawing on several administrative data sets and covering the period 2014-19, we find that the program durably increased lending to female entrepreneurs. Importantly, we show that when public funds are channeled through private banks, existing regional variation in the banking landscape determines where these funds are being disbursed (and have an impact). In particular, we find that lending to female entrepreneurs increased especially in districts where banks participating in the program initially had lower market shares in the credit market for female entrepreneurs. In such districts, participant banks increased lending especially to their existing clients but also poached clients from other banks. In contrast, they crowded in female entrepreneurs who borrow for the first time into the system only in districts where they were market leaders. Hence, the effect of the blended finance program vary quite a bit across locations based on local credit market competition.

Our results suggest that increased access to credit as part of the program helped female entrepreneurs grow their companies and increase their chances of survival. However, we should note that our current methodology does not allow us to differentiate between the two main mechanisms through which such a positive impact can be realised. The first mechanism is that treated banks may be better at selecting entrepreneurs who are already on track to grow their companies. If such selection occurs based on soft information, which is observed to banks participating in the program but unobserved to the econometrician, then we may over-estimate the true impact of the program. The second mechanism is that treated banks do not actually lend to women who are ex ante on (or in anticipation of) a different trajectory to women borrowing from never-treated banks, but rather they offer different loan terms to their borrowers, which enable their companies to grow. Future research can help shed light on whether blended finance adds value more through better selection of traditionally under-represented entrepreneurs or through the improvement of existing borrowing conditions.

References

Abadie, A., Diamond, A., and Hainmueller, J. (2010). Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. *Journal of the American Statistical Association*, 105(490):493–505.

Agarwal, S., Alok, S., Ghosh, P., Ghosh, S., Piskorski, T., and Seru, A. (2017). Banking the Unbanked: What do 255 Million New Bank Accounts Reveal about Financial Access? *Columbia Business School Research Paper*, (17-12).

Agarwal, S. and Hauswald, R. (2010). Distance and Private Information in Lending. *Review of Financial Studies*, 23(7):2757–2788.

Agarwal, S., Kigabo, T., Minoiu, C., Presbitero, A., and Silva, A. F. (2021). Serving the Underserved: Microcredit as a Pathway to Commercial Banks. *Review of Economics and Statistics*, forthcoming.

Aghion, P., Fally, T., and Scarpetta, S. (2007). Credit Constraints as a Barrier to the Entry and Post-Entry Growth of Firms. *Economic Policy*, 22(52):732–779.

Alesina, A. F., Lotti, F., and Mistrulli, P. E. (2013). Do Women Pay More for Credit? Evidence from Italy. *Journal of the European Economic Association*, 11(s1):45–66.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W., and Wager, S. (2021). Synthetic Difference-in-Differences. *American Economic Review*, 111(12):4088–4118.

Arping, S., Lóránth, G., and Morrison, A. D. (2010). Public Initiatives to Support Entrepreneurs: Credit Guarantees versus Co-funding. *Journal of Financial Stability*, 6(1):26–35.

Aterido, R., Beck, T., and Iacovone, L. (2013). Access to Finance in Sub-Saharan Africa: Is There a Gender Gap. *World Development*, 47:102–120.

Augsburg, B., De Haas, R., Harmgart, H., and Meghir, C. (2015). The Impacts of Microcredit: Evidence from Bosnia and Herzegovina. *American Economic Journal: Applied Economics*, 7(1):183–203.

Ayyagari, M., Demirgüç-Kunt, A., and Maksimovic, V. (2008). How Important are Financing Constraints? The Role of Finance in the Business Environment. *World Bank Economic Review*, 22(3):483–516.

Bach, L. (2014). Are Small Businesses Worthy of Financial Aid? Evidence from a French Targeted Credit Program. *Review of Finance*, 18(3):877–919.

Banerjee, A. V. and Duflo, E. (2014). Do Firms Want to Borrow More? Testing Credit Constraints using a Directed Lending Program. *Review of Economic Studies*, 81(2):572–607.

Beck, T., Demirgüç-Kunt, A., and Maksimovic, V. (2005). Financial and Legal Constraints to Growth: Does Firm Size Matter? *Journal of Finance*, 60(1):137–177.

Beck, T., Demirgüç-Kunt, A., and Maksimovic, V. (2008). Financing Patterns around the World: Are Small Firms Different? *Journal of Financial Eonomics*, 89(3):467–487.

Bircan, C. and Saka, O. (2021). Lending Cycles and Real Outcomes: Costs of Political Misalignment. *Economic Journal*, 131(639):2763–2796.

Borusyak, K., Jaravel, X., and Spiess, J. (2021). Revisiting Event Study Designs: Robust and Efficient Estimation. *Available at SSRN 2826228*.

Brock, M. and De Haas, R. (2022). Discriminatory Lending: Evidence from Bankers in the Lab. *American Economic Journal: Applied Economics*, forthcoming.

Brown, M., Guin, B., and Kirschenmann, K. (2016). Microfinance Banks and Financial Inclusion. *Review of Finance*, 20(3):907–946.

Bruhn, M. and Love, I. (2014). The Real Impact of Improved Access to Finance: Evidence from Mexico. *Journal of Finance*, 69(3):1347–1376.

Buera, F. J., Kaboski, J. P., and Shin, Y. (2011). Finance and Development: A Tale of Two Sectors. *American Economic Review*, 101(5):1964–2002.

Buera, F. J., Kaboski, J. P., and Shin, Y. (2015). Entrepreneurship and Financial Frictions: A Macrodevelopment Perspective. *Annual Review of Economics*, 7(1):409–436.

Burgess, R. and Pande, R. (2005). Do Rural Banks Matter? Evidence from the Indian Social Banking Experiment. *American Economic Review*, 95(3):780–795.

