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Female Entrepreneurship, Financial Frictions and Capital Misallocation in the US[*]

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Abstract

We document and quantify the effect of a gender gap in credit access on both entrepreneurship and input misallocation in the US. We show that female-owned firms are more likely to be rejected when applying for a loan and have a higher average product of capital, a sign of gender-driven capital misallocation across firms. Calibrating a heterogeneous agents model of entrepreneurship to the US economy, we establish that such gap in credit access explains the bulk of the gender differences in capital allocation across firms, and more than a third of their disparities in entrepreneurial rates. In a counterfactual exercise, we illustrate that eliminating this credit imbalance leads to a 4% increase in output, and that fiscal policies affect differently female and male entrepreneurial margins in the presence of gender gaps in financial access.

Keywords: Entrepreneurship, Misallocation, Aggregate Productivity, Gender Differences, Financial Constraints.

JEL Classification: O11 E44 D11

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1 Introduction

Entrepreneurs play a pivotal role in enhancing productivity, job creation and innovation in the US.[1] Yet, sizable gender gaps persist both in firm ownership rates and in several dimensions of firm performance. For instance, female owners constitute only 35% of the entrepreneurial pool,[2] suggestive of an imbalance along the *extensive* margin of entrepreneurship.[3] Focusing instead on business financing, in 2018 women received just 2.2% of total US start-up funding.[4] This type of asymmetry operates along the *intensive* margin of entrepreneurship and can be responsible for distortions affecting the optimal allocation of productive inputs. However, to the best of our knowledge, empirical evidence of gender-based frictions at the firm-level is scarce, and quantitative estimates of their macroeconomic impact are yet to be provided. In this paper, we exploit rich micro data to document both gender disparities in firms' access to credit and gender-driven capital misallocation. Then, through a heterogeneous agents model, we quantify the effect of such financing gaps on entrepreneurial talent allocation, capital misallocation and aggregate output.

For our empirical analysis, we use the restricted-access version of the Kauffman Firm Survey (KFS hereafter), a panel of nearly 5,000 US nascent entrepreneurs that covers the years between 2004 and 2011 and contains detailed information on both owners' characteristics and balance sheet variables.[5] In principle, gender imbalances in entrepreneurship may be related to several factors, such as gaps in accessing finance – our main focus – as well as differences in labor attachment or social backgrounds. Owing to the richness of our data, we can control for other potential sources of heterogeneities across genders and restrict our attention to understanding whether significant gender gaps in credit access still exist, and how they affect female entrepreneurial outcomes. We thus ask the following questions: (i) Do female entrepreneurs face tighter financial constraints compared to men? (ii) How does this affect total production and capital allocation? (iii) How much would the US economy gain if the gender gap in credit access was to be eliminated?[6]

First, we find evidence that credit constraints penalize female entrepreneurs relatively more. In particular, after controlling for agents' observable traits and firm and industry characteristics, no gender differences exist in the likelihood of applying for a business loan, suggesting a weaker role for any gender heterogeneity in the *demand* for credit. However, not only do female entrepreneurs report lower levels of business debt, but, among loan applicants, women have also a 10% higher

[1] See Davis and Haltiwanger (1999).

[2] US Census Data for 2018: `https://www.census.gov/newsroom/press-releases/2018/employer-firms.html`

[3] As shown in Figure A.1, gender participation gaps are more severe for entrepreneurs than for employed workers; the fraction of female business owners lags behind the share of female agents in the employed workforce, which is now around 46% (see also Figure A.1 for a comparison of the gender earnings gap for employed and self-employed).

[4] See `https://fortune.com/2017/03/13/female-founders-venture-capital/`

[5] We focus on privately held firms, which are likely to be affected by financial frictions. Moreover, private firms are of paramount relevance in the US and account for over 70% of employment and 50% of output (see Asker et al. (2015)).

[6] For example, Hsieh et al. (2019) argue that 20-40% of US growth in aggregate output between 1960 and 2010 can be explained by the improved allocation of talent due to the convergence in the occupational distribution between white men, women, and black men. Here, we ask by how much aggregate output could benefit from releasing gender-based firm borrowing constraints and from improving entrepreneurial talent allocation and capital allocation in the economy.

probability of being rejected. Bank loans are the main source of financing for entrepreneurs in our sample, and an impaired access to such credit is likely to harm the business operations of female producers. Moreover, we further establish that the higher loan rejection rates faced by women are not due to worse risk profiles or lower profitability. Specifically, female entrepreneurs run businesses with better credit risk scores, higher profit margins and higher total factor productivity in revenues (hereafter *tfpr)*. In this regard, our evidence suggests that a lower access to credit may be acting as a barrier to entrepreneurship for female individuals, and it is hence consistent with a phenomenon of *selection* into entrepreneurship of marginally more productive women.

Second, female-led firms have a 12% higher average revenue product of capital (hereafter *arpk*) relative to male ones of similar characteristics. Following the misallocation literature (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2013), we interpret such gap in the return on assets as a sign of misallocation of capital across firms. Importantly, no differences exist in the average revenue product of labor (hereafter *arpl*) across genders, consistent with the fact that female entrepreneurs face higher barriers in accessing credit and, consequently, in financing capital acquisition. Moreover, the average female *arpk* decreases (and the average female business debt increases) in states where female representation among the entrepreneurial pool is stronger. Coupled with the evidence on differential credit access, we suggest that gender disparities in financial frictions could be responsible for the sub-optimal allocation of capital across female and male entrepreneurs. While misallocation alone is often regarded as an indicator of latent heterogeneities in financial constraints, it is important to stress that we are able to directly document a gender gap in credit access, and hence link that result to the observed gender-driven capital misallocation.

To rationalize our empirical findings, we build on Buera and Shin (2013) and develop a general equilibrium heterogeneous agents model of entrepreneurial choice under financial frictions in which individuals differ by wealth, productivity and gender. In our framework, female entrepreneurs are subject to a tighter borrowing constraint in renting entrepreneurial capital, which leads to lower female representation and stricter selection into the entrepreneurial pool. Such gender-based heterogeneity in accessing external funding is also responsible for the differences in *arpk* across female and male entrepreneurs, as financially constrained female-led firms are forced to operate with relatively lower levels of capital compared to male ones. Consequently, as explained in Midrigan and Xu (2014), the negative effect of capital misallocation on aggregate production is particularly severe if highly productive agents are frequently credit constrained.

We then calibrate the model on available US data,[7] following the strategies used in Buera and Shin (2013), Midrigan and Xu (2014), and Cagetti and De Nardi (2006). Despite introducing only one type of heterogeneity across genders in our baseline economy, the model can generate plausible differences in the levels of entrepreneurial capital, total output and total factor productivities across genders. In fact, as a consequence of the gender-based financial frictions, female entrepreneurs in our calibrated framework have roughly 11% higher *arpk* and 14% lower capital-

[7] KFS sample, the Census Annual Survey of Entrepreneurs and the Census of Business and Dynamics Statistics.

to-labor ratio, whereas no such differences exist in their respective *arpl*, similar to what is documented in the data. In this sense, we are able to replicate between 70% and 90% of the gender differences in the level of capital observed in the KFS sample, while the model can also match other salient features of the data, including the size and distribution of debt, profits and revenues across firms, both in aggregate and by gender. Moreover, we can explain up to a third of the gender differences in US entrepreneurial rates. We also consider alternative versions of our setup that include a corporate sector, as well as gender heterogeneities in risk aversion, operational costs and returns to scale, which nonetheless all deliver consistent qualitative results and predictions.

Finally, we use the model to quantify the aggregate effects of the gender gap in credit access, by running a counterfactual exercise in which the gender imbalance in financial markets is eliminated. Guaranteeing equal access to credit to both male and female entrepreneurs improves the allocation of entrepreneurial talent and of capital, and consequently raises total production. In particular, the female entrepreneurial rate increases by 10% and capital misallocation decreases by 12%. Since marginally more productive agents join the entrepreneurial pool and can produce at their optimal scale, total production and aggregate welfare increase by up to 3.82% and 3.50% respectively. In a different set of exercises, we instead keep fixed the gender gap in credit access and analyze the effect of fiscal policies targeting entrepreneurs on male and female-led firms. Specifically, we introduce subsidies to the profits, labor costs, capital costs or the credit needs of business owners. We find that these fiscal schemes foster female entrepreneurship, but the extent to which they mitigate the negative effects of the gender gap in credit access on both capital misallocation and female entrepreneurial under-representation depends on the specific subsidy implemented.

Related Literature. Our paper builds on the body of applied research that examines the relationship between entrepreneurs' gender and business performance, focusing on access to funding, selection into less profitable sectors, and policies to support female entrepreneurship.[8] Within this broad topic, some papers have specifically used the KFS dataset to examine gender differences in firm financing, profits and business growth in the US (see Coleman and Robb (2009), Coleman and Robb (2010), Robb and Watson (2012)). We add to this literature by documenting not only a gender gap in US entrepreneurial financing, but also a novel empirical fact on the dispersion in *arpk* across genders and the resulting capital misallocation across female and male-led firms.

In addition, our work relates to macroeconomic studies that have analyzed the impact of rising female employment on US output growth (see Hsieh et al. (2019) and Heathcote et al. (2017)). Focusing instead on self-employment, Bento (2021) investigates the increase in US female entrepreneurship from 1982 to 2012, and interprets such trend through the lens of a Hopenhayn (1992) model. We also direct our attention on US female entrepreneurship and empirically document both the nature of one still existing gender imbalance, namely the gap in credit access, and the extent of gender-driven capital misallocation, whose impact is then quantified through an entrepreneurship model. In a similar spirit, Chiplunkar and Goldberg (2021) examine the effect of

[8] See De Mel et al. (2008), Campbell and De Nardi (2009), Fairlie and Robb (2009), Cirera and Qasim (2014), Cuberes and Teignier (2016), Faccio et al. (2016), Delis et al. (2020), Naaraayanan (2019), Delecourt and Ng (2020).

barriers to female entrepreneurship in India and show that eliminating gender-based distortions with respect to entry, business registration and hiring costs can lead to sizable productivity and welfare gains, both for female agents and for the economy as a whole.

Moreover, our paper contributes to the literature on the productivity losses and resource misallocation generated by financial frictions (see Hsieh and Klenow (2009), Buera et al. (2011) and Midrigan and Xu (2014)), as well as to the strand of research investigating the importance of personal wealth in determining entrepreneurial choices (see Cagetti and De Nardi (2006)). Differently from these studies, we allow for gender-based heterogeneity in access to capital, and assess the quantitative effect of a gender gap in credit access on misallocation and aggregate output in the US. Along similar lines, Goraya (2020) investigates the relative importance of the caste system in explaining resource misallocation in India and quantifies its impact on aggregate productivity. Finally, our analysis of the effects of fiscal policies on entrepreneurship relates to the works of Li (2002) and Kitao (2008). We analyze fiscal instruments that foster entrepreneurship in an economy characterized by gender-based financial frictions and compare the consequences of subsidies on the credit needs, the capital and labor costs and the profits of female and male-owned firms.

The remainder of this paper is organized as follows. In Section 2, we use the KFS data to document gender differences in credit access and in *arpk*, our empirical indicators of gender-based financial frictions and gender-driven misallocation of capital. In Sections 3–4, we develop a model of entrepreneurial choice and gender-based borrowing constraints, and calibrate it on available US data. In Sections 5–6, we quantify the macroeconomic effects of the gender gap in credit access and the gender-driven misallocation, and assess if fiscal policies targeting all entrepreneurs can affect differently female and male-owned firms in the presence of gender gaps in borrowing constraints. Finally, in Section 7 we conclude.

2 Empirical Evidence

2.1 Data Description

Throughout the paper, we make use of the restricted access version of the KFS 2004–2011 sample, and cross-check our main empirical findings using the US Survey of Consumer Finances (SCF) whenever possible and applicable. For the calibration of the quantitative model later on, we also use the US Census Annual Survey of Entrepreneurs (ASE), and the US Census Business and Dynamics Statistics (BDS). We proceed to briefly discuss the main characteristics of the KFS survey below, while we leave the description of the other datasets for the Appendix.

