Blended Finance and Female Entrepreneurship

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Female-owned firms suffer especially from lack of three C's

- Many small firms lack credit history, connections, collateral $\rightarrow$ financial frictions and credit rationing (Jaffee and Russell, 1976; Stiglitz and Weiss, 1981
- Many women-led small firms also face discriminatory laws (Naaraayanan, 2020) or lenders (Alesina et al., 2013; Brock and De Haas, 2022)

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- Many women-led small firms also face discriminatory laws (Naaraayanan, 2020) or lenders (Alesina et al., 2013; Brock and De Haas, 2022)
- Removing barriers to female entrepreneurship can boost aggregate TFP (Chiplunkar and Goldberg, 2022; Morazzoni and Sy, 2022) and speed up economic convergence
- More credit to high-ARPK female firms would reduce gendered capital misallocation (Banerjee and Moll, 2010; David and Venkateswaran, 2019)

Blended finance as a tool to broaden credit access

- Public development bank provides credit lines to private commercial banks for on-lending to a specific target segment (Eslava and Freixas, 2016)

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- Typically combines:
  1. Senior credit lines with a use-of-proceeds clause, complemented by banks
  2. First-loss risk cover $\rightarrow$ partial credit guarantee
  3. Training and technical assistance

Blended finance: A new consensus in the development community?

- Increasingly popular
  - ☞ IFC: Women Entrepreneurs Opportunity Fund → USD 1.45 billion
  - ☞ IFC: Banking on Women Program → USD 3 billion
  - ☞ AfDB: Affirmative Finance Action for Women in Africa → USD 1.3 billion
  - ☞ EIB: SheInvest Program → USD 2 billion
  - ☞ IADB: Women Entrepreneurship Banking Programme → USD 0.8 billion
  - ☞ Women Entrepreneurs Finance Initiative (We-Fi) → USD 1 billion
- Unclear whether blended finance helps target segments to access credit and to become more productive (World Bank, 2005/2014, Eurodad, 2013)

We provide an anatomy of blended finance

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Merge several micro datasets to trace the financial and real impacts, and uncover the underlying mechanisms, of a blended finance program for Turkish female entrepreneurs:

1. Can blended finance durably increase bank lending to female entrepreneurs?
2. Which types of women-owned businesses (if any) gain better access to credit?
3. What are the real economic impacts (if any) of the easing of credit constraints?

The Women in Business (WIB) program

1. Credit lines (EUR 300 million) to five commercial banks for on-lending to female entrepreneurs during the 2015-2017 period
    - Banks to blend with own funding
    - Total of EUR 417 million by end of 2017
    - Banks' stock of lending was around EUR 5 billion by end of 2014

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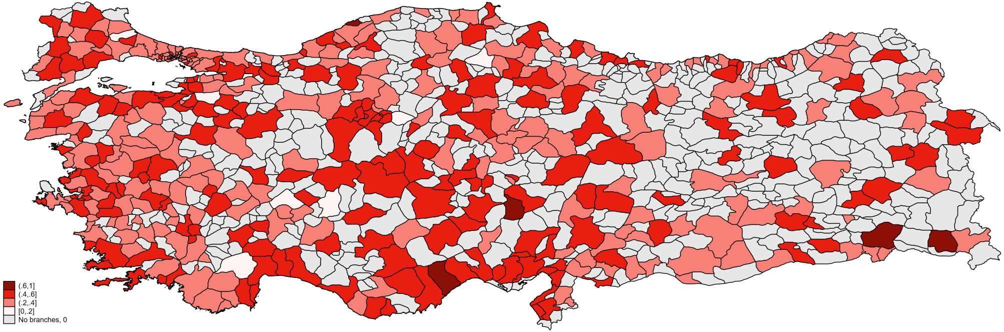
3. Technical assistance to banks
   - Consulting on how to increase exposure to female entrepreneurs
   - Baseline assessment, gender-responsive sales, training-of-trainers modules
   - Optimisation of MIS to gather, monitor, and analyse gender-disaggregated data