Callaway, B. and Sant'Anna, P. H. C. (2020). Difference-in-differences with Multiple Time Periods. *Journal of Econometrics*.

Calomiris, C. W., Larrain, M., Liberti, J., and Sturgess, J. (2017). How Collateral Laws Shape Lending and Sectoral Activity. *Journal of Financial Economics*, 123(1):163–188.

Carletti, E., Senbet, L., Cull, R., Allen, F., Qian, Q., and Valenzuela, P. (2021). Improving Access to Banking: Evidence from Kenya. *Review of Finance*, forthcoming.

Carpenter, R. E. and Petersen, B. C. (2002). Is the Growth of Small Firms Constrained by Internal Finance? *Review of Economics and statistics*, 84(2):298–309.

Carvalho, D. (2014). The Real Effects of Government-owned Banks: Evidence from an Emerging Market. *Journal of Finance*, 69(2):577–609.

Cengiz, D., Dube, A., Lindner, A., and Zipperer, B. (2019). The Effect of Minimum Wages on Low-wage Jobs. *Quarterly Journal of Economics*, 134(3):1405–1454.

Chiplunkar, G. and Goldberg, P. K. (2021). Aggregate Implications of Barriers to Female Entrepreneurship. Technical report, National Bureau of Economic Research.

Claessens, S. and Laeven, L. (2004). What Drives Bank Competition? Some International Evidence. *Journal of Money, Credit and Banking*, pages 563–583.

De Chaisemartin, C. and d'Haultfoeuille, X. (2020). Two-way Fixed Effects Estimators with Heterogeneous Treatment Effects. *American Economic Review*, 110(9):2964–96.

De Mel, S., McKenzie, D., and Woodruff, C. (2008). Returns to Capital in Microenterprises: Evidence from a Field Experiment. *Quarterly Journal of Economics*, 123(4):1329–1372.

Demirgüç-Kunt, A., Beck, T., and Honohan, P. (2008). *Finance for All?: Policies and Pitfalls in Expanding Access*. World Bank Policy Research Report, World Bank, Washington, D.C.

Demirgüç-Kunt, A., Klapper, L. F., and Singer, D. (2013). Financial Inclusion and Legal Discrimination against Women: Evidence from Developing Countries. World Bank Policy Research Working Paper No. 6416, Washington D.C.

Demirgüç-Kunt, A. and Maksimovic, V. (1998). Law, Finance, and Firm Growth. *Journal of Finance*, 53(6):2107–2137.

Demirguc-Kunt, A., Maksimovic, V., and Beck, T. (2005). Financial and Legal Constraints to Firm Growth: Does Size Matter? *Journal of Finance*, 60:125–139.

Detragiache, E., Tressel, T., and Gupta, P. (2008). Foreign Banks in Poor Countries: Theory and Evidence. *Journal of Finance*, 63(5):2123–2160.

Dinç, I. S. (2005). Politicians and Banks: Political Influences on Government-owned Banks in Emerging Markets. *Journal of Financial Economics*, 77(2):453–479.

Eslava, M. and Freixas, X. (2016). Public Development Banks and Credit Market Imperfections. *Journal of Money, Credit and Banking*.

Field, E., Jayachandran, S., and Pande, R. (2010). Do Traditional Institutions Constrain Female Entrepreneurship? A Field Experiment on Business Training in India. *American Economic Review*, 100(2):125–29.

Ghanem, D., Sant'Anna, P. H., and Wüthrich, K. (2022). Selection and parallel trends. *arXiv preprint arXiv:2203.09001*.

Giuliano, P. (2020). Gender and Culture. *Oxford Review of Economic Policy*, 36(4):944–961.

Goodman-Bacon, A. (2021). Difference-in-differences with Variation in Treatment Timing. *Journal of Econometrics*.

Gormley, T. A. and Matsa, D. A. (2011). Growing out of Trouble? Corporate Responses to Liability Risk. *Review of Financial Studies*, 24(8):2781–2821.

Gutierrez, E., Rudolph, H. P., Homa, T., and Beneit, E. B. (2011). Development Banks: Role and Mechanisms to Increase their Efficiency. *World Bank Policy Research Working Paper*, (5729).

Hainz, C. and Hakenes, H. (2012). The Politician and His Banker: How to Efficiently Grant State Aid. *Journal of Public Economics*, 96(1-2):218–225.

Hardy, M. and Kagy, G. (2018). Mind the (Profit) Gap: Why are Female Enterprise Owners Earning Less than Men? *AEA Papers and Proceedings*, 108:252–55.

Hauswald, R. and Marquez, R. (2006). Competition and Strategic Information Acquisition in Credit Markets. *The Review of Financial Studies*, 19(3):967–1000.

Hsieh, C.-T. and Klenow, P. J. (2009). Misallocation and Manufacturing TFP in China and India. *Quarterly Journal of Economics*, 124(4):1403–1448.

Jaffee, D. M. and Russell, T. (1976). Imperfect Information, Uncertainty, and Credit Rationing. *Quarterly Journal of Economics*, 90(4):651–666.

Jiménez, G., Peydró, J.-L., Repullo, R., and Saurina Salas, J. (2018). Burning Money? Government Lending in a Credit Crunch. CEPR Discussion Paper No. DP13267, Center for Economic Policy Research, London.

Khwaja, A. I. and Mian, A. (2005). Do Lenders Favor Politically Connected Firms? Rent Provision in an Emerging Financial Market. *Quarterly Journal of Economics*, 120(4):1371–1411.

Klapper, L. F. and Parker, S. C. (2011). Gender and the Business Environment for New Firm Creation. *World Bank Research Observer*, 26(2):237–257.