The KFS sample includes 4,928 US new firms that started their operations in 2004 and have been followed until 2011. Over the sample period, some firms exit the market, as shown in Figure A.8, which tracks the share of active and exiting firms over time.[9] The survey contains exhaustive demographic details for up to 10 owners per firm, including their age, gender, race,

[9] Table A4 in the Appendix also provides estimates of proportional hazard models across female and male-led firms.

working hours, marital status, education, as well as working and other start-up experience. It also reports which owners are actively managing their businesses, which we focus on in the current analysis following similar strategies in the literature (see for example Cagetti and De Nardi (2006)).[10] At the same time, the survey includes detailed information on the geographical location and industry codes of the businesses, as well as on balance sheet variables such as the wage bill, assets, revenues, and profits of the firms, and their different types of financing sources (debt and equity). Table 1 provides the summary statistics of the main variables of interest. Importantly, throughout the analysis, we define a female-led business to have female active owners only, and a male-led business to have male active owners only. In the Appendix, we also report robustness checks according to alternative definitions of the gender of the ownership, based on the gender of the primary owner and a continuous measure of female ownership. Moreover, we use sample weights to ensure the representativeness of the sample.[11]

Table 1: Summary Statistics – KFS Data

	Full Sample		Male	Female	
	Mean	Std. Dev.	Mean	Mean	p-value of diff
ln (Assets)	9.75	3.39	9.85	8.82	0.0000
ln (Business Debt)	2.67	4.47	2.87	1.90	0.0000
ln (Equity)	4.07	4.73	4.08	3.78	0.0011
ln (Revenues)	8.70	5.07	8.82	7.84	0.0000
ln (Profits)	8.78	3.34	8.94	8.11	0.0000
ln (Fixed Assets)	8.29	4.37	8.33	7.40	0.0000
ln (Wage Bill)	4.90	5.54	5.23	3.41	0.0000
Employees	3.51	6.24	3.72	1.95	0.0000
Loan rejection	0.22	0.41	0.19	0.32	0.0053
Observations	17,825		11,281	3,545	

Notes: Loan rejection is the average probability that loan applications are rejected. Survey weights are used to compute the averages. In the Appendix, we also provide an overview of owners' demographic characteristics, while Figure A.7 shows the evolution of some of these variables over time.

The richness of the KFS data differentiates it from other datasets that do not contain enough details both at the owner and at the firm level.[12] In terms of gender-representativeness, we also stress that the share of female and male entrepreneurs in the KFS sample closely resembles the one in the Census ASE (see Table A1). Focusing instead on firm size, Figure A.3 further compares the distribution of KFS firms over size bins (measured in terms of employees) to the one obtained from BDS, which comprises information on the size of more than 3 millions US firms per year, between

[10] Our analysis focuses on agents actively engaged in entrepreneurial activities, as there could be enterprises where the legal ownership is female but the person(s) actively involved in strategies and activities is(are) male. In these cases, it would be difficult to distinguish clearly gender differences in accessing credit and in business capital utilization.

[11] Note that we also run our robustness checks without sample weights. All the results are available upon request.

[12] Instead, the KFS has two main limitations. First, it surveys entrepreneurs that have *already* started a firm. This comes at the expense of not being able to further investigate all the crucial forces driving agents into entrepreneurship. Second, being a panel of start-ups, it over-samples young firms and does not contain truly well-established businesses.

1978 and 2014. With respect to BDS, KFS moderately oversamples small firms (1-4 employees), whereas there are no other sizable differences across the two distributions.

2.2 Credit Access

Our first step is to investigate potential gender heterogeneities in firm financing across the entrepreneurs in the KFS sample. We start by classifying firm funding into two main categories: business debt (a commonly used *external* source) and equity (which is mostly an *internal* source, especially for non-publicly traded firms like the ones in the KFS dataset). As reported in Figure A.11 and Figure A.12, bank loans and credit lines make up for most of the funding across firms in the KFS sample and hence constitute the primary focus of our analysis.

In Table 2, we document that female entrepreneurs operate with lower business debt, regardless of their personal traits and the characteristics of their business. Figure A.15 breaks down the regression residuals by industry to further show that this result is not driven by one sector only and is therefore to be interpreted as a *within* sector and *across* sectors phenomenon. We also establish that female entrepreneurs do not compensate such lower levels of debt with higher equity.[13]

Table 2: Business Debt and Equity

	(1)	(2)
	log(Business Debt)	log(Equity)
Female	-0.3594***	-0.0895
	(0.1170)	(0.1102)
Controls	Y	Y
Sector FE	Y	Y
Region FE	Y	Y
Year FE	Y	Y
Observations	13,031	14,373
R^2	0.162	0.234

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Survey weights are used. Controls for individual characteristics include education, experience, race and age. Other controls include the number of owners, legal status of the firm, and size. Size is measured by log(*revenues*).

However, the fact that female-owned enterprises report lower firm liabilities may be potentially imputed to an interplay of both supply and demand factors. Lower levels of business debt may be due to the fact that women find it more difficult to access credit (*supply*-side constraints), but women could also deliberately seek less external funding (*demand* effect). To partially disentangle these two relevant channels, in Table A7 we first document that there is no statistically robust difference in the likelihood of applying for a loan across genders, suggesting a weaker role

[13]In the Appendix, we provide a comprehensive breakdown of the capital structure decision of female- and male-owned firms. Consistent with Table 2, we find in Table A5 that female-owned firms hold lower levels of debt and this is not compensated with more equity financing. We also verify this finding using data from the SCF in Table A18.

for any heterogeneity in the *demand* for credit.[14] We then focus on entrepreneurs who applied for funding and examine gender differences in loan rejections, as KFS provides data on credit application outcomes for the years between 2007 and 2011. In our sample, 22% of business loan applicants are turned down by financial institutions, with the average rejection rate being higher for female entrepreneurs (32%) compared to male ones (19%).[15] We then estimate the likelihood of loan rejection for male and female owners in our sample by running the following probit regression:[16]

$$Pr(Reject_{it} = 1) = F\left(\beta_0 + \beta_1 \mathbb{1}_{female} + \delta' \mathbf{\Gamma}_{it} + \alpha_t + \eta_{s(it)} + \nu_{r(it)}\right) \tag{1}$$

where $Reject_{it}$ is a binary variable that takes a value of 1 if loan applications are rejected, and 0 if loan applications are approved. The key explanatory variable is $\mathbb{1}_{female}$, a dummy variable equal to 1 if the firm is 100% female-owned and to 0 if it is 100% male-owned. The regression includes a set of controls $\mathbf{\Gamma}$, which capture factors that may affect whether a loan application gets rejected or not (e.g. age, race, education, previous experience, personal debt of owners, firms' legal status,[17] size and leverage), as well as sector, region and year fixed effects ($\eta_{s(it)}$, $\nu_{r(it)}$ and α_t respectively).[18]

Table 3: Loan Application Rejections

	(1)	(2)	(3)	(4)	(5)
Female	0.0970**	0.0848*	0.0992**	0.0949*	0.1127**
	(0.0458)	(0.0517)	(0.0457)	(0.0503)	(0.0470)
Controls	Y	Y	Y	Y	Y
Leverage	N	Y	N	Y	Y
Personal debt	N	N	Y	Y	Y
Credit risk score	N	N	N	N	Y
Sector FE	Y	Y	Y	Y	Y
Region FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Observations	613	458	589	445	404
Pseudo-R^2	0.236	0.275	0.271	0.311	0.401

Notes: Estimates are average marginal effects. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Survey weights are used. The dependent variable is a binary indicator = 1 if loan applications are rejected, and = 0 if loan applications are approved. Control variables include the number of owners, legal status of the firm, number of hours worked per week and size as measured by log(*revenues*), as well as owners' characteristics such as education, experience, race, and age.

As reported in Table 3, female ownership strongly correlates with a higher probability of loan rejection, suggesting that women face more constraints in accessing credit. In particular, female entrepreneurs face a 10% higher probability of having their loan application denied, and this is

[14] This is further confirmed by a similar regression specification using SCF data (see Table A19 in the Appendix).

[15] In Figure A.13, we show that this gap in rejection rates persists over the time spanned by the KFS.

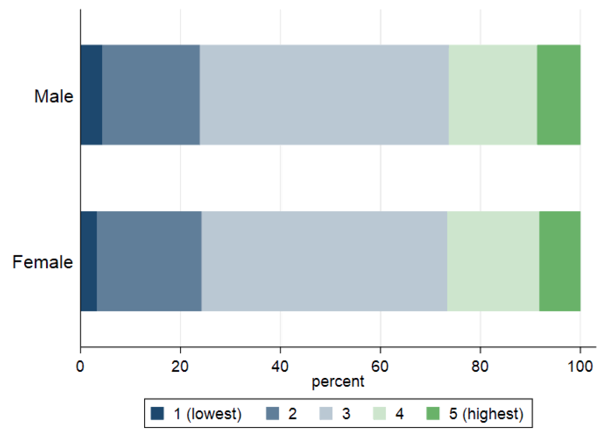
[16] We report results from robustness checks using linear probability model regressions in Table A9 in the Appendix.

[17] See Table A3 for a break down and discussion of firm's legal status by gender.

[18] As further check on the relevance of gender differences in loan application outcomes, we also run probit regressions interacting the gender dummy with experience, personal debt of owners, legal form of the enterprise, size, and a dummy indicator for recession years. We nonetheless find that the gender margin remains statistically significant.

likely to have a strong impact on the firm's ability to fund its operations, as the main source of financing for entrepreneurs in the KFS sample, regardless of their gender, is precisely bank loans.[19] Crucial control variables in our regression strategy are the leverage of the firm, the personal debt burden of owners and business credit risk scores. This is particularly important since entrepreneurial and business risk are often regarded as key determinants of loan application approval. If female entrepreneurs were to run riskier enterprises, this could be a candidate reason for facing higher rejection rates on their business loans applications. Finally, the correlation between female ownership and the likelihood of being denied credit access is relevant and statistically significant when different definitions of female ownership are considered (see Table A8).

Figure 1: Credit Risk Scores of Male and Female Entrepreneurs



Note: This figure shows the Dun & Bradstreet credit risk scores of entrepreneurs in KFS. Credit risk scores are given on a scale of 1 to 5, where 1 represents the lowest risk class and 5 is the highest risk class.

To provide additional evidence on the risk profile of female and male-owned firms, we examine the official credit risk scores assigned by the Dun & Bradstreet rating agency to the firms in our sample. Figure 1 shows that, overall, female entrepreneurs are not rated riskier than male entrepreneurs (on a scale 1 to 5, numbers closer to 1 refer to low credit risk). Focusing then on loan requests, female-owned businesses show consistently better credit scores. Among successful applicants, male entrepreneurs' average risk score is 2.62 whereas for female entrepreneurs it is 2.44. As for rejected loan requests, the average score of male entrepreneurs is 3.22, while for female entrepreneurs is 2.87. Hence, female-led firms have better credit risk profiles among both *accepted* and *rejected* loan applications.[20] Next, we focus on their leverage and on the volatility of return on assets, often used in finance as measures of business risk (see Faccio et al. (2016)). Leverage is defined as business debt over assets, while the volatility of return on assets is measured as the

[19] We also cross-check our results using SCF data (see Table A19 in the Appendix).

[20] Table A6 in the Appendix further analyzes differences in gender attitudes towards external financing, with a break down by credit risk score. There is no difference in the overall fraction of female and male entrepreneurs that did not apply for a loan due to fear of being rejected, notwithstanding their credit risk score. Moreover, Figure A.17 shows that female entrepreneurs do not have different attitudes towards business growth expectations and uncertainty.

standard deviation of profits over assets in a three-year rolling window.[21] As shown in columns (1) and (2) of Table 4, there is no statistically significant difference between the leverage and volatility of returns across genders. Coupled with the evidence on credit risk scores, our empirical findings suggest that female entrepreneurs are not riskier clients for banks, which may exclude differential business risk as a confounding factor determining gender disparities in credit access.

Table 4: Measures of Risk-Taking and Profitability

	(1)	(2)	(3)	(4)
	leverage	sd(ROA)	$\frac{Profit}{Assets}$	$\frac{Profit}{Revenues}$
Female	0.0264	0.1504	0.3610**	0.0239*
	(0.0238)	(0.1317)	(0.1367)	(0.0130)
Controls	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	7,846	4,726	5,901	5,811
R^2	0.094	0.133	0.111	0.339

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Survey weights are used. Control variables include the number of owners, legal status of the firm, number of hours worked per week and size as measured by $\log(revenues)$, as well as owners' characteristics such as education, experience, race, and age. The regression on sd(ROA) also includes leverage as a control variable, following Faccio et al. (2016).