Market share of participating banks in each district



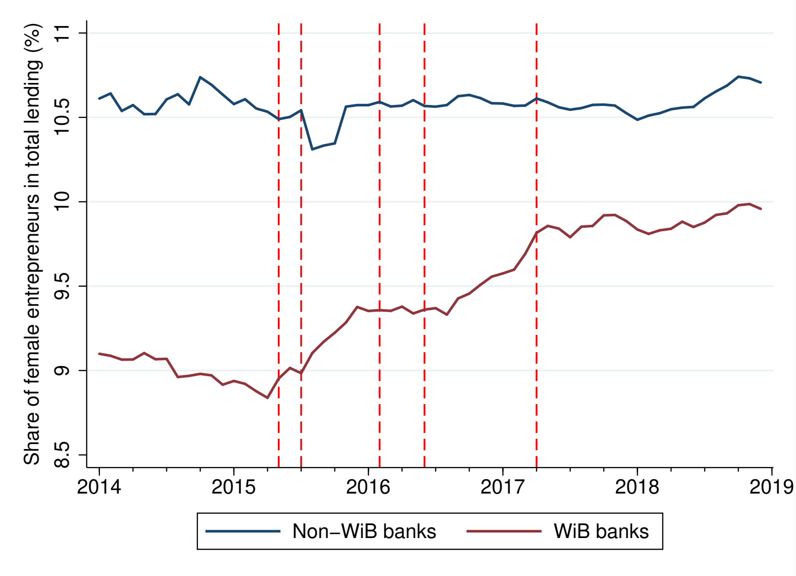
Map showing share of WiB bank branches.

We combine three administrative datasets

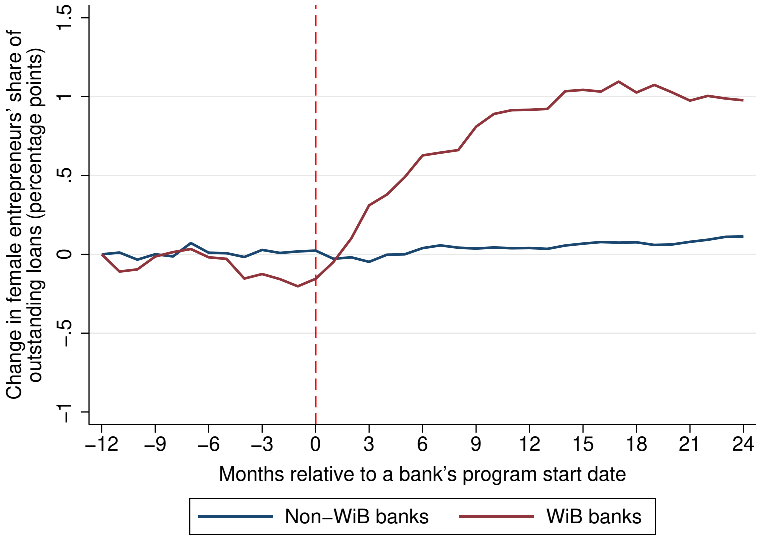
1. Turkey's credit register (CBRT)
   - ✓ No reporting threshold
   - ✓ Borrower gender observable
   - ✓ Classify borrowers into repeat, poached, or first-time
2. Firm-level VAT tax records (Ministry of Treasury and Finance)
   - ✓ Covers all buyer-supplier links in Turkey
   - ✓ Allows focus on real effects
3. Firm financials (Ministry of Treasury and Finance)
   - ✓ Also includes gender so we can track the universe of female (and male) entrepreneurs

→ 1/5 entrepreneurs is a woman; but 1/10 entrepreneurs with credit access is a woman

Banks joined the program at different times



Lending share to female entrepreneurs increased after program start



Bank-level identification: Staggered DiD

- 5 treated and 21 control banks Balance table

- Aggregate loan-level data (new issuance) to the bank(b)-time(t) level:

$$y_{bt} = \alpha + \beta_1 WIB_b * Post_{bt} + \beta_2 x_{bt} + \gamma_b + \delta_t + \epsilon_{bt}$$

- Exploit staggered program roll-out (restrict to window of -/+8 quarters)

- TWFE biased? Use stacking (Cengiz et al., 2019; Gormley and Matsa, 2014)
  - ☞ Compare WIB participating banks to never-participating banks
  - ☞ Interact controls and FE with cohort indicators

Bank-level results: Lending to female firms

	All borrowers	Repeat borrowers	Poached borrowers	First-time borrowers
	(1)	(2)	(3)	(4)
A. Lending to female entrepreneurs				
Post x WiB Bank	1.302***	1.217***	1.051***	0.840***
	(0.282)	(0.310)	(0.249)	(0.192)
Adjusted R-squared	0.960	0.860	0.870	0.918
Observations	1,870	1,870	1,870	1,870
Mean dep. var.	8.350	7.742	6.205	5.911
B. Number of female entrepreneurs				
Post x WiB Bank	0.747***	0.679***	0.518***	0.448***
	(0.141)	(0.157)	(0.136)	(0.125)
Adjusted R-squared	0.961	0.960	0.944	0.951
Observations	1,870	1,870	1,870	1,870
Mean dep. var.	4.655	4.231	3.107	3.094
Bank controls x Cohort FE	y	y	y	y
Bank x Cohort FE	y	y	y	y
Quarter x Cohort FE	y	y	y	y