La Porta, R., Lopez-de Silanes, F., and Shleifer, A. (2002). Government Ownership of Banks. *Journal of Finance*, 57(1):265–301.

La Porta, R., Lopez-de Silanes, F., Shleifer, A., and Vishny, R. W. (1998). Law and Finance. *Journal of Political Economy*, 106(6):1113–1155.

McKenzie, D. and Woodruff, C. (2008). Experimental Evidence on Returns to Capital and Access to Finance in Mexico. *World Bank Economic Review*, 22(3):457–482.

Morazzoni, M. and Sy, A. (2022). Female Entrepreneurship, Financial Frictions, and Capital Misallocation in the US. *Journal of Monetary Economics*, 129(C):93–118.

Naaraayanan, S. L. (2020). Women's Inheritance Rights and the Entrepreneurship Gap. *mimeo*.

Pagano, M. and Jappelli, T. (1993). Information Sharing in Credit Markets. *Journal of Finance*, 48(5):1693–1718.

Panizza, U. (2021). State-Owned Commercial Banks. CEPR Discussion Paper No. DP16259, Center for Economic Policy Research, London.

Paravisini, D. (2008). Local Bank Financial Constraints and Firm Access to External Finance. *Journal of Finance*, 63(5):2161–2193.

Petersen, M. A. and Rajan, R. G. (1994). The Benefits of Lending Relationships: Evidence from Small Business Data. *Journal of Finance*, 49(1):3–37.

Rajan, R. and Zingales, L. (1998). Financial Development and Growth. *American Economic Review*, 88(3):559–586.

Sapienza, P. (2004). The Effects of Government Ownership on Bank Lending. *Journal of Financial Economics*, 72(2):357–384.

Shleifer, A. and Vishny, R. W. (1994). Politicians and Firms. *Quarterly Journal of Economics*, 109(4):995–1025.

Stiglitz, J. E. and Weiss, A. (1981). Credit Rationing in Markets with Imperfect Information. *American Economic Review*, 71(3):393–410.

Tahir, W., Girod, T., Rex, P., and Belot, P. (2021). Directed Lending: Current Practices and Challenges. CDC Discussion Paper, CDC, London.

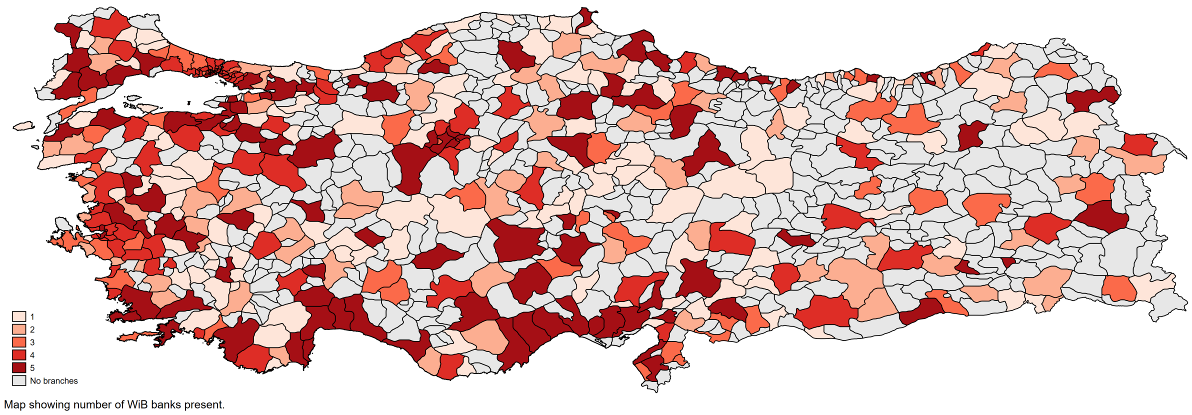
World Bank (2005). OED Review of Bank Lending for Lines of Credit. Report No. 31131, Washington, D.C.

World Bank (2014). The Big Business of Small Enterprises. Evaluation of the World Bank Group Experience with Targeted Support to Small and Medium-size Enterprises. Report of the World Bank Group Independent Evaluation Group.

World Bank (2018). 2017 Survey of National Development Banks. World Bank Report No. 102017-TR, Washington, D.C.

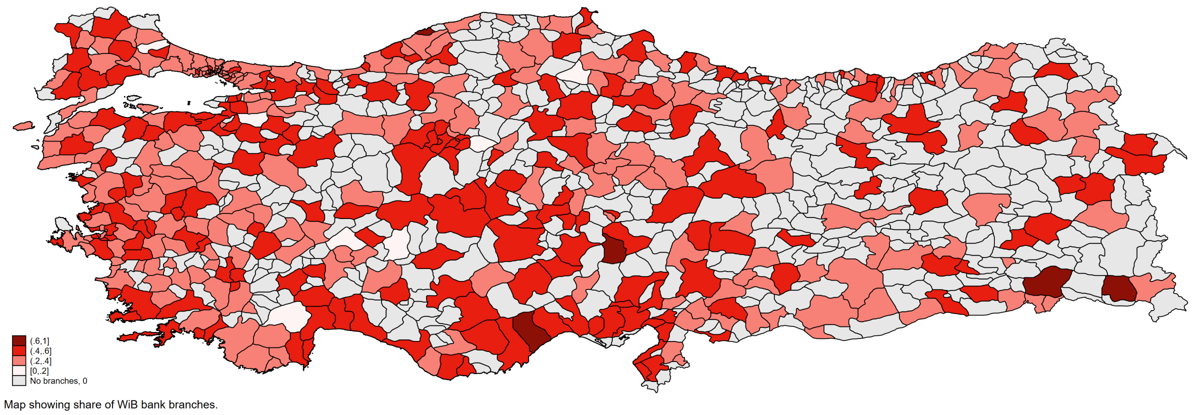
Zia, B. H. (2008). Export Incentives, Financial Constraints, and the (Mis)Allocation of Credit: Micro-level Evidence from Subsidized Export Loans. *Journal of Financial Economics*, 87(2):498–527.