It can also be questioned whether the higher loan rejection rates faced by female owners may be due to gender differences in firm profitability. We hence compute standard profitability measures such as profits over assets $\frac{Profit}{Assets}$, and the profit margin $\frac{Profit}{Revenues}$, and compare them across female and male entrepreneurs.[22] As reported in columns (3) and (4) of Table 4 and in Figure A.9, after controlling for individuals' observable characteristics and other well-known determinants of firm performance, female-led firms seem to be more profitable compared to male ones.[23] This result holds when using different definitions of female ownership (see Table A10), and a different sample of entrepreneurs from the SCF dataset (see Table A20). As such, it can be argued that the observed gap in external funding is not evidently related to different firm profitability across genders.[24] Moreover, the fact that female-owned businesses may actually have better profit margins

[21] In Faccio et al. (2016), the computation is done over a five-year rolling window whereas we opt for a smaller window because the KFS panel is shorter and covers only the years between 2004 and 2011.

[22] We also check whether and how much entrepreneurs invest in their businesses through research and development (*R&D*) – e.g. worker training, product/service design, brand, software and organizational development – whose relevance for business performance has been widely documented (see Corrado et al. (2009)). As reported in Figure A.10, even if female-owned firms are on average smaller and hence spend less in absolute terms, there are no statistically significant gender differences in the resources devoted by their businesses to *R&D* as a share of total expenses or total revenues even if slightly less female entrepreneurs invest in R&D relative to males (13% and 16% respectively).

[23] Using KFS data from 2004 to 2008, Robb and Watson (2012) find no difference in the performance between female- and male-owned businesses. However, we make use of the entire sample, which potentially can explain our different conclusions. We nonetheless note that their finding is not inconsistent with the idea that the funding gap across genders is not being driven by differences in profitability, which is the main point made in our analysis.

[24] Our results are also consistent with a 2018 study by the Boston Consulting Group, which found that for every $1

is consistent with a phenomenon of stricter *selection* into the entrepreneurial pool. In particular, if female agents face tighter borrowing constraints, this can imply that only the marginally more productive ones manage to start a business, resulting in the observed higher profitability ex-post.

2.3 Misallocation

The next set of results documents the presence of gender-driven capital misallocation in the KFS sample. To conceptualize the notion of misallocation, we can imagine an economy populated by heterogeneous firms that differ in their productivity A_i and produce an homogeneous good according to $y_i = A_i f(k_i, l_i)$, where f is a strictly increasing and concave production function in capital k and labor l. As explained by Restuccia and Rogerson (2017), absent misallocating forces, there should exist a unique choice for how labor and capital are allocated across firms to maximize total output. Misallocation across heterogeneous producers may arise if inputs do not flow to firms according to their idiosyncratic productivity A_i, and empirical differences in the average products of inputs are often a good indicator of the misallocation of resources across producers (see Hsieh and Klenow (2009)). For example, capital-constrained firms may run their operations with lower than average levels of capital, resulting in empirically higher average product of capital.

Following this reasoning, our approach is to measure misallocation of productive inputs at the firm-level and by gender,[25] and try to establish a link with the observed credit gap across female and male-led firms. We begin by computing the average returns to capital and labor as follows:[26]

$$arpk_{it} := \ln(ARPK_{it}) = \ln\left(\frac{Y_{it}}{k_{it}}\right) \qquad \text{and} \qquad arpl_{it} := \ln(ARPL_{it}) = \ln\left(\frac{Y_{it}}{l_{it}}\right)$$

where the Y_{it} is revenues, k_{it} is capital, and l_{it} refers to firm's labor. Following Hsieh and Klenow (2009), we use wage bill instead of employment as a measure of the labor input to control for differences in labor quality and actual hours worked across firms. Fixed assets are computed as the sum of all non-current asset categories in the KFS dataset, including inventory, equipment and machinery, land, buildings, vehicles and other properties.[27] We then run the following regression:

$$y_{it} = \beta_0 + \beta_1 \mathbb{1}_{female} + \delta' \mathbf{\Gamma}_{it} + \alpha_t + \eta_{s(it)} + \nu_{r(it)} + \varepsilon_{it} \tag{2}$$

where $y_{it} = \{arpk_{it}, arpl_{it}\}$. The key explanatory variable is $\mathbb{1}_{female}$, a dummy variable that takes on a value of 1 if the firm is 100% female-owned and 0 if it is 100% male-owned. The regressions include a set of controls $\mathbf{\Gamma}$, which captures various factors apart from gender that may affect the allocation of inputs of production across firms, as well as sector, region and year fixed effects. As

of investment raised, women-owned startups generated \$0.78 in revenue, whereas men-run startups generated only \$0.31, see `https://www.bcg.com/publications/2018/why-women-owned-startups-are-better-bet`

[25]See Goraya (2020) for an example of a similar approach to misallocation by caste in India.

[26]Dispersion in *average* returns is a clear indicator used in the literature to signal the instance of misallocation without imposing any specific production function on the data (as opposed to marginal returns).

[27]Current assets in the KFS sample are cash and accounts receivable (see also Kochen and Guntin (2020)).

shown in Table 5, female-owned businesses are associated with 8-12% higher *arpk*, depending on the preferred regression specification.[28] This suggests the presence of gender-driven misallocation of capital across firms, and that female entrepreneurs are operating with lower levels of capital compared to men, which, to the best of our knowledge, had never been documented for the US.

Table 5: *arpk* and *arpl* across genders

	(1)	(2)	(3)	(4)
	arpk	*arpl*	*arpk* revenues>$10,000	*arpl* revenues>$10,000
Female	0.0836*	0.0230	0.1219**	0.0689
	(0.0498)	(0.0545)	(0.0561)	(0.0565)
Controls	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	7,766	5,955	5,723	4,873
R^2	0.236	0.175	0.263	0.207

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Survey weights are used. Control variables include the number of owners, legal status of the firm, and number of hours worked per week, as well as owners' characteristics such as education, experience, race, and age.

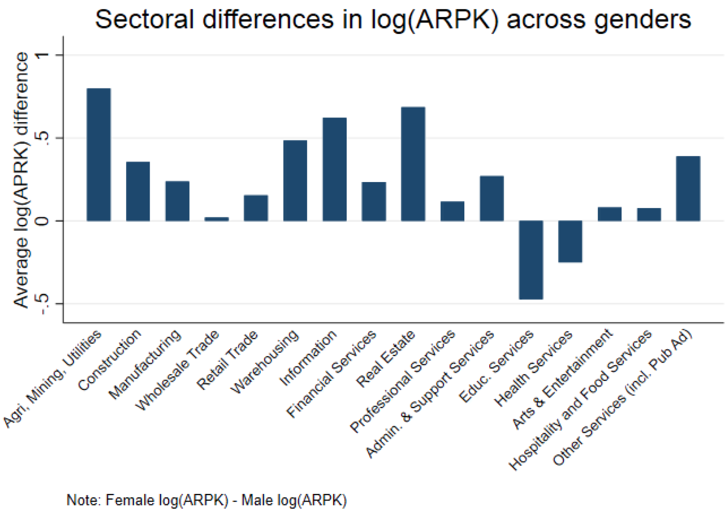
Moreover, Table 5 illustrates that there is no statistically significant difference between the *arpl* of male and female-owned firms. This finding is consistent with Bento (2021), who takes a historical perspective and uses US Census aggregate data to argue that the gender gap in firms' *arpl* has lost relevance in recent years. Note that, while our main specification refers to firms where all owners are female or male, results are robust to using a continuous measure of female ownership or focusing on the gender of the primary owner (see Table A11 in the Appendix).

We also stress that the documented gender-driven capital misallocation is a *within* sector phenomenon, insofar as the gender differences in firms' *arpk* are not imputed to specific industries only but are pervasive *across* most sectors in the economy. To this end, Figure 2 reports the residual differences in female and male *arpk* under the regression specification in Table 5 and across 2-digits sectors. Coupled with the evidence shown earlier on the presence of gender disparities in financial frictions, this suggests that differential access to credit across genders may be driving the sub-optimal allocation of capital that we observe in the data *across* nearly all sectors.

Importantly, the misallocation literature has often attributed the presence and extent of resource misallocation to latent frictions that may disproportionately affect some entrepreneurs, such as borrowing constraints (see Hopenhayn (2014) for a review). Along these lines and to better highlight the potential link between credit and capital misallocation in our sample of firms, we expand the baseline regression in equation (2) and interact the female dummy $\mathbb{1}_{female}$ with a measure of debt holdings. We then specifically look at both business debt and personal debt to see

[28] Column (3) and (4) in Table 5 show the regressions on firms with empirically relevant levels of revenues per year.

Figure 2: Gender Differences in $arpk$ Across Industries



how each type of liability can differently affect capital allocation across entrepreneurs of opposite genders by running the following regression specification:

$$arpk_{it} = \beta_0 + \beta_1 \mathbb{1}_{female} + \beta_2 \log(\text{Debt}) + \beta_3 \mathbb{1}_{female} \times \log(\text{Debt}) + \delta' \mathbf{\Gamma}_{it} + \alpha_t + \eta_{s(it)} + \nu_{r(it)} + \varepsilon_{it} \quad (3)$$

Table 6: $arpk$ and Debt

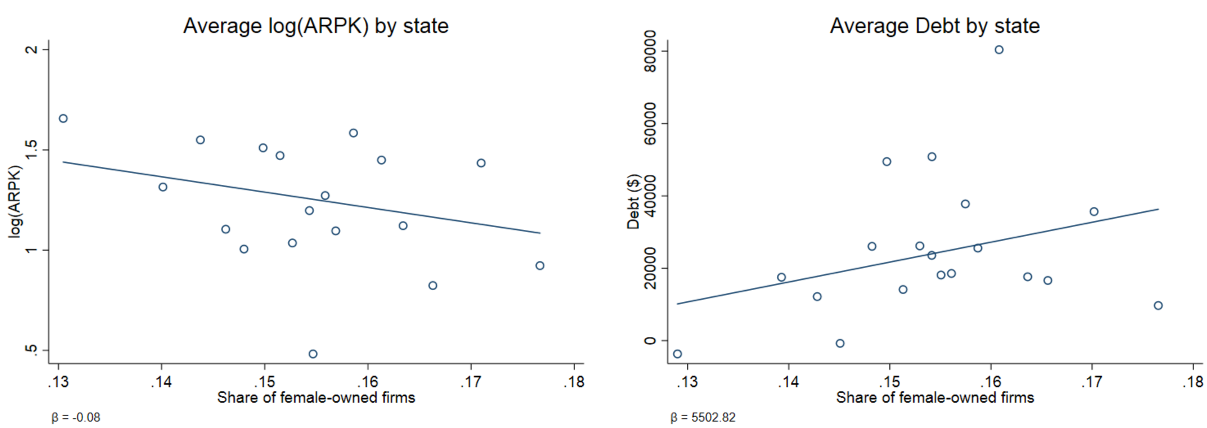
	Business Debt	Personal Debt
	$arpk$	$arpk$
Female	0.1121*	0.2154***
	(0.0668)	(0.0747)
log(Debt)	-0.0121**	-0.0107**
	(0.0048)	(0.0047)
Female × log(Debt)	-0.0200*	-0.0237**
	(0.0112)	(0.0100)
Controls	Y	Y
Sector FE	Y	Y
Region FE	Y	Y
Year FE	Y	Y
Observations	5,074	5,557
R^2	0.277	0.274

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Survey weights are used. Control variables include the number of owners, legal status of the firm, and number of hours worked per week, as well as owners' characteristics such as education, experience, race, and age. Firms with revenues>$10,000 are considered.

Focusing on firms with empirically relevant levels of revenues and based on our main definition of female ownership, we find evidence of a strong interplay between debt and $arpk$, as reported in Table 6.[29] In particular, a statistically significant coefficient on the female dummy means that, on average, there is misallocation of capital across genders that cannot be attributed to differences in the level of debt. The negative correlation between debt and $arpk$ suggests that being able to borrow more can relax the financial constraint of firms and hence lower capital misallocation. Finally, a negative and statistically significant coefficient on the interaction term means that the effect is stronger for female entrepreneurs, suggestive of tighter frictions on their part. This precisely corroborates the idea that we want to convey in this paper – that female entrepreneurs' lower access to credit could be related to the misallocation of capital observed in the data.