Bank-level results: Share of lending to female firms

	All borrowers	Repeat borrowers	Poached borrowers	First-time borrowers
	(1)	(2)	(3)	(4)
A. Share of female lending				
Post x WiB Bank	0.020***	0.011	0.035***	0.040***
	(0.007)	(0.009)	(0.008)	(0.011)
Adjusted R-squared	0.236	0.109	0.145	0.208
Observations	1,870	1,870	1,870	1,870
Mean dep. var.	0.086	0.075	0.081	0.141
B. Share of female entrepreneurs				
Post x WiB Bank	0.015*	0.012	0.031***	0.040***
	(0.008)	(0.009)	(0.010)	(0.011)
Adjusted R-squared	0.339	0.200	0.121	0.248
Observations	1,870	1,870	1,870	1,870
Mean dep. var.	0.100	0.092	0.094	0.144
Bank controls x Cohort FE	y	y	y	y
Bank x Cohort FE	y	y	y	y
Quarter x Cohort FE	y	y	y	y

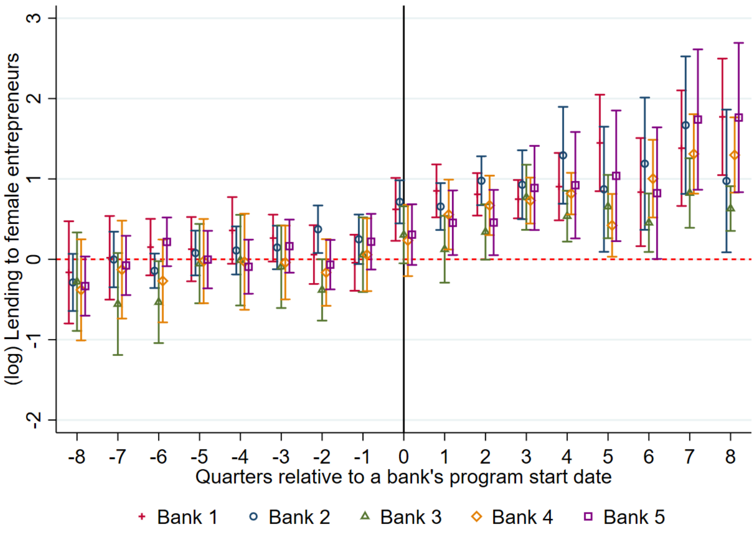
First approach to deal with selection: Synthetic DiD

- SDiD estimator combines features of DiD and synthetic control approach (Arkhangelsky et al., 2021)
- Use time and unit weights to match pre-program trends $\rightarrow$ reduces reliance on parallel trends in the raw data (cf. SC)
- Allows for valid large-panel inference (cf. DiD)
- Can produce event-study plots for each individual treated bank

Synthetic DiD: Program impact on lending to female firms

	All borrowers	Repeat borrowers	Poached borrowers	First-time borrowers
	(1)	(2)	(3)	(4)
A. Lending to female entrepreneurs				
ATT	1.382***	1.347***	0.890***	0.574**
	(0.434)	(0.437)	(0.318)	(0.278)
B. Number of female entrepreneurs				
ATT	0.444***	0.501***	0.329**	0.194
	(0.142)	(0.165)	(0.135)	(0.229)
C. Share of female lending				
ATT	0.018***	0.014**	0.016	0.041***
	(0.005)	(0.007)	(0.010)	(0.014)
D. Share of female entrepreneurs				
ATT	0.019**	0.014	0.020*	0.052***
	(0.009)	(0.011)	(0.011)	(0.015)

Synthetic DiD: Event-study plot for all lending



Second approach to deal with selection: Tighter DiD at the bank-gender level

- Aggregate loan-level data to the bank(b)-gender(g)-time(t) level:

$$y_{bgt} = \alpha + \beta_1 WIB_b * Post_{bt} * Female_g + \gamma_{bg} + \delta_{bt} + \epsilon_{bgt}$$

- Allows for bank×gender FE and bank×time FE to capture unobservables
- Use stacking methodology as before
- Confirm results

Do WIB lenders target female entrepreneurs most in need of credit?