Figure 1: Branch presence of WiB banks, 2014



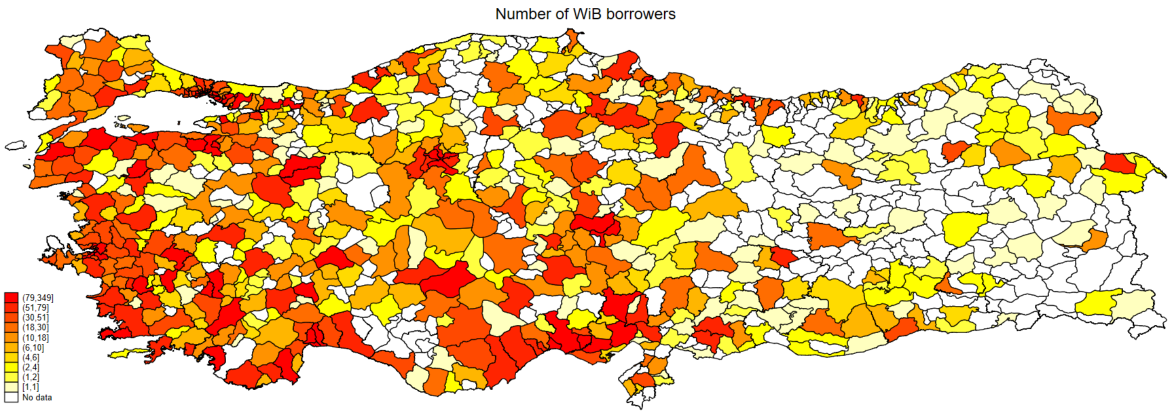
Notes: This figure shows, at the district level, how many of the WiB banks operated at least one physical branch as of end-2014.

Figure 2: Share of bank branches operated by WiB banks, 2014



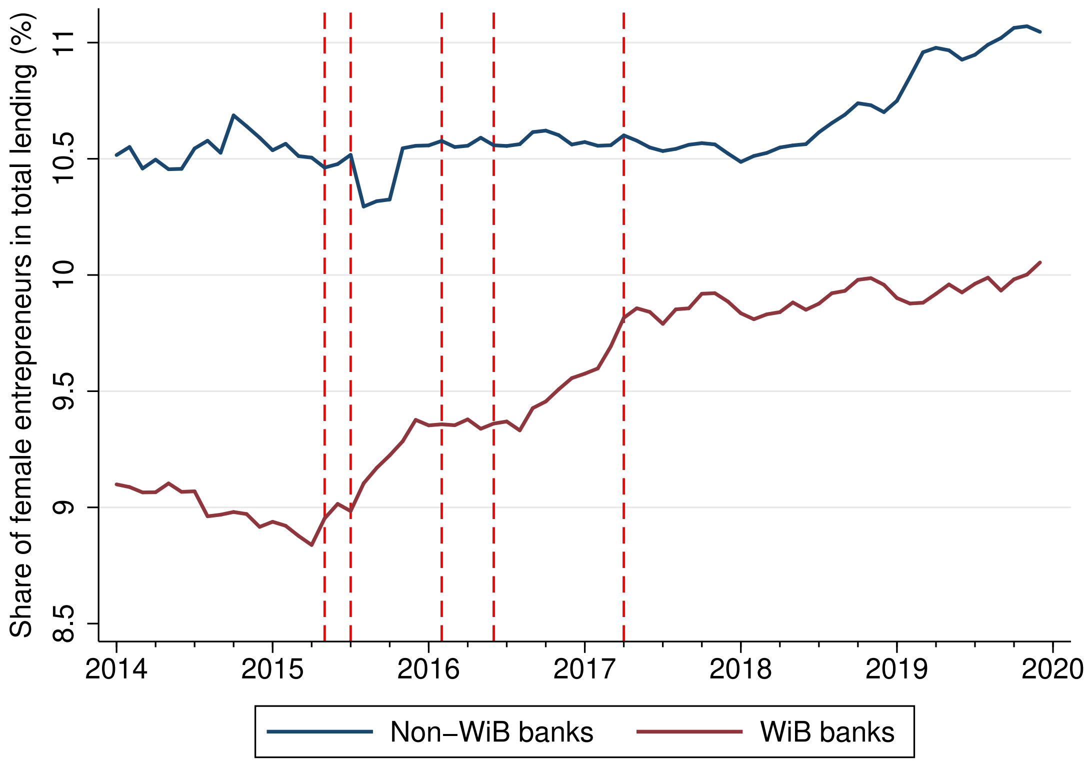
Notes: This figure shows, at the district level, the share of all bank branches that are operated by WiB banks as of end-2014.