As a further validation exercise and to complement our analysis, the left panel of Figure 3 shows the relationship between female $arpk$ and the share of female-owned firms across states, controlling for all the variables included in our main regressions. Note that to compute a representative share of female-owned enterprises for each state, we use US Census statistics for the year 2007.[30] In states where women are more represented within the entrepreneurial force, female $arpk$ is lower, implying lower gender-driven capital misallocation. Similarly, the right panel of Figure 3 documents that the average debt level of female-owned enterprises is higher in states with a higher share of female entrepreneurs. Capital misallocation and credit differences across genders seem hence to be lower wherever female entrepreneurial representation is higher.[31]

Figure 3: Female $arpk$ and Debt Across States



Note: Average $arpk$ and debt level of female-owned firms versus the share of female-owned firms across states. Note that the plot (a binscatter) groups together states with similar female entrepreneurial rates and allows to control for all the variables used in our main regressions. See Figure A.18 for the break down by state.

Finally, in previous paragraphs we have shown that female-owned firms are associated to

[29]The results are robust to alternative definitions of female ownership, as documented in Table A12 and Table A13. Additional results for the entire sample are available upon request.

[30]SBO Census statistics for the entrepreneurial universe in the US were available for the years 2002 and 2007. Since the KFS spans the period between 2004 and 2011, we work with estimates from the 2007 SBO sample.

[31]A higher share of female entrepreneurs could relate to cultural norms, federal laws, or gender stereotypes, that may be more (less) present in some States. In Figure B.1, we also document that in states where there is higher female representation in financial sector jobs (computed using the 4 digit occupational categories available in the US Current Population Survey for the period between 1980 and 2019), the average debt of female-owned firms is also higher.

higher average business profitability, and argued that this phenomenon is in principle consistent with a mechanism of *selection*. If female-owned firms face higher barriers after entry – for example, by means of an impaired access to credit, as we document – only marginally more productive women may find optimal to become entrepreneurs, resulting ex-post in firm profitability differences across genders. To illustrate further this point, we follow Hsieh and Klenow (2009) and compute a revenue-based measure of total factor productivity – $tfpr$ – as the ratio between firm revenues and output. This procedure requires taking a stand on the functional form of the production function, which we have abstracted from so far, as we have focused on *average* and not *marginal* input products. Using a standard Cobb-Douglas, we define firm-level $tfpr$ as follows:

$$tfpr := \ln(TFPR_{it}) = \ln\left(\frac{Y_{it}}{(k_{it}^{\alpha} l_{it}^{1-\alpha})}\right)$$

where Y_{it} is revenues, k_{it} is capital measured using fixed assets, l_{it} is labor measured as wage bill, and $\alpha = 0.33$ as standard. We then regress firm-level $tfpr$ following the same specification as in Equation 2. Across different definitions of female ownership, we nevertheless find that $tfpr$ is higher for female-led firms. Consequently, it is possible to interpret this result as further evidence of a stricter *selection* process of productive women into entrepreneurship.

Table 7: $tfpr$ across genders

	Baseline	Primary Owner	Share of Female Owners
Female	0.0937*	0.1117***	0.1153***
	(0.0487)	(0.0384)	(0.0427)
Controls	Y	Y	Y
Sector FE	Y	Y	Y
Region FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	4,024	5,050	5,091
R^2	0.215	0.208	0.201

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Survey weights are used. Control variables include the number of owners, legal status of the firm, and number of hours worked per week, as well as owners' characteristics such as education, experience, race, and age.

Our analysis has hence documented gender gaps in financial frictions and in capital utilization. Previous papers have also found instances of gender imbalances with respect to firm financing, see Cavalluzzo et al. (2002), Bellucci et al. (2010), Aristei and Gallo (2016), De Andres et al. (2020) and Montoya et al. (2020) on the topic of loan requests, and Hebert (2020) and Ewens and Townsend (2020) on external funding. Other works have instead uncovered gender differences in the interest rate paid on loans (see Coleman (2000) and Alesina et al. (2013)), as well as in the frequency and size of the collateral asked to firms (see Calcagnini et al. (2015) and Xu et al. (2016)).[32] In

[32]In Figure A.14, we verify that female-owned firms in the KFS sample are more likely to be requested collateral both

our investigation, having established as a novel empirical fact the presence and extent of gender-driven capital misallocation, we also suggest that the observed differential access to credit across genders in the KFS may be driving the misallocation of capital that we document empirically.

The nature of our data, however, does not allow to reach a clear-cut conclusion on what is driving the heterogeneity in the access to credit across male and female entrepreneurs in our sample. In the Appendix, we discuss different types of discrimination that could be responsible for the observed gender gap in business financing. We examine taste-based and implicit-bias explanations proposed by previous literature for which we find some suggestive support in our analysis, but we do not take any conclusive stand. Instead, in our quantitative investigation, we will condense this discussion in developing a heterogeneous agents entrepreneurship model enriched with gender-based borrowing limits, and treat the heterogeneity in firm debt across genders as stemming from the credit supply side of the economy. Even if reduced-form, such asymmetry in the access to funding is in line with the evidence on the tighter financial constraints faced by female entrepreneurs in KFS, and delivers consistent gender differences in capital utilization.

3 Theoretical Framework

The empirical evidence gathered so far suggests that tighter financial frictions may be causing distortions in the level of capital with which female entrepreneurs operate their businesses. Our goal is hence to model and quantify the impact of gender differences in the degree of borrowing constraints, which can lead to distortions along both the *extensive margin* (i.e. entrepreneurial participation) and the *intensive margin* (i.e. optimal allocation of resources) of entrepreneurship.

Following Buera and Shin (2013), we develop a general equilibrium heterogeneous agents model in which individuals of different genders, entrepreneurial productivities and assets can decide whether to be workers or entrepreneurs. Entrepreneurs produce according to a decreasing returns to scale technology using both labor and capital, and the amount of capital that they can rent depends on their stock of assets. Such limit is gender-based and may constrain female entrepreneurs to borrow less compared to male entrepreneurs with similar wealth and productivity. In particular, along the *extensive margin*, tighter financial frictions cause women to face higher barriers in starting a business, discouraging their participation into entrepreneurship and contributing to gender differences in the way agents *select* into the entrepreneurial pool. Along the *intensive margin*, differential borrowing constraints influence women's optimal choice of capital, leading to consequent losses in aggregate production and to the misallocation of capital.[33]

among successful and rejected loan applicants, whereas the reason for getting a loan application rejected is more often imputed to motivations that abstract from business performance, see Figure A.13.

[33] This leaves open the possibility of introducing other gender differences across entrepreneurs, which we abstract from in the current analysis but explore in the Appendix. Here, we show that a model of entrepreneurship and financial frictions, enriched with a gender gap in credit access, is sufficient to match well the observed features of our data.

3.1 Model Primitives

Time is discrete and the environment is populated by a continuum of infinitely-lived agents characterized by different productivity z, assets a, and gender g, giving rise to a distribution of individuals $H(z,a,g)$ in each t. While agents' productivity follows an exogenous stochastic process, financial wealth is determined endogenously by a standard consumption-saving problem.

Occupation: At every point in time, agents decide their occupation $o(a,z,g)$, based on their wealth a, idiosyncratic entrepreneurial productivity z and gender g. They can choose to be either entrepreneurs (*entr*) or workers (*work*). Entrepreneurs own a firm and earn business profits π, while workers inelastically supply one unit of labor and earn a wage w, determined in general equilibrium. For simplicity, we assume that the wage w is independent of agents' characteristics.[34]

Productivity: Entrepreneurial productivity z follows an exogenous stochastic process given by:

$$z_t = \rho_z z_{t-1} + \epsilon_t \quad \text{with} \quad \epsilon \sim \mathcal{N}(0, \sigma_\epsilon^2)$$

which is further characterized by the conditional distribution $d\Xi(z'|z)$. In particular, ρ_z is the persistence in productivity, while ϵ_t is the idiosyncratic risk component. Hence, our model features idiosyncratic shocks to entrepreneurial productivity and no source of aggregate uncertainty.

Preferences: Agents have a strictly increasing concave utility function, which satisfies standard Inada conditions. The coefficient of risk aversion is denoted by γ and assumed to be the same across genders (this can be relaxed without changing the nature of our results).[35] Moreover, agents discount the future at a rate β and maximize utility over the following stream of consumption:

$$\mathbb{E}_t \sum_{t=0}^{\infty} \beta^t \frac{c_t^{1-\gamma} - 1}{1-\gamma}$$

3.2 Firms' Production

Technology: Entrepreneurs produce with a standard production function that combines together entrepreneurial productivity z, capital k and labor l. The production function is increasing in all its arguments, strictly concave in capital and labor, and decreasing returns to scale, allowing for a non-degenerate distribution of the enterprise size. In particular, $f(z,k,l)$ is given by:

$$f(z,k,l) = e^z (k^\alpha l^{1-\alpha})^{1-\nu}, \quad \text{with} \qquad 0 < 1-\nu < 1$$

[34]Our analysis hence abstracts from studying the gender gap in workers' earnings and rather focuses on the entrepreneurial credit gap only. We believe future work is needed to understand the relative strength and importance of both the wage and credit gaps, and further investigate their impact on female occupational choices.

[35]Our choice is motivated by the fact that we cannot find robust empirical evidence of gender difference in risk aversion in both KFS and SCF data, as explained in Appendix. Nonetheless, we note that a higher coefficient of risk aversion would further discourage women from becoming entrepreneurs, inducing a stronger selection effect and amplifying capital misallocation. In this case, our baseline results would be a conservative estimate of the negative aggregate effects caused by the gender-driven misallocation of talent and capital (see Section B3).

where $1 - \nu$ is the span of control as in Lucas (1978).[36] Both capital and labor are static inputs and rented on their respective markets at each point in time. Entrepreneurs therefore pay capital rental costs $(r + \delta)k$ – where δ is the depreciation rate – and salaries wl as variable input costs.[37]

3.3 Financial Markets

There is a perfectly competitive intermediary sector that receives deposits from savers and lends funds to firms, without intermediation costs. The rental rate of capital is given by r_t, where r_t is the deposit rate determined in general equilibrium. Financial markets are incomplete, and entrepreneurs can borrow up to a fraction of their assets a_t. Capital constraints are hence given by:

$$k_t \leq \lambda_g a_t; \qquad a_t \geq 0$$

where $a_t \geq 0$ (intertemporal borrowing is ruled out for simplicity) and λ_g measures the degree of the constraints, which varies by gender. If $\lambda_g = 1$, agents operate in a zero credit environment, as opposed to the case in which $\lambda_g = \infty$ and individuals can borrow according solely to their productivity, regardless of their financial wealth. In addition to that, we allow for the possibility that female entrepreneurs in the model may borrow less than male ones, namely for $\lambda_m - \lambda_f > 0$.

3.4 Profit Maximization

Entrepreneurs maximize revenues net of capital renting costs and labor costs, with the only gender disparity being the different borrowing constraint female entrepreneurs face when renting capital. Since output price is normalized to one, profit maximization can be written as:

$$\pi_t = \max_{l_t, k_t} \left\{ e^{z_t} (k_t^{\alpha} l_t^{1-\alpha})^{1-\nu} - w_t l_t - (r_t + \delta) k_t, \quad \text{s.t.} \quad k_t \leq \lambda_g a_t \right\} \tag{4}$$

Importantly, we do not assume any gender difference in the labor hiring process (or in labor costs), which is consistent with the findings in Section 2. As shown in Table 5, female entrepreneurs are associated with higher *arpk*, whereas no gender heterogeneities exist with respect to *arpl*.[38]

3.4.1 Understanding Gender-Driven Misallocation

An intuitive way to disentangle the mechanism engineered by the gender differences in financial frictions is to derive the profit maximization problem for a female entrepreneur and compared it to the one of any male entrepreneur. We may assume in this analysis that $\lambda_f = \lambda_m - \tau > 0$, where

[36] In the Appendix, we also discuss a version enriched with gender differences in the span of control.

[37] In the Appendix, we discuss a model version that includes differential operational costs.

[38] We check the extent of gender differences in the wages paid to their employees across KFS entrepreneurs inTable B1. We stress again that our analysis also abstracts from modeling any (employee) gender wage gap, for we do not observe the break down of the wage bill across employees' gender for the female and male business owners in the KFS sample.