- Objective 1: Identify the impact of WIB-induced credit-supply shocks on firms' borrowing and real outcomes
- Objective 2: Study how the increase in credit supply was allocated across firms

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- Challenge: Disentangle changes in borrowing driven by supply vs. demand forces

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- Objective 1: Identify the impact of WIB-induced credit-supply shocks on firms' borrowing and real outcomes
- Objective 2: Study how the increase in credit supply was allocated across firms
- Challenge: Disentangle changes in borrowing driven by supply vs. demand forces
- Solution: Isolate credit supply shocks to individual female entrepreneurs by exploiting variation in bank lending at the national level (Chodorow-Reich, 2014 and Cong et al., 2019):

$$\Delta \hat{L}_{idst} = \sum_{b \in B} \omega_{bi,t=0} \times \Delta \log L_{b,-ds,t}$$

where ω is the relationship strength between firm i and bank b in the baseline year

We rely on two assumptions for identification

1. Bank-firm relationships are persistent over time
    - Likely in the context of small business lending
    - Test: regress new relationship (0/1) on all possible pairs
2. Cross-sectional variation in bank lending only reflects supply forces due to WIB or observable borrower characteristics, but is uncorrelated with unobservable borrower characteristics that affect credit demand
    - We show the stability of our estimates to adding a set of controls, including observables and set of fixed effects
    - We exploit variation in change in lending across banks within the same firm (Khwaja and Mian, 2008)
    - Test: regress Δcredit at firm-bank level on bank-level supply shocks

Testing (1): firm-bank relationships are sticky

Dependent variable:	New loan			
Sample:	All possible firm-bank relationship pairs			
	(1)	(2)	(3)	(4)
Pre-existing relationship	0.980***	0.993***	0.898***	0.911***
	(0.001)	(0.001)	(0.001)	(0.001)
R-squared	0.480	0.486	0.525	0.530
Observations	14,012,300	14,012,300	14,012,300	14,012,300
District FE	y	n	y	n
Industry FE	y	n	y	n
Year FE	y	y	y	y
Bank FE	n	n	y	y
Firm FE	n	y	n	y

Testing (2): credit supply shocks lead to more firm borrowing

Dependent variable:	Δ(log) Credit to female entrepreneur			
Sample:	All firms		Multi-lender firms	
	(1)	(2)	(3)	(4)
$\Delta \log L_{b,-ds,t}$	0.194***	0.188**	0.268***	0.279***
	(0.071)	(0.088)	(0.073)	(0.063)
R-squared	0.025	0.244	0.188	0.456
Observations	783,176	702,740	253,491	217,530
District FE	y	n	n	n
Industry FE	y	n	n	n
Year FE	y	y	y	n
Firm FE	n	y	y	n
Firm-year FE	n	n	n	y

Documenting the effects of credit supply shocks on firm-level outcomes

- We estimate the following equation at the firm-level:

$$\Delta \mathrm{y}_{it} = \alpha + \beta_1 \mathrm{WIB} \times \Delta \hat{L}_{idst} + \beta_2 \text{Non-WIB} \times \Delta \hat{L}_{idst} + \gamma_i + \delta_t + \epsilon_{it}$$

  where $\Delta \hat{L}_{idst}$ is the firm-level credit supply shock

- We differentiate between the effect of WIB and non-WIB shocks

- We look at $\Delta \mathrm{y}_{it}$ over 1-, 2-, and 3-year horizon

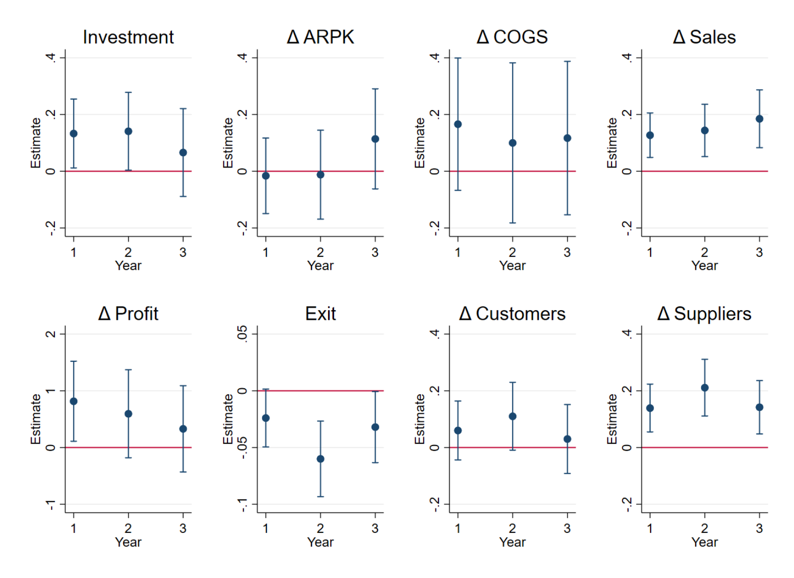
Credit supply by WIB participation and firm-level borrowing