Figure 3: Spatial distribution of female business borrowers of treated banks who participated in the WiB programme



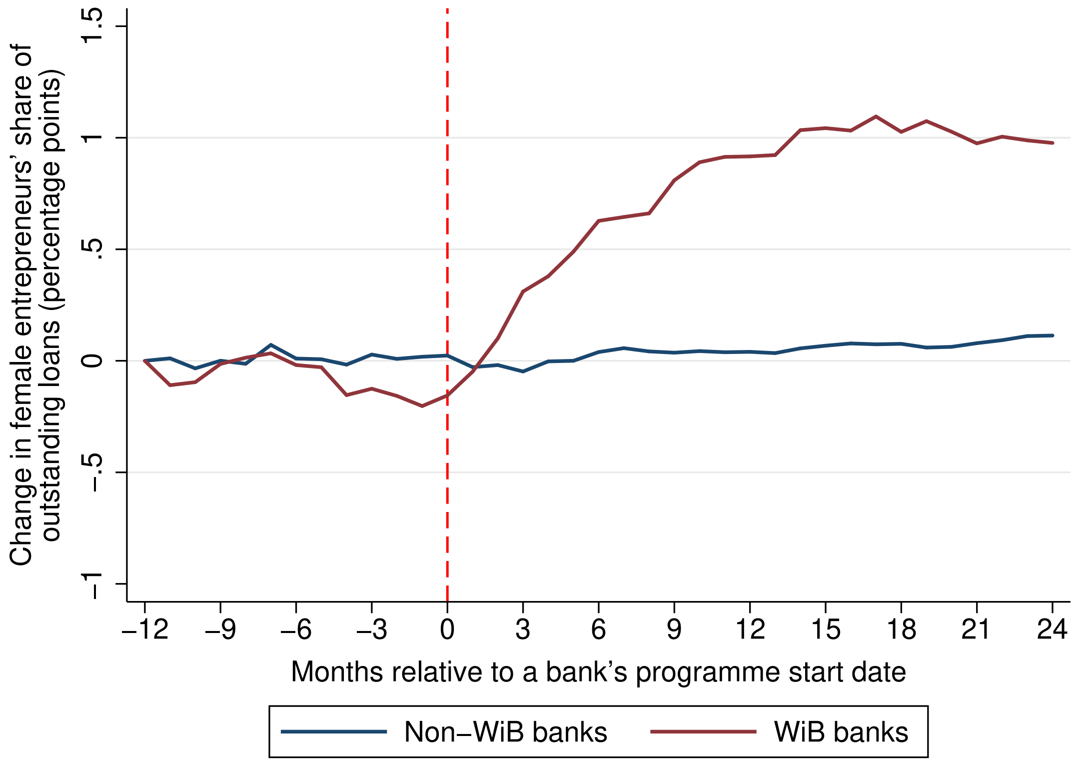
Notes: This figure shows, at the district level, the total number of female entrepreneurs who took out at least one loan from a WiB bank during the sample period as part of the WiB program.

Figure 4: Staggered roll-out of WiB credit program and the share of lending to female entrepreneurs



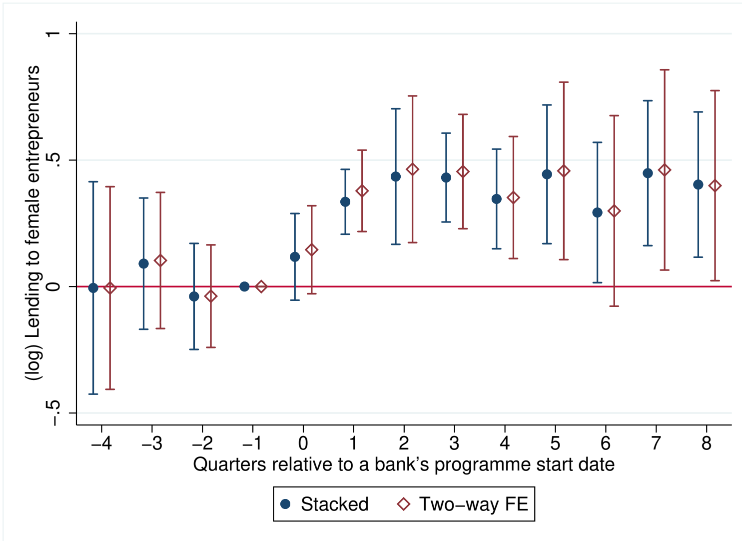
Notes: This figure shows the share of female entrepreneurs in lending to all entrepreneurs during the sample period. Vertical dashed lines indicate when each of the five banks that participated in the WiB program disbursed their first loan as part of the program: May 2015, July 2015, February 2016, June 2016, and April 2017.

Figure 5: Change in the share of lending to female entrepreneurs around WiB programme dates

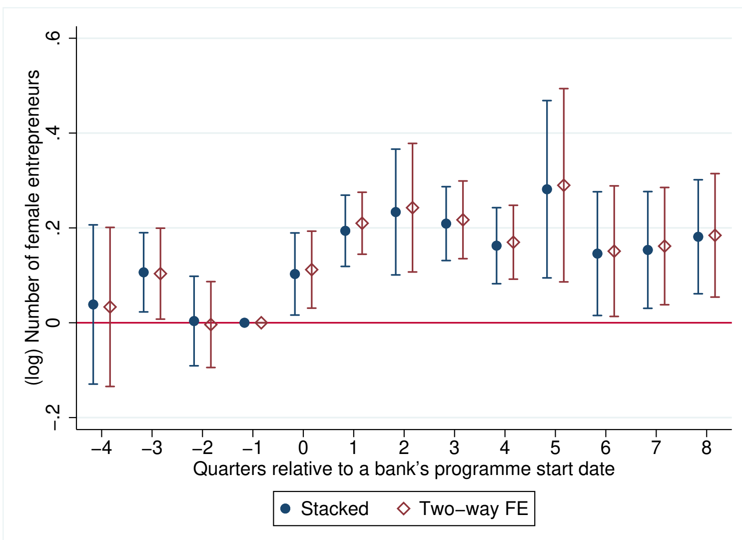


Notes: This figure shows the average bank-level change in the share of female entrepreneurs in lending to all entrepreneurs before and after banks start participating in the WiB programme. For each of the five banks that participated in the WiB programme, we normalize the month in which the bank disbursed its first loan as part of the programme to 0. For banks that never participated in the WiB programme, we use their monthly observations corresponding to the normalised time scale for each WiB participant bank. We then calculate the average share of lending to female entrepreneurs in each month relative to the start of the programme across WiB banks and non-Wib banks separately.