τ is interpreted as a wedge on the capital input. Thus, for a female entrepreneur, we can write:

$$\max_{l_t,k_t} \left\{ e^{z_t}(k_t^{\alpha} l_t^{1-\alpha})^{1-\nu} - w_t l_t - (r_t+\delta)k_t - \mu_t \left(\frac{k_t}{\lambda_m - \tau} - a_t \right) \right\} \tag{5}$$

where μ_t is the Lagrangian multiplier on the financial constraint. Deriving the optimality conditions for both labor and capital, we first observe that:

$$l_t^{opt} = \left(\frac{(1-\nu)(1-\alpha)e^{z_t}(k_t^{\alpha})^{1-\nu}}{w_t} \right)^{\frac{1}{1-(1-\alpha)(1-\nu)}} \tag{6}$$

$$k_t^{opt} = \left(\frac{(1-\nu)\alpha e^{z_t}(l_t^{1-\alpha})^{1-\nu}}{r_t+\delta+\frac{\mu_t}{\lambda_m-\tau}} \right)^{\frac{1}{1-\alpha(1-\nu)}} \tag{7}$$

Gender differences in borrowing constraints do not affect female entrepreneurs' optimal choice of labor l_t^{opt}, while they do negatively impact their k_t^{opt} if $\mu_t \neq 0$. In this case, higher values of τ (which corresponds to lower values of the borrowing limit λ_f) reduce k_t^{opt} for a female entrepreneur relative to a male one. Specifically, borrowing constraints (captured by μ_t) distort all entrepreneurial capital choices, while the different borrowing limit across genders further biases downwards women's k_t^{opt} with respect to men's k_t^{opt}.[39] Thinking of the firms for which constraints are more likely to bind – for example young or small businesses – female-owned firms of such kind would be more often constrained relative to male-owned firms, which may create distortions in female entrepreneurs' business operations and limit their growth and expansion.

To provide a direct theoretical counterpart to the misallocation measures estimated empirically in the KFS sample and discussed in Section 2, we proceed to compute the model equivalent of the average product of capital and labor for a given female and male entrepreneur at time t:

$$\begin{aligned}
arpk_f &:= \ln(ARPK_f) = \ln\left(\frac{Y_f}{k_f}\right) = \frac{r_t+\delta+\frac{\mu}{\lambda_m-\tau}}{(1-\nu)\alpha} \\
arpl_f &:= \ln(ARPL_f) = \ln\left(\frac{Y_f}{l_f}\right) = \frac{w_t}{(1-\nu)(1-\alpha)} \\
arpk_m &:= \ln(ARPK_m) = \ln\left(\frac{Y_m}{k_m}\right) = \frac{r_t+\delta+\frac{\mu}{\lambda_m}}{(1-\nu)\alpha} \\
arpl_m &:= \ln(ARPL_m) = \ln\left(\frac{Y_m}{l_m}\right) = \frac{w_t}{(1-\nu)(1-\alpha)}
\end{aligned}$$

Proposition 1 *: Denote the difference between $arpk_f(\tau)$ and $arpk_m$ as $D_k(\tau)$, where $D_k(\tau) = arpk_f(\tau) - arpk_m = \frac{\tau\mu}{(\lambda_m-\tau)\lambda_m}$. When $\mu_t \neq 0$, the following two results hold:*

1. $\frac{\partial D_k}{\partial \tau} = \frac{\mu_t \lambda_m^2}{((\lambda_m-\tau)\lambda_m)^2} > 0$

[39] An increase in λ_m and λ_f results in a release of borrowing limits. Since agents expect financial constraints to bind less often, the entrepreneurial productivity cutoff of both genders decreases, causing higher entry into entrepreneurship. However, if such increase is proportional, gender differences in credit access and in business performance remain.

2. *If* $\tau = 0$ *then* $D_k(\tau) = 0$

Similarly, denote the difference between $arpl_f$ *and* $arpl_m$ *as* D_l*, where* $D_l = arpl_f - arpl_m = 0$*.* D_l *does not increase with the difference in borrowing constraints across gender* τ*.*

Figure 4: Proposition 1

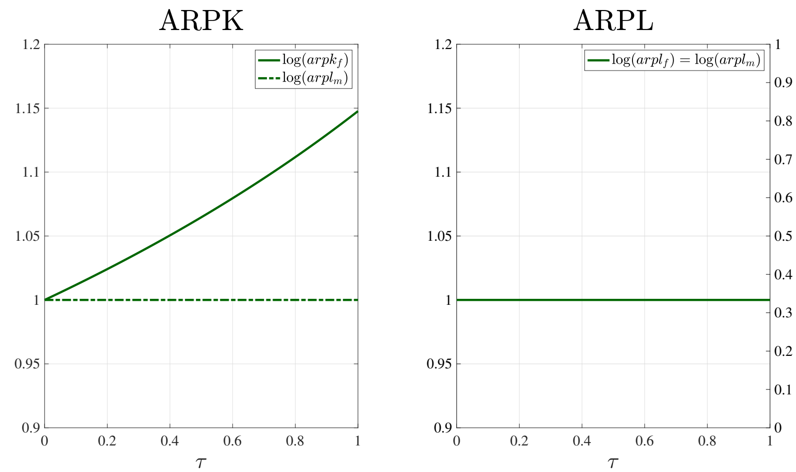


Figure 4 gives a graphical representation of Proposition 1 by plotting $arpk_f$ and $arpk_m$ (left panel), as well as $arpl_f$ and $arpl_m$ (right panel) as functions of the gender difference in the financial constraint wedge τ. The gender gap in credit access not only discourages women from becoming entrepreneurs, but also produces heterogeneities in the average product of capital across female and male-owned firms in the model. These effects can be reconciled with US aggregate evidence on lower female entrepreneurial rates, and with the gender differences in the level of financial constraints and *arpk* documented in Section 2. As such, the quantitative purpose of this paper will be to estimate such borrowing wedge τ and assess how much it can impact the allocation of entrepreneurial talent and capital, as well as aggregate productivity in the economy.

3.5 Individual's Problem

In each t, agents maximize expected utility given factor prices $\{w, r\}$, their assets and productivity, such that the budget constraint always binds. The value function that individuals maximize is:

$$V(a,z,g) = \max\{V^{work}(a,z,g), V^{entr}(a,z,g)\} \tag{8}$$

Specifically, workers' value function is given by:

$$V^{work}(a,z,g) = \max_{c,a' \geq 0} \; u(c) + \beta \int V'(a',z',g) dY(z'|z) \tag{9}$$

$$s.t. \quad c + a' \leq w + (1+r)a \tag{10}$$

while entrepreneurs' value function is given by:

$$V^{entr}(a,z,g) = \max_{c,a'\geq 0} u(c) + \beta \int V'(a',z',g) d\Xi(z'|z) \tag{11}$$

$$s.t. \quad c + a' \leq e^z (k^\alpha l^{1-\alpha})^{1-\nu} - wl - (r+\delta)k + (1+r)a \tag{12}$$

$$k \leq \lambda_g a \tag{13}$$

3.6 Recursive Equilibrium

At time 0, given the distribution $H_0(z,a,g)$, the equilibrium of the economy is characterized by a sequence of allocations $\{o_t, c_t, a_{t+1}, k_t, l_t\}_{t=0}^{\infty}$, factor prices $\{w_t, r_t\}_{t=0}^{\infty}$, and $H_t(z,a,g)_{t=1}^{\infty}$ such that:

1. $\{o_t, c_t, a_{t+1}, k_t, l_t\}_{t=0}^{\infty}$ solves the individuals' policy functions for given factor prices $\{w_t, r_t\}_{t=0}^{\infty}$.

2. Capital, labor and good markets clear:

$$\int_{o_t(a,z,g)=e} k_t dH_t(a,z,g) - \int a dH_t(a,z,g) = 0$$

$$\int_{o_t(a,z,g)=e} l_t dH_t(a,z,g) - \int_{o_t(a,z,g)=w} dH_t(a,z,g) = 0$$

$$\int_{o_t(a,z,g)=e} \left[e^{z_t}(k_t^\alpha l_t^{1-\alpha})^{1-\nu}\right] dH_t(a,z,g) = \int c_t dH_t(a,z,g) + \delta k_t$$

4 Quantitative Results

This section of the paper quantifies how much of the gender differences in entrepreneurial rates and capital utilization can be explained by the gender gap in access to credit, and evaluates the output losses implied by the resource misallocation operating both at the *extensive* and *intensive* margin of entrepreneurship. We first begin by estimating the model on the US economy using various sources of data, and we then analyze the main quantitative predictions of our framework in terms of individual choices and aggregate outcomes. Next, we run counterfactual exercises to assess the positive effect of removing gender heterogeneities in credit access on the allocation of entrepreneurial talent and capital, as well as on aggregate output and welfare in the economy.

4.1 Calibration

In what follows, we present our calibration strategy and discuss the quantitative fit of our framework with respect to targeted moments from the data. A model period is one year. Of the nine parameters we need to estimate, summarized in Table 8, three are fixed outside the model. As in Cagetti and De Nardi (2006), we set the coefficient of risk aversion $\gamma = 1.5$ and the capital share $\alpha = 0.33$, while we opt for a depreciation rate $\delta = 0.1$.[40] As for the internally fitted parameters,

[40] Commonly used values for δ range from 0.06, as in Buera and Shin (2013), to 0.1, as in Clementi and Palazzo (2016).

we choose to match six related empirical moments for the US economy that are further reported in Table 9, following mostly Buera and Shin (2013) and Midrigan and Xu (2014).

Table 8: Calibration

Parameter	Value	Description	Reference
Fixed			
γ	1.5	Coefficient of risk aversion	Cagetti & De Nardi (2006)
α	0.33	Physical capital share	Cagetti & De Nardi (2006)
δ	0.1	Capital depreciation (annual)	Clementi & Palazzo (2016)
Fitted			
β	0.925	Discount factor	
$1-\nu$	0.835	Span of control	
σ_ϵ	0.265	Std. deviation idiosyncratic productivity shock	
ρ_z	0.93	Persistence idiosyncratic productivity	
λ_m	2.7	Borrowing constraint male	
λ_f	1.9	Borrowing constraint female	

First, we pick $\beta = 0.925$ to match an average annual interest rate $r = 4\%$ for the US.[41] Second, the span of control parameter is fitted such that the income share of the top 5% agents in the distribution of earnings is the same in the data and in the model. This choice is motivated by the fact that $1-\nu$ regulates firms' scale of operations and, as a consequence, affects the profits of the entrepreneurs that are likely to be at the top decile of the earnings distribution. In that, we follow a recent and extensive literature on earnings and wealth distributions in the US (see Batty et al. (2019) and Zucman (2019) for example), which shows that the top 5% richest Americans make up for almost 35% of total earnings in the economy.[42] Our estimated value for the span of control parameter $1-\nu = 0.835$ is close to the one obtained by several other papers on US entrepreneurship.[43] As a robustness check, we can alternatively calibrate $1-\nu$ to match the share of entrepreneurial wealth in aggregate wealth, without changing the nature of our results.

To identify the volatility of the entrepreneurial productivity shock, we then target the employment share of the top 10% largest firms, which is computed using the KFS dataset. A bigger σ_ϵ implies greater dispersion in the productivity process (by means of thicker tails in the distribution) and higher employment generation by large businesses.[44] Our final value $\sigma_\epsilon = 0.265$ is in

[41] This number reflects well the average interest rate prevailing in the American economy over the last 30 years.

[42] In the period between 1997 and 2017, it is reported that the top 10% income share oscillates between 45% and 50%.

[43] In quantitative works based on the US, values for $1-\nu$ usually range from 0.79, as in Buera and Shin (2013) to 0.88, as in Cagetti and De Nardi (2006). As noted by Hsieh and Klenow (2009), a lower span of control tend reduce the (negative) impact on output stemming from capital misallocation. At the same time, in our setup, a lower span of control worsens the (negative) impact on output stemming from changes in the number of firms. In fact, a lower $1-\nu$ negatively affects entrepreneurial profits and even less women find it optimal to become entrepreneurs. These two effects on aggregate output tend to offset each other, meaning that the exact value of $1-\nu$ is not responsible for amplifying or reducing the effect of a gender imbalance in credit access on aggregate production.