Dependent variable:		ΔCredit	
	(1)	(2)	(3)
$\Delta\hat{L}_{idst}$	0.667***		
	(0.058)		
WiB $\times\Delta\hat{L}_{idst}$		0.871***	0.693***
		(0.067)	(0.093)
Non-WiB $\times\Delta\hat{L}_{idst}$		0.611**	0.659***
		(0.064)	(0.093)
WiB $\times\Delta\hat{L}_{idst}\times$ pre-program ARPK			0.065**
			(0.031)
Non-WiB $\times\Delta\hat{L}_{idst}\times$ pre-program ARPK			-0.017
			(0.029)
R-squared	0.281	0.281	0.281
Observations	51,842	51,842	51,842
Mean dep. var.	-0.005	-0.005	-0.005
F-test WiB $\times$ $\Delta\hat{L}_{idst}$ = Non-WiB $\times$ $\Delta\hat{L}_{idst}$		11.23	
p-value		0.001	
Year FE	y	y	y
Firm FE	y	y	y

Impact of credit supply on firm-level outcomes

Dependent variable:	Investment	ΔARPK	ΔCOGS	ΔSales	ΔProfit	Exit	ΔCustomers	ΔSuppliers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WiB $\times \Delta\hat{L}_{idst}$	0.133**	-0.016	0.166	0.127***	0.815**	-0.024*	0.060	0.139***
	(0.062)	(0.068)	(0.119)	(0.040)	(0.360)	(0.013)	(0.053)	(0.043)
Non-WiB $\times \Delta\hat{L}_{idst}$	0.012	-0.051	-0.067	-0.034	0.214	-0.009	0.020	0.054*
	(0.041)	(0.049)	(0.059)	(0.028)	(0.208)	(0.008)	(0.035)	(0.032)
R-squared	0.258	0.246	0.217	0.303	0.178	0.376	0.234	0.218
Observations	51,842	51,842	51,842	51,842	51,842	51,842	42,080	47,502
Mean dep. var.	0.102	-0.049	0.050	0.052	-0.190	0.034	0.006	-0.007
F-test WiB $\times \Delta\hat{L}_{idst}$ = Non-WiB $\times \Delta\hat{L}_{idst}$	3.933	0.255	3.758	15.375	3.219	1.356	0.557	3.837
p-value	0.048	0.613	0.053	0.000	0.073	0.245	0.456	0.051
Year FE	y	y	y	y	y	y	y	y
Firm FE	y	y	y	y	y	y	y	y

Impact of credit supply on firm-level outcomes: dynamic estimates



Did WIB banks target existing clients most in need of credit?

- We estimate the following equation at the firm-level:

$$
\begin{aligned}
\Delta \mathrm{y}_{it} = {} & \alpha + \beta_1 \mathrm{WIB} \times \Delta \hat{L}_{idst} + \beta_2 \mathrm{WIB} \times \Delta \hat{L}_{idst} \times \text{pre-program ARPK} \\
& + \beta_3 \text{Non-WIB} \times \Delta \hat{L}_{idst} + \beta_4 \text{Non-WIB} \times \Delta \hat{L}_{idst} \times \text{pre-program ARPK} \\
& + \gamma_i + \delta_t + \epsilon_{it}
\end{aligned} \tag{1}
$$