Figure 6: Event study plots for the impact of the program on female entrepreneurs' access to credit



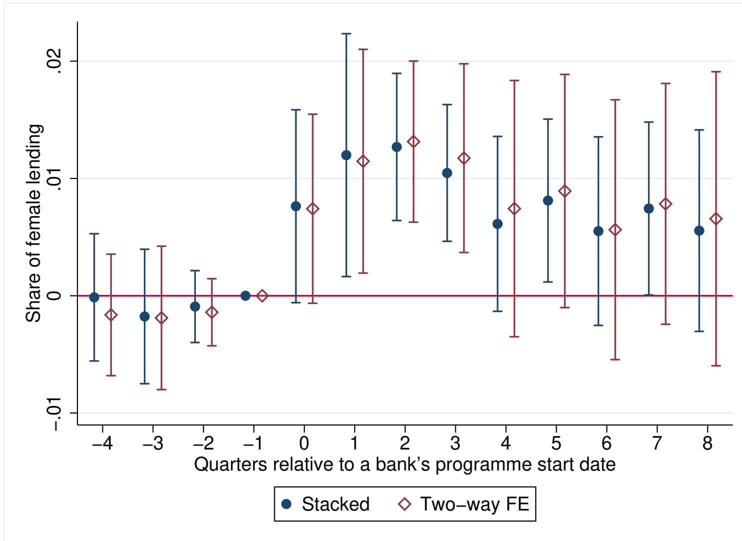
(a) Loan volume



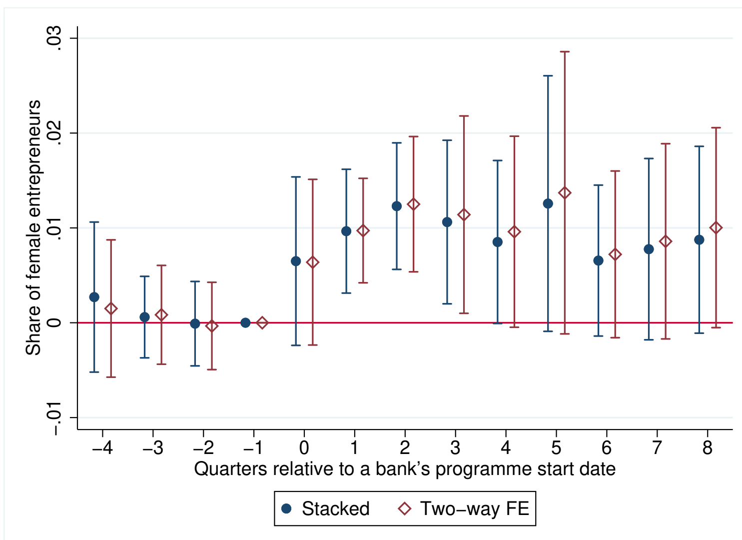
(b) Number of borrowers

Notes: These figures show estimates of Equation (1) in an event study setup using the stacking method of Gormley and Matsa (2011) and Cengiz et al. (2019). The dependent variable is (log) total loan volume to female entrepreneurs in Panel A and (log) Number of female borrowers in Panel B. Standard errors are clustered at the bank level; 95% confidence intervals are shown.

Figure 7: Event study plots for the impact of the program on female entrepreneurs' share of lending



(a) Loan volume



(b) Number of borrowers

Notes: These figures show estimates of Equation (1) in an event study setup using the stacking method of Gormley and Matsa (2011) and Cengiz et al. (2019). The dependent variable is the share of female entrepreneurs in total loan volume to all entrepreneurs in Panel A and the share of female borrowers in all borrowers in Panel B. Standard errors are clustered at the bank level; 95% confidence intervals are shown.

Table 1: Pre-program bank characteristics

	Treated banks	Mean	Control banks	Mean	Diff.
Asset size	5	18.694	19	16.942	-1.752**
Liquidity	5	0.147	19	0.166	0.019
Profitability	5	0.012	19	0.009	-0.004
Non-performing loans	5	0.021	19	0.021	0.001
Loan-loss reserves	5	0.012	19	0.009	-0.004
Capital adequacy	5	0.109	19	0.107	-0.001
Market share in credit	5	0.077	19	0.029	-0.049**
Market share in entrepreneurial credit	5	0.057	19	0.037	-0.021
Share of female lending	5	0.090	19	0.119	0.029

Notes: This table shows summary statistics of bank characteristics as of end-2014. Asset size is in logs of Turkish Liras. Liquidity, profitability, non-performing loans, loan-loss reserves, capital adequacy are all scaled by total assets. Market share in corporate credit is a bank's national market share in lending to corporates. Market share in entrepreneurial credit is a bank's national market share in lending to small businesses, for which we can identify the gender of the owner. Share of female lending is a bank's share of credit to female-led small businesses in credit to all small businesses.