[44] Size is measured in terms of total employees, as also in Buera and Shin (2013) and Midrigan and Xu (2014).

line with the range of US estimates provided by Lee and Mukoyama (2015). For further comparison, we also compute the average employment shares by firm size using BDS data. In both BDS and KFS we find that the employment share of the top 10% largest producers oscillates between 0.65 and 0.7, close to what found by Buera and Shin (2013). As previously stressed in Section 2, the KFS sample is representative of the US firm distribution, and the distributions of businesses over size bins computed using both KFS and BDS overlay particularly for larger firms.

Table 9: Internally Targeted Moments

	US Data	Model
Interest Rate	0.04	0.04
Earnings Share of Top 5% Individuals	0.35	0.36
Employment Share of Top 10% Firms	0.65	0.66
Average Persistence in Firms' Employment	0.73	0.80
Credit(Non-Financial Private Sector)/GDP	0.41	0.41
$\frac{Debt_f}{Debt_m}$	0.55	0.55

Next, to calibrate the parameters λ_m and λ_f, which govern the extent of the gender-based financial frictions, we use the difference in business debt across genders, together with the US debt/GDP ratio. We first measure the average female and male entrepreneurs' business debt in KFS, noting that women take on 45% less debt with respect to men. Second, since the KFS spans a relatively short period of time and surveys nascent businesses, we choose to match the average US non-financial corporate debt over GDP between 1990 and 2014,[45] and provide related alternatives.[46] Moreover, we focus on non-financial corporate debt because other measures of total debt merge together household and corporate debt and cannot be mapped correctly into our theoretical framework.[47] The model identifies λ_m to be roughly 30% higher than λ_f, and Section 6 will quantify the impact of such gap on both aggregate production and the allocation of resources.

Finally, we use the KFS data to compute the average serial correlation of employment across firms and hence identify the persistence in the entrepreneurial productivity process ρ_z. Specifically, we estimate an AR(1) process on the total wage bill for both female-owned and male-owned KFS firms and get an estimated value for the persistence in employment in the entire sample. We then calibrate $\rho_z = 0.93$ in our baseline economy to generate the same persistence in the model and in the data.[48] As reported in Table 9, the average persistence in business employment is 0.73 in the KFS sample, which our simulated economy slightly over-predicts. This can be due to two

[45] See the entire series on FRED website: `https://fred.stlouisfed.org/graph/?g=VLW#0`.

[46] The average debt-to-output ratio in the KFS sample is 0.49, close to the credit to non-financial corporate sector/GDP reported by the Federal Reserve Bank of St. Louis for the same period (about 0.42). Moreover, we conduct a robustness check by computing the ratio of current liabilities over revenues in Compustat, an extensive dataset covering publicly listed North American firms between 1965 and 2017. We obtain a ratio of 0.41, which is also close to our target.

[47] This choice constitutes the only significant difference in our calibration with respect to Buera and Shin (2013).

[48] Our estimate is similar to the one found by relevant papers on this field such as Lee and Mukoyama (2015). As discussed in Clementi and Palazzo (2016), estimates for ρ can be found to be as low as 0.8 and as high as 0.97.

reasons. First, the fact that our panel covers only 8 years may hinder the precision in the empirical estimation of the persistence in business employment. Second, producers in our sample are very young and this may exacerbate the volatility of their performance particularly in early years.[49]

4.2 Results

4.2.1 Untargeted Moments

To validate the performance of our framework, we test it against other moments from the data that were not targeted during the calibration, focusing on both mean values and distributional properties.[50] As shown in Table 10, our baseline model replicates the bulk of the gender differences in the *arpk* and *k/l* ratio across firms. Note that while the gap in credit access may not be the only reason behind the gender differences in capital utilization, it is the main margin we have estimated in our data and modeled theoretically. Due to the heterogeneity in the borrowing limits captured by λ_f and λ_m, female entrepreneurs in the model have on average an 11% higher $arpk$ and a 14% lower *k/l* with respect to male ones, while these differences amount to 12% and 8.5% in the data.[51]

Table 10: Untargeted Moments

	Data	Model
Capital		
% difference Female $arpk$ vs Male $arpk$	0.12	0.11
% difference Female k/l vs Male k/l	-0.085	-0.14
Business Dynamism		
Difference Male vs Female Entrepreneurial Rates	3 p.p.	1 p.p.
Average Entrepreneurial Rate	0.053	0.065
Average Exit Rate	0.10	0.11

Turning to business rates, we are able to match the overall entrepreneurial and business exit rate in the US,[52,53] while accounting for roughly 30% of the observed percentage points (p.p.) gender differences in entrepreneurial rates. This may be due to the fact that the gap in credit access

[49] We could also set ρ_z according to available estimates for the US, such as the ones reported in Lee and Mukoyama (2015) or in Clementi and Palazzo (2015). This strategy, while easier to adopt, would lead us to make use of external estimates that might have been drawn from a sample of firms slightly different from the ones in the KFS dataset.

[50] A list with all moments from the data and how we computed them is included in the Appendix.

[51] In addition, we compute the ratio between average assets and average revenues for female and male entrepreneurs both in the data and in the model simulation. This moment is tightly linked to the ability to take on debt, especially because financing is used to rent the capital employed in production. In the absence of gender-based borrowing constraints, there should be no differences in the unconditional assets-to-revenues ratio across genders, even if female and male entrepreneurs were to run businesses of different sizes. However, we find that female entrepreneurs in the KFS data have an 11% smaller assets-to-revenues ratio, consistent with the documented gender disparities in the *k/l* ratio, and our calibrated model estimates the difference in the female and male capital-to-output ratios to be roughly 16%.

[52] In the last 20 years, the fraction of entrepreneurs – men and women – in the total US labor force is estimated to be around 4 to 6%, see `https://data.oecd.org/entrepreneur/self-employed-with-employees.htm`

[53] The average exit rate in KFS is 10.43%, similar to the one estimated by Buera and Shin (2013) using BDS data.

is potentially not the only reason behind the observed gender heterogeneities in firm ownership rates. In the Appendix, we hence explore two alternative model specifications. The first one allows for an *operational cost* that differs across female and male entrepreneurs, for which we target the relative difference in exit rates across genders. Introducing an extra cost that reduces female entrepreneurial profits strengthens the mechanism of women's *selection* into entrepreneurship, and allows for a more precise match of the share of female business owners. In the second alternative, we include gender heterogeneities in the *span of control* parameter, quantitatively pinned down by the ratio of the standard deviation of profits of female and male-owned firms. Since the span of control influences business earnings, a lower value for female entrepreneurs can negatively affect their participation choices, improving the fit of the gender differences in entrepreneurial rates.

Table 11: Wealth and Business Debt Distributions

	Data	Model
Business Debt Distribution		
Top 10% Debt Share - All firms	0.59	0.63
Top 10% Debt Share - Female Firms	0.69	0.62
Top 10% Debt Share - Male Firms	0.58	0.63
Wealth Distribution		
Wealth Share in Top 10%	0.70	0.80
Entrepreneurial Wealth Share	0.30	0.47

We then assess the performance of our framework with respect to the distributional properties of business debt and individual wealth across entrepreneurs and workers. As Table 11 shows, the model matches the debt share of the top 10% most indebted firms in KFS, considering both the aggregate pool of entrepreneurs and female and male-owned businesses separately (the goodness of the quantitative fit varies between 90% for the female sample and 60% for the male one). Moreover, a general property of the entrepreneurial frameworks we have built on is to replicate well both the degree of skewness known to characterize the wealth distribution in the US, as well as the relative share of entrepreneurial wealth over the total. This is due to the fact that savings are crucial for entrepreneurs, who constitute a smaller fraction of the population and yet hold a sizable share of the wealth in the economy. In particular, our model moderately over-predicts the US top 10% wealth share, which recent work by Zucman (2019) has estimated to be around 70%. In addition to that, as reported in Table 11, entrepreneurial wealth in the data accounts for 30% of the aggregate (see Cagetti and De Nardi (2006)), and for 47% in our baseline economy.

As a final quantitative exercise, Table 12 collects several moments related to the distribution of revenues and profits in the model and in the KFS data, which were also not targeted during the calibration. After having assessed its performance with respect to the properties and gender differences in capital, debt, wealth and entrepreneurial rates, we verify that the model can also

Table 12: Distributional Properties: Revenues and Profits

	All		Male		Female	
	Data	Model	Data	Model	Data	Model
Top 10% Profit Share	0.60	0.69	0.59	0.70	0.60	0.68
Top 10% Revenues Share	0.68	0.62	0.68	0.62	0.73	0.62
By Size Bins						
Top 25% Profit Share	0.59	0.72	0.58	0.75	0.57	0.70
Top 25% Revenues Share	0.68	0.66	0.68	0.67	0.69	0.65

match the tails of the profit and revenues distributions, overall and by gender. Its fit is less accurate when computing the profit share of the top 25% largest firms – defining size using employment bins – whilst the revenues share of the top 25% largest firms is instead satisfactorily matched.

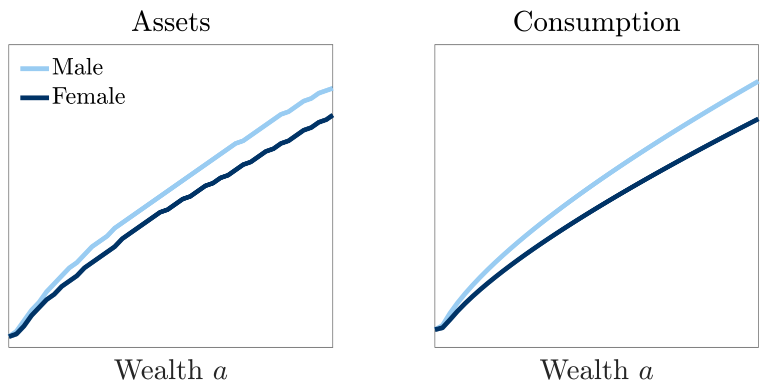
4.3 The Effect of the Gender Gap in Credit Access

In this section, we use our calibrated model to take a closer look at the effect of gender-based financial frictions on individual choices regarding wealth, occupation and production outcomes. First, in Figure 5, we plot consumption and savings policies comparing two equally highly-productive agents, one male and one female. For the same level of wealth, male individuals accumulate more savings and sustain higher levels of consumption. This is precisely due to the fact that highly-productive male agents that pursue entrepreneurship face lower financial frictions with respect to female ones, and have on average higher entrepreneurial profits, consumption and wealth.

Moreover, differences in asset accumulation are also reflected in the distribution of wealth across genders. As shown in Table 11, wealth is heavily concentrated in our model economy and, in particular, the distribution of wealth is more skewed to the left for female agents, as documented in Figure 6. There are two reasons for this. First, as underlined in the previous graphs, women are able to accumulate less assets due to lower entrepreneurial profits. Second, since accumulating assets is particularly crucial for entrepreneurs to overcome financial frictions, women at the bottom of the wealth distribution have marginally lower incentives to do so, as they anticipate that entrepreneurship will be a harder choice for them and refrain from it more often.

In terms of entrepreneurial outcomes, occupational decisions in our model economy depend on the idiosyncratic productivity, wealth and gender of the agents. Higher productivity and/or greater levels of assets have a positive effect on agents' decision to become entrepreneurs. However, since women face tighter financial constraints, they have a lower probability of becoming entrepreneurs, as reported in Table 13. Turning to the choices of capital and labor inputs, Figure 7 shows instead the level of capital and implied output as a function of entrepreneurial idiosyncratic productivity z. Based on their wealth, we compare a poor and a rich male entrepreneurs, and a poor and a rich female ones. Within both wealth categories and due to the tighter borrowing

Figure 5: Savings and Consumption Policies



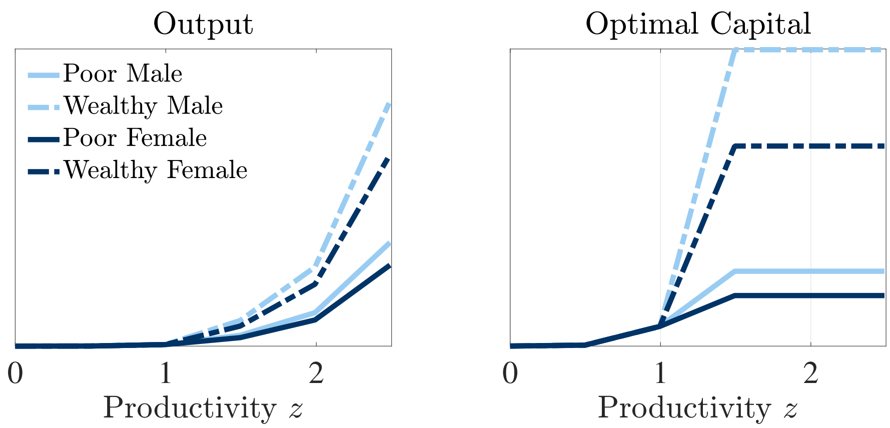
constraints they face, female entrepreneurs produce smaller quantities of final output and operate with inefficiently low levels of capital, resulting in the higher *arpk* further summarized in Table 13. Moreover, as shown in Figure B.4, the log difference in the *arpk* of female and male entrepreneurs decreases along with the reduction in the log difference in business size. In fact, as female-led firms grow bigger, they are able to accumulate wealth and operate at a higher scale, gradually bridging the gap in the level of capital used in production with respect to male-led firms.