where $\Delta \hat{L}_{idst}$ is the firm-level credit supply shock

Targeting of credit & outcomes based on pre-program ARPK: 1-year

Dependent variable:	Investment	ΔARPK	ΔCOGS	ΔSales	ΔProfit	Exit	ΔCustomers	ΔSuppliers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WiB $\times \Delta \hat{L}_{idst}$	-0.034	0.413***	0.322	2.318***	0.386***	-0.003	0.315***	0.134
	(0.080)	(0.110)	(0.250)	(0.723)	(0.069)	(0.023)	(0.086)	(0.082)
WiB $\times \Delta \hat{L}_{idst}$ $\times$ initial ARPK	0.060*	-0.155***	-0.056	-0.546***	-0.094***	-0.008	-0.092***	0.002
	(0.032)	(0.041)	(0.066)	(0.189)	(0.021)	(0.006)	(0.025)	(0.022)
Non-WiB $\times \Delta \hat{L}_{idst}$	-0.269***	0.300***	0.035	0.582	0.008	-0.005	0.108*	0.014
	(0.057)	(0.090)	(0.143)	(0.468)	(0.058)	(0.015)	(0.057)	(0.079)
Non-WiB $\times \Delta \hat{L}_{idst}$ $\times$ initial ARPK	0.096***	-0.120***	-0.035	-0.123	-0.014	-0.001	-0.030*	0.013
	(0.023)	(0.031)	(0.037)	(0.111)	(0.015)	(0.004)	(0.017)	(0.021)
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Year FE	y	y	y	y	y	y	y	y
Firm FE	y	y	y	y	y	y	y	y

Did the program have any general equilibrium effect?

- Adopt a similar approach to Greenstone et al. (2020) & Berton et al. (2018) in relating district-level credit supply shocks ($\hat{L}_{dt}$) to district-level outcomes

- Calculate district-level outcomes for all female entrepreneurs (regardless of access to credit):

$$\Delta X_{dt} = \frac{X_{dt} - X_{d,t-1}}{0.5 \times X_{dt} + 0.5 \times X_{d,t-1}}$$

- Symmetric and bounded between -2 and +2.

GE effects of WIB on district-level outcomes are minimal

Dependent variable:	Δ Credit	Exit rate	Δ Entrepreneurs	Δ Sales	Δ Profit
	(1)	(2)	(3)	(4)	(5)
WiB $\times \Delta \hat{L}_{dt}$	0.243***	-0.028	-0.044	-0.101	-0.253
	(0.080)	(0.038)	(0.078)	(0.136)	(0.521)
Non-WiB $\times \Delta \hat{L}_{dt}$	0.122**	-0.001	-0.020	-0.015	-0.082
	(0.050)	(0.011)	(0.031)	(0.034)	(0.088)
R-squared	0.328	0.264	0.266	0.230	0.171
Observations	3,352	3,352	3,352	3,352	3,352
Mean dep. var.	0.225	0.112	0.116	0.194	0.181
Year FE	y	y	y	y	y
District FE	y	y	y	y	y

To sum up

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- ✐ Banks shift lending to female-owned firms with relatively high capital productivity

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- ✏ Recipient entrepreneurs use credit from WIB banks to increase investment, sales, profitability and survival probability

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- ✐ Treated banks expand credit to pre-existing female borrowers (50%); poach clients from competitors (31%); but also crowd in first-time borrowers (19%)
- ✐ Banks shift lending to female-owned firms with relatively high capital productivity
- ✐ Recipient entrepreneurs use credit from WIB banks to increase investment, sales, profitability and survival probability
- ✐ But there are limited aggregate effects

Treatment-control balance: Bank-level

	Treated banks	Mean	Control banks	Mean	Diff.
Asset size	5	18.663	21	16.902	-1.762**
Market share in corporate credit	5	0.078	21	0.027	-0.051***
Market share in entrepreneurial credit	5	0.056	21	0.034	-0.022
Share of female lending	5	0.090	21	0.102	0.012
Liquidity	5	0.144	21	0.184	0.040
Profitability	5	0.009	21	0.008	-0.002
Non-performing loans	5	0.021	21	0.021	0.000
Loan-loss reserves	5	0.009	21	0.008	-0.001
Capital adequacy	5	0.106	21	0.108	0.002

back

Adverse selection of first-time borrowers?

- Nudging (while not training) loan officers to accept more credit risk at the extensive margin may backfire (Augsburg et al., 2015)

- How did first-time female borrowers who enter the system via WIB banks fare compared with those who enter via non-WIB banks?

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

No adverse selection of first-time borrowers

Dependent variable:	Check default	Loan default	Loans from entry bank	Termination of entry bank	New banking relationship	Loans from new banks
	(1)	(2)	(3)	(4)	(5)	(6)
First-time WiB borrower	0.002	-0.003	0.012	-0.014	0.146***	0.213***
	(0.003)	(0.002)	(0.029)	(0.011)	(0.031)	(0.031)
R-squared	0.105	0.120	0.093	0.209	0.103	0.089
Observations	400,237	400,237	400,237	400,237	400,237	400,237
Mean dep. var.	0.002	0.0002	0.624	0.329	0.147	0.123
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

back