Table 2: **Summary statistics for bank-district level outcomes**

	WIB banks				Non-WIB banks			
	N	Mean	S.D.	Median	N	Mean	S.D.	Median
A. Lending to female entrepreneurs (in logs)								
All borrowers	20,761	4.77	2.23	5.34	202,511	5.13	2.37	5.76
Repeat borrowers	20,761	4.19	2.42	4.88	202,511	4.59	2.45	5.29
New borrowers	20,761	2.10	2.31	0.00	202,511	2.04	2.42	0.00
New-to-bank borrowers	20,761	1.80	2.18	0.00	202,511	2.55	2.62	2.40
First-time borrowers	20,761	2.89	2.41	3.58	202,511	3.27	2.68	4.06
B. Number of female entrepreneurs (in logs)								
All borrowers	20,761	1.56	0.96	1.61	202,511	1.89	1.17	1.95
Repeat borrowers	20,761	1.27	0.92	1.10	202,511	1.60	1.10	1.61
New borrowers	20,761	0.51	0.60	0.00	202,511	0.49	0.64	0.00
New-to-bank borrowers	20,761	0.46	0.59	0.00	202,511	0.76	0.89	0.69
First-time borrowers	20,761	0.79	0.75	0.69	202,511	0.99	0.96	0.69
C. Share of female lending								
All borrowers	20,761	0.09	0.09	0.07	202,511	0.10	0.11	0.08
Repeat borrowers	20,761	0.08	0.10	0.05	202,511	0.09	0.11	0.06
New borrowers	20,761	0.10	0.19	0.00	202,511	0.09	0.17	0.00
New-to-bank borrowers	20,761	0.15	0.26	0.00	202,511	0.13	0.21	0.03
First-time borrowers	20,761	0.13	0.19	0.06	202,511	0.12	0.17	0.06
D. Share of female entrepreneurs								
All borrowers	20,761	0.11	0.08	0.10	202,511	0.11	0.09	0.10
Repeat borrowers	20,761	0.10	0.08	0.09	202,511	0.10	0.10	0.09
New borrowers	20,761	0.11	0.17	0.00	202,511	0.09	0.15	0.00
New-to-bank borrowers	20,761	0.16	0.24	0.00	202,511	0.13	0.19	0.06
First-time borrowers	20,761	0.14	0.16	0.10	202,511	0.12	0.15	0.09

Notes: This table shows the number of observations (N), mean, standard deviation (S.D.), and median for variables at the bank-branch-quarter level over the sample period for WIB and non-WIB banks separately.

Table 3: Impact of the program at the bank level – synthetic DID results

	All borrowers (1)	Repeat borrowers (2)	New borrowers (3)	New-to-bank borrowers (4)	First-time borrowers (5)
A. Lending to female entrepreneurs					
ATT	1.500***	1.509***	1.052***	1.168***	0.726**
	(0.536)	(0.574)	(0.352)	(0.356)	(0.317)
B. Number of female entrepreneurs					
ATT	0.641***	0.633***	0.506***	0.446**	0.338
	(0.210)	(0.222)	(0.192)	(0.182)	(0.247)
C. Share of female lending					
ATT	0.019**	0.014*	0.018	0.021*	0.038**
	(0.008)	(0.008)	(0.013)	(0.011)	(0.017)
D. Share of female entrepreneurs					
ATT	0.019	0.014	0.027**	0.023	0.056***
	(0.014)	(0.013)	(0.013)	(0.016)	(0.017)

Notes: This table shows coefficient estimates of Equation (1) following the SDID methodology of Arkhangelsky et al. (2021). Standard errors are calculated using the "placebo method" and shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Impact of the program on access to credit for female entrepreneurs

	All borrowers (1)	Repeat borrowers (2)	New borrowers (3)	New-to-bank borrowers (4)	First-time borrowers (5)
A. Lending to female entrepreneurs					
Post x WiB Bank	0.347***	0.225*	0.341***	0.253*	0.270***
	(0.105)	(0.129)	(0.126)	(0.133)	(0.102)
Adjusted R-squared	0.695	0.685	0.578	0.401	0.626
Observations	223,272	223,272	223,272	223,272	223,272
B. Number of female entrepreneurs					
Post x WiB Bank	0.148***	0.085	0.111**	0.078*	0.075**
	(0.034)	(0.055)	(0.047)	(0.042)	(0.036)
Adjusted R-squared	0.870	0.856	0.735	0.518	0.745
Observations	223,272	223,272	223,272	223,272	223,272
Bank controls x Cohort FE	y	y	y	y	y
Bank x District x Cohort FE	y	y	y	y	y
District x Quarter x Cohort FE	y	y	y	y	y

Notes: This table shows coefficient estimates of Equation (2) using the stacking method of Gormley and Matsa (2011) and Cengiz et al. (2019). The dependent variable is lending to female entrepreneurs in Panel A and number of female entrepreneurs with access to credit in Panel B, both in logs. Column (1) reports totals for all female entrepreneurs, while the remaining columns report totals by type of borrower. Standard errors are clustered at the bank level and shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Impact of the program on female shares of lending and entrepreneurs

	All borrowers	Repeat borrowers	New borrowers	New-to-bank borrowers	First-time borrowers
	(1)	(2)	(3)	(4)	(5)
A. Share of female lending					
Post x WiB Bank	0.009***	0.007**	0.014**	0.011*	0.027***
	(0.003)	(0.003)	(0.006)	(0.007)	(0.009)
Adjusted R-squared	0.286	0.289	0.068	0.042	0.073
Observations	223,272	223,272	223,272	223,272	223,272
B. Share of female entrepreneurs					
Post x WiB Bank	0.008**	0.006	0.014**	0.010	0.028***
	(0.003)	(0.004)	(0.006)	(0.007)	(0.009)
Adjusted R-squared	0.371	0.357	0.104	0.070	0.091
Observations	223,272	223,272	223,272	223,272	223,272
Bank controls x Cohort FE	y	y	y	y	y
Bank x District x Cohort FE	y	y	y	y	y
District x Quarter x Cohort FE	y	y	y	y	y

Notes: This table shows estimates of Equation (2) using the stacking method of Gormley and Matsa (2011) and Cengiz et al. (2019). The dependent variable is share of female lending in Panel A and share of female entrepreneurs with access to credit in Panel B. Column (1) reports totals for all entrepreneurs, while the remaining columns report totals by type of borrower. Standard errors are clustered at the bank level and shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Impact of the program on access to credit for female entrepreneurs – district-level heterogeneity