Figure 6: Wealth Distribution

Furthermore, as reported in the last column of Table 13, female entrepreneurs in our model have higher total factor productivity (*tfpr*) compared to male entrepreneurs,[54] consistent with the empirical evidence shown in Table 7. Going back to our empirical results, female-led firms in the KFS sample have on average a 10% higher *tfpr* compared to male-led firms, while in our calibrated economy the log difference in *tfpr* across genders is roughly 6%. As previously argued, tighter financial constraints make entrepreneurship a relatively harder occupational choice for women, causing a stricter *selection* into the entrepreneurial pool. Consequently, if only very productive female agents manage to operate businesses in a profitable way, this implies that the marginal

[54] A discussion of how *tfpr* is calculated in case of decreasing returns to scale functions is provided in the Appendix.

Figure 7: Total Output and Optimal Capital



female entrepreneur will be relatively more productive than the male one, resulting in the higher average *tfpr* observed in the sample of female firm owners both in the data and in the model.

Table 13: Model Results

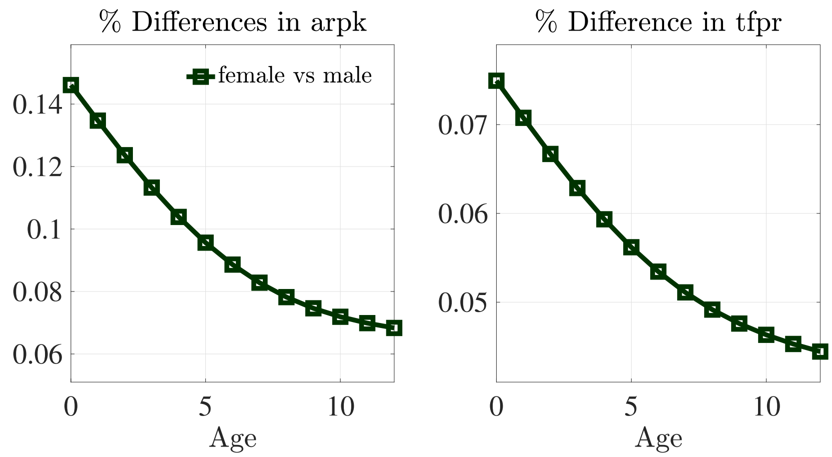
	Entrepreneurial Rates	$arpk$	k/l	$arpl$	$tfpr$
Female	0.06	0.92	4.10	1.26	1.12
Male	0.07	0.81	4.76	1.26	1.06

Finally, we note that the gender differences in both *arpk* and *tfpr* decrease over time as firms grow older, as reported in Figure 8. Importantly, the relationship between the age of a business and the progressive release of financial constraints has been pointed out in several other contexts, see for example Davis and Haltiwanger (1999). Similarly, in our simulated economy, the progressive reduction in the difference in both *arpk* and *tfpr* across genders is due to the fact that, as time passes, female entrepreneurs are able to accumulate wealth and partially overcome the tighter financial constraints that they face by means of a higher asset base. As a consequence, they are able to rent higher levels of capital and expand their production, which leads to lower *arpk* and *tfpr*. In Figure B.3 in the Appendix, we illustrate further the change in growth rates of capital, output and *arpk* over the age of the firm for female and male business owners.

5 Counterfactuals: Removing Gender-Based Financial Frictions

In this section, we quantify the macroeconomic effect of removing the gender gap in financial constraints on both female entrepreneurial performance and aggregate outcomes. In particular, we show that guaranteeing equal access to credit across genders not only improves the allocation of entrepreneurial talent and capital, but also generates output and welfare gains for the whole economy. Our main result echoes the findings in Chiplunkar and Goldberg (2021), who focus on the negative impact of several barriers to female entrepreneurship in India, represented by

Figure 8: Gender Differences in *arpk* and *tfpr* over Firms' Age



higher hiring costs and business formation/registration expenses. In their counterfactual exercise, the release of barriers to female entrepreneurship allows for a substantial increase in female entrepreneurial rates, total output and welfare, similarly to what we find in our different setup.

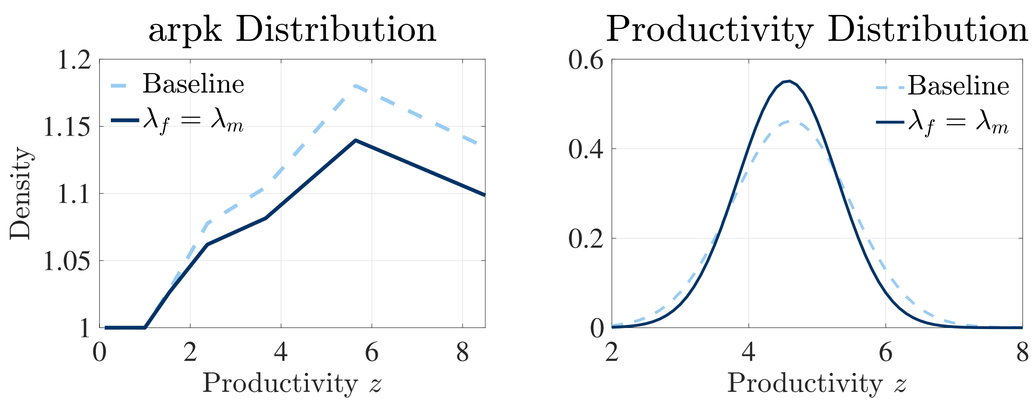
In our model economy, eliminating the gender gap in borrowing constraints has a major impact on what we have already defined as the *extensive margin*, fostering female participation in entrepreneurship. The economy benefits from a better allocation of entrepreneurial talent, insofar as marginally more productive (female) agents become entrepreneurs and crowd out less talented (male) ones. Moreover, removing the gender imbalance in credit access generates a more efficient allocation of resources across productive units, reducing capital misallocation and bringing relevant improvements along the *intensive margin*. Consequently, if female entrepreneurs are able to rent higher levels of capital, they also produce more output, which increases aggregate welfare.

Table 14: Policy Simulation Results

$\lambda_f = \lambda_m$	Total Output	Total Welfare	Female *arpk*	Female k/l Ratio	% Female Entrepreneurs
Increase wrt Baseline	+ 3.82%	+ 3.50%	-11.85%	+ 22.15%	+ 9.32%

In the main counterfactual exercise reported in Table 14, we remove the difference between the borrowing constraints λ_m and λ_f. Note that λ_f is 30% lower than λ_m in the baseline calibration (see Table 8). Relaxing the tighter credit constraint that female entrepreneurs face increases their participation in the entrepreneurial pool and their *k/l* ratio by roughly 10% and 22% respectively. Female business owners can hence operate their firms with higher levels of capital and, as a result, their *arpk* decreases by 12% when $\lambda_f = \lambda_m$. As shown in the left panel of Figure 9, the mean of the distribution of female entrepreneurs' *arpk* substantially decreases when shifting from the baseline to the counterfactual case. In addition, an easier access to credit for female agents allows for a better allocation of entrepreneurial talent, as marginally more productive female individuals find it profitable to enter entrepreneurship and start a firm. As illustrated in the right panel of Figure 9, this implies a leftward shift in the mean of female business owners' productivity, as the productivity cutoff for women to become entrepreneurs decreases.

Figure 9: Female *arpk* and Productivity in Counterfactual



In summary, when $\lambda_f = \lambda_m$, female and male entrepreneurial rates equalize and absent any other gender difference, men and women operate with the same *k/l* ratio and produce the same level of output. The fact that marginally more productive female agents can enter the pool of entrepreneurs and produce with an optimal level of capital has hence a direct effect on the quantity of output that is ultimately supplied in the economy, due to a better allocation of entrepreneurial talent and productive inputs. As reported in Table 14, the subsequent increase in aggregate output with respect to the baseline case reaches a maximum of 3.82%. Using the US GDP of 2019 as a reference, and given that entrepreneurial output is estimated to contribute by 40% to US total production,[55] this could represent a potential increase of roughly 0.35 trillion US dollars in GDP.

Such scenario is also desirable from a welfare perspective. Considering both entrepreneurs and workers, we compute welfare as the sum of agents' utilities over consumption in the counterfactual economy and compare it to the one obtained in the baseline case. When $\lambda_f = \lambda_m$, aggregate welfare grows by 3.50%. This substantial increase in welfare is also due to strong general equilibrium effects. Since more productive female agents become entrepreneurs and crowd out marginally more inefficient male ones, both the demand of capital and labor in the economy increase.[56] In particular, a higher wage benefits the workforce, whereas a rise in the interest rate leads to higher wealth accumulation, despite increasing production costs for entrepreneurs.[57]

Breaking down this result further, we find that aggregate female welfare increases by +5.04%, while aggregate male welfare increases by +2%. In fact, the average welfare of male workers scales

[55]See https://advocacy.sba.gov/2019/01/30

[56]In fact, if we run the same counterfactual in partial equilibrium, keeping fixed the rental rate and wage as in the baseline economy, the final aggregate increase in welfare would be 1.5% instead of +3.50%.

[57]As a consequence of rising production costs, some marginal male firm owners are also crowded out from the entrepreneurial pool, which partially offsets the gain in aggregate output achieved by higher female participation into entrepreneurship. In fact, performing the same exercise in a partial equilibrium setting would achieve a higher increase in aggregate production and in female entrepreneurial rates (by roughly 3 and 7 percentage points respectively).

up by +3.09%, as the new counterfactual economy features higher wages, but the average welfare of male entrepreneurs decreases by -6.03%. Since entrepreneurs represent a smaller fraction of the male labor force, the average welfare of the total male population still improves.[58] Finally, note that the only productive sector in our economy is the entrepreneurial one, which amplifies the increase in welfare and output achieved by eliminating the gender gap in credit access. In fact, if we include another productive sector in our model, composed of financially unconstrained corporate firms, the resulting gains are lower but still quantitatively relevant, as shown in Table B10.

6 Fiscal Policies

In this final section, we explore and evaluate the differential effects that fiscal policies specifically targeting entrepreneurs have on female and male-led firms. Around the world, both in developed and developing countries, there are instances of government subsidies that have the typical goal of fostering entrepreneurial activities and investments, for example by easing the access to credit or by subsidizing production costs. In this spirit, the US Small Business Administration (SBA) has put forward a few programs to facilitate the funding of business owners, both male and female.[59] Currently, the SBA does not lend money directly to entrepreneurs, but instead sets guidelines for loans made by its nationwide network of partnering lenders. It can also guarantee loans between $500 and $5.5 million that can be used for most business purposes, thereby reducing risk for lenders and making it easier for entrepreneurs to access credit.[60] Other examples of subsidies that address entrepreneurs (or female entrepreneurs explicitly) are discussed in the Appendix.

Along these lines, we enrich our model with a public sector that collects lump-sum taxes on all households and redistributes them as entrepreneurial subsidies to business owners. First, we consider fiscal measures targeting either the profits, the employment costs or the capital costs of firms. Second, we analyze subsidies that aim to expand the asset base of entrepreneurs, by providing government-backed collateral or government credit to firms that are financially constrained. We stress that, in these exercises, *all* entrepreneurs are targeted by the government subsidies. While in principle it may be sensible to envision fiscal policies directed to female entrepreneurs only, especially in the context of the documented gender gap in credit access, such policies may be difficult to justify and concretely adopt (we discuss this issue and provide examples in the Appendix).