	All borrowers	Repeat borrowers	New borrowers	New-to-bank borrowers	First-time borrowers
	(1)	(2)	(3)	(4)	(5)
A. Lending to female entrepreneurs					
Post x WiB Bank	0.529***	0.380***	0.445***	0.312***	0.335***
	(0.108)	(0.125)	(0.123)	(0.105)	(0.106)
Post x WiB Bank x Market share	-2.055***	-1.751***	-1.182*	-0.667	-0.731
	(0.464)	(0.513)	(0.644)	(0.590)	(0.598)
Adjusted R-squared	0.695	0.685	0.578	0.401	0.626
Observations	223,272	223,272	223,272	223,272	223,272
B. Number of female entrepreneurs					
Post x WiB Bank	0.202***	0.133**	0.125***	0.080**	0.085**
	(0.040)	(0.058)	(0.045)	(0.033)	(0.037)
Post x WiB Bank x Market share	-0.608***	-0.535***	-0.147	-0.028	-0.111
	(0.161)	(0.169)	(0.174)	(0.197)	(0.131)
Adjusted R-squared	0.870	0.856	0.735	0.518	0.745
Observations	223,272	223,272	223,272	223,272	223,272
Bank controls x Cohort FE	y	y	y	y	y
Bank x District x Cohort FE	y	y	y	y	y
District x Quarter x Cohort FE	y	y	y	y	y

Notes: This table shows coefficient estimates of Equation (2) using the stacking method of Gormley and Matsa (2011) and Cengiz et al. (2019). The dependent variable is lending to female entrepreneurs in Panel A and number of female entrepreneurs with access to credit in Panel B, both in logs. Column (1) reports totals for all female entrepreneurs, while the remaining columns report totals by type of borrower. Standard errors are clustered at the bank level and shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Impact of the program on female shares of lending and entrepreneurs – district-level heterogeneity

	All borrowers	Repeat borrowers	New borrowers	New-to-bank borrowers	First-time borrowers
	(1)	(2)	(3)	(4)	(5)
A. Share of female lending					
Post x WiB Bank	0.021***	0.017***	0.023***	0.021***	0.032**
	(0.006)	(0.004)	(0.008)	(0.007)	(0.015)
Post x WiB Bank x Market share	-0.138***	-0.111***	-0.102***	-0.110***	-0.047
	(0.045)	(0.039)	(0.039)	(0.025)	(0.095)
Adjusted R-squared	0.286	0.290	0.068	0.042	0.073
Observations	223,272	223,272	223,272	223,272	223,272
B. Share of female entrepreneurs					
Post x WiB Bank	0.020***	0.014***	0.022***	0.018***	0.033**
	(0.005)	(0.004)	(0.007)	(0.006)	(0.014)
Post x WiB Bank x Market share	-0.127***	-0.096***	-0.088**	-0.088***	-0.062
	(0.019)	(0.010)	(0.038)	(0.031)	(0.080)
Adjusted R-squared	0.371	0.357	0.104	0.070	0.091
Observations	223,272	223,272	223,272	223,272	223,272
Bank controls x Cohort FE	y	y	y	y	y
Bank x District x Cohort FE	y	y	y	y	y
District x Quarter x Cohort FE	y	y	y	y	y

Notes: This table shows estimates of Equation (2) using the stacking method of Gormley and Matsa (2011) and Cengiz et al. (2019). The dependent variable is share of female lending in Panel A and share of female entrepreneurs with access to credit in Panel B. Column (1) reports totals for all entrepreneurs, while the remaining columns report totals by type of borrower. Standard errors are clustered at the bank level and shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Ex-post performance of first-time female business borrowers: credit outcomes

	New banking relationship	Termination of entry bank	Loans from entry bank	Loans from new banks	Check default	Loan default
	(1)	(2)	(3)	(4)	(5)	(6)
First-time WiB borrower	0.177***	-0.015	0.015	0.245***	0.002	-0.003
	(0.030)	(0.011)	(0.034)	(0.029)	(0.003)	(0.002)
R-squared	0.108	0.208	0.091	0.099	0.105	0.143
Observations	391,520	391,520	391,520	391,520	391,520	391,520
Bank x District x Cohort FE	y	y	y	y	y	y
District x First Quarter x Cohort FE	y	y	y	y	y	y

Notes: This table shows estimates of Equation (3). Standard errors are clustered at the bank level and shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Ex-post performance of first-time female business borrowers: real economic outcomes

	Firm exit (0/1) (1)	Total sales (2)	Number of customers (3)	Number of suppliers (4)	Total purchases (5)
A. Changes in one year					
WiB bank borrower (0/1)	-0.015***	0.032***	0.008	0.030***	0.064***
	(0.002)	(0.007)	(0.005)	(0.005)	(0.006)
Observations	79,554	60,955	60,955	70,617	70,617
R-squared	0.030	0.005	0.004	0.007	0.014
B. Changes in two years					
WiB bank borrower (0/1)	-0.041***	0.062***	0.042***	0.067***	0.107***
	(0.003)	(0.011)	(0.008)	(0.007)	(0.010)
Observations	50,738	35,614	35,614	41,008	41,008
R-squared	0.020	0.004	0.007	0.018	0.023
C. Changes in three years					
WiB bank borrower (0/1)	-0.061***	0.111***	0.081***	0.071***	0.129***
	(0.005)	(0.018)	(0.014)	(0.012)	(0.017)
Observations	23,750	14,881	14,881	17,289	17,289
R-squared	0.020	0.011	0.012	0.019	0.027

Notes: This table shows estimates of Equation (4). Standard errors are clustered at the bank level and shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.