Finally, before proceeding with the analysis, we emphasize that our baseline model features both a borrowing constraint that limits the rental of capital for all entrepreneurs in the economy, and a gender-specific wedge that decreases further the borrowing capacity of female-led firms with respect to male-led ones. The goal of our fiscal policies exercise is hence twofold. First, we explore the effects of different subsidies on both the *extensive* and *intensive* margin of entrepreneur-

[58] As a final consideration, we note that it is not beneficial to lower the borrowing constraint of male entrepreneurs until it reaches the one of women, as it constitutes a tightening of financial frictions for the productive sector as a whole.

[59] https://www.sba.gov/partners/lenders/7a-loan-program/types-7a-loans#section-header-12.

[60] Li (2002) analyzes 1984-1998 SBA programs that involved interest subsidies to entrepreneurs. These subsidies lowered borrower payments by 7.2 percent on average.

ship, comparing the consequences of each fiscal measure on entrepreneurial rates and capital utilization.[61] Second, we examine if and how public policies that generally target entrepreneurs can have a different impact on male and female firm owners in light of the heterogeneity in the access to credit that characterizes our model economy.[62]

6.1 Profits, Labor and Capital Costs

In the first set of exercises, we introduce a government that collects lump-sum taxes on all the agents and redistribute them to entrepreneurs in order to target either their profits, their labor costs, or their capital costs. We make use of our calibrated economy – where the borrowing constraint for female-led firms is 30% lower than the one of male-led firms – and assess the effect that such fiscal measures have on both entrepreneurial rates and inputs choices for both female and male agents. In what follows, we proceed to characterize how the profit maximization problem of entrepreneurs is affected by each subsidy – indicated by the rates θ^{π}, θ^{l} and θ^{k} – and how we ensure that the fiscal budget constraint of the public sector clears in each period t.

1. **Subsidy to Entrepreneurial Profits.** The profits of entrepreneurs would be given by:

$$\pi_t = (1+\theta^{\pi})\left(e^{z_t}(k_t^{\alpha} l_t^{1-\alpha})^{1-\nu} - w_t l_t - (r_t+\delta)k_t\right) \tag{14}$$

   Moreover, the budget constraint for all agents in the economy would be given by:

$$a_{t+1} = \max\{\pi_t(a,z,c;r_t,w_t), w_t\} + (1+r_t)a_t - c_t - T_t \tag{15}$$

   Hence, for the budget constraint of the fiscal sector to hold, in each t it must be true that:

$$\int_{o_t(a,z,g)=e} \theta^{\pi}\pi_t = T_t = T_t \tag{16}$$

2. **Subsidy to Labor Costs.** The profits of entrepreneurs would be given by:

$$\pi_t = \left(e^{z_t}(k_t^{\alpha} l_t^{1-\alpha})^{1-\nu} - (1-\theta^{l})w_t l_t - (r_t+\delta)k_t\right) \tag{17}$$

[61] Itskhoki and Moll (2019) discuss examples of optimal policies in a standard growth model with financial frictions that involve taxing entrepreneurs. In our setup, taxes on firms make entrepreneurship even less profitable for female agents, and add to the barriers created by the gender-based gap in credit access. For example, taxing entrepreneurial profits entails lowering entrepreneurial rates, labor demand and the equilibrium wage. At the margin, a fraction of wealthy/productive agents still choose to become entrepreneurs and produces facing lower labor costs, while lump-sum redistribution towards workers, who have the highest marginal utilities, increases welfare. However, such sequence of effects penalizes relatively more female agents who already face a barrier in entering entrepreneurship due to tighter borrowing constraints. Seeing their potential profits further been lowered by a tax, less female agents choose to become entrepreneurs, which worsens the underrepresentation of women in entrepreneurship and capital allocation.

[62] In these exercises, government taxation introduces a fiscal burden on all agents in the economy. As such, the resulting GE effect on welfare is generally negative under our baseline calibration. Yet, the spirit of this analysis is not to propose optimal entrepreneurial policies, but to discuss the impact of fiscal subsidies on male and female-led firms.

Moreover, the budget constraint for all agents in the economy would be given by:

$$a_{t+1} = \max\{\pi_t(a, z, c; r_t, w_t), w_t\} + (1 + r_t)a_t - c_t - T_t \tag{18}$$

Hence, for the budget constraint of the fiscal sector to hold, in each t it must be true that:

$$\int_{o_t(a,z,g)=e} \theta^l w_t l_t = T_t \tag{19}$$

3. **Subsidy to Capital Costs.** The profits of entrepreneurs would be given by:

$$\pi_t = \left(e^{z_t}(k_t^{\alpha} l_t^{1-\alpha})^{1-\nu} - w_t l_t - (1 - \theta^k)(r_t + \delta)k_t\right) \tag{20}$$

Moreover, the budget constraint for all agents in the economy would be given by:

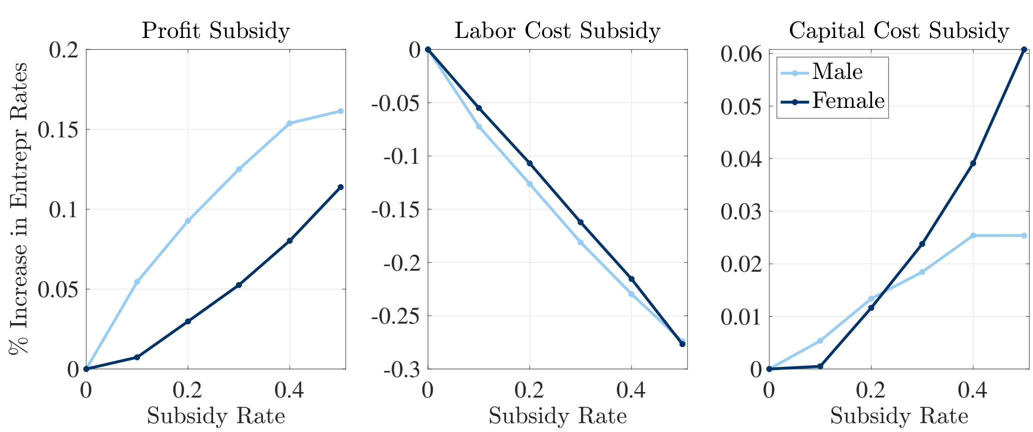
$$a_{t+1} = \max\{\pi_t(a, z, c; r_t, w_t), w_t\} + (1 + r_t)a_t - c_t - T_t \tag{21}$$

Hence, for the budget constraint of the fiscal sector to hold, in each t it must be true that:

$$\int_{o_t(a,z,g)=e} \theta^k (r_t + \delta)k_t = T_t \tag{22}$$

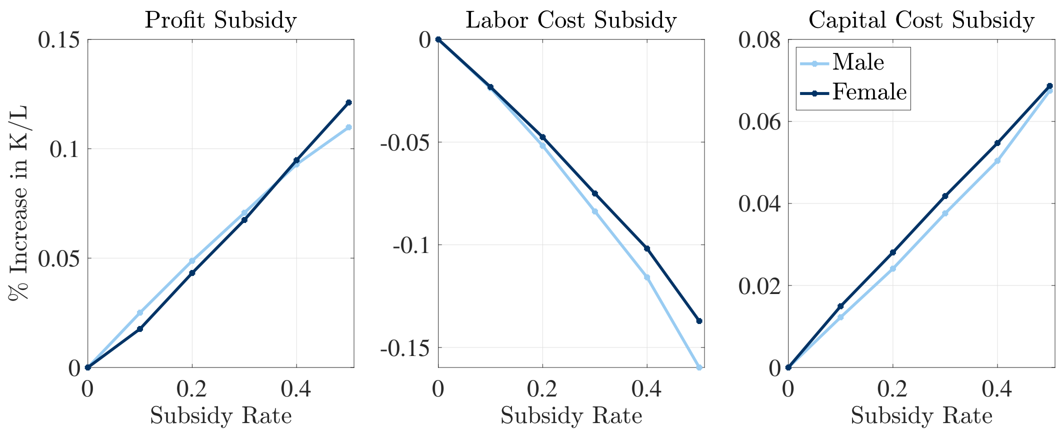
We create a grid of values for the subsidy rates θ^{π}, θ^l and θ^k ranging from 0 (our baseline economy) to 0.5 (half of the respective profits or costs gets subsidized), and we solve for the steady state equilibrium. Then, we compute entrepreneurial rates and quantities of inputs for both female and male agents in the counterfactual economies and compare them in Figure 10 and Figure 11.

Figure 10: Effect of Entrepreneurial Subsidies on the Extensive Margin



As reported in the first panel of Figure 10, subsidizing entrepreneurial profits naturally fosters the entry into entrepreneurship of both men and women, as it decreases the attractiveness of the outside option of becoming workers. However, this fiscal measure causes a bigger increase in the *extensive* margin of men, as the existing gender gap in credit access still makes entrepreneurship a relatively harder occupational choice for women compared to men. Moreover, even if the subsidy to entrepreneurial profits does not introduce distortions in firms' optimal choices of capital and labor, the first panel of Figure 11 shows that the k/l ratio of both female and male-owned firms increases when profit subsidies are held in place. This is due to the fact that entrepreneurs can take advantage of higher profits to save more, increase the asset base against which they borrow on financial markets and hence raise the level of capital ultimately used in production.

Figure 11: Effect of Entrepreneurial Subsidies on the Intensive Margin



In contrast, a subsidy on entrepreneurial labor hiring costs has a negative impact on both the *extensive* and *intensive* margin of entrepreneurship, with no stark distinction across male and female-led businesses. In particular, a subsidy on the labor costs wl directly affects the optimal hiring decision of firms, by increasing their demand for labor and hence the equilibrium wage. In turn, fewer agents prefer to run an enterprise over being workers, which depresses entrepreneurial rates, as documented in the second panel of Figure 10. At the same time, since it becomes cheaper for firms to produce using relatively more labor, the increased reliance on workers in the production process decreases the k/l ratio, as documented in the second panel of Figure 11.

Finally, a publicly-financed subsidy to the rental cost of capital faced by entrepreneurs makes capital a relatively cheaper input and hence boosts its use in production, as shown in the third panel of Figure 11. There are no stark gender differences in the subsequent increase in the k/l ratio because constrained entrepreneurs – especially female ones – cannot equally scale up their demand for capital despite the reduction in its marginal cost. Moreover, such fiscal measure positively affects the firm ownership rates of both men and women in our model economy, as it reduces firms' capital costs $(r + \delta)k$ and increases entrepreneurial profits. However, as shown in the third panel of Figure 10, the resulting increment in the *extensive* margin of entrepreneurship is relatively bigger for female agents. This is due to the fact that, at the margin, the subsidy to capital costs raises the attractiveness of starting a business by relatively more for female agents who are more often credit-constrained and hence limited in their optimal choices of capital.

6.2 Credit Needs

In the second set of exercises, we introduce a lump-sum tax that is levied on all agents and subsequently rebated as a credit or collateral subsidy θ for entrepreneurs in the economy. Note that in the first case, the debt that is used to finance capital acquisition can come from both financial markets and the government. The credit subsidy increases the amount business owners of any gender g are able to borrow according to $k_t \leq \lambda_g * a_t + \theta$, without modifying their specific credit limit parameter λ_g. In the second case, the collateral subsidy increases the amount that male and female owners are able to pledge to finance their capital renting, and turns their borrowing constraint into $k_t \leq \lambda_g * (a_t + \theta)$. Under such modification, entrepreneurial wealth constitutes only part of the collateral for the debt issued on financial markets, while the rest is actually covered by the government. As in the previous exercises, we first characterize the profit maximization problem of entrepreneurs and the budget constraint of the fiscal sector in these two scenarios.

1. **Credit Subsidy.** The profit maximization problem of entrepreneurs would be given by:

$$\max_{l_t, k_t} \left\{ e^{z_t} (k_t^{\alpha} l_t^{1-\alpha})^{1-\nu} - w_t l_t - (r_t + \delta) k_t, \quad \text{s.t.} \quad k_t \leq \lambda_f a_t + \theta \right\} \tag{23}$$

Moreover, the budget constraint for all agents in the economy would be given by:

$$a_{t+1} = \max\{\pi_t(a, z, c; r_t, w_t), w_t\} + (1 + r_t) a_t - c_t - T_t \tag{24}$$

Hence, for the resource constraint of the fiscal sector to hold, in each t it must be true that:

$$\int_{o_t(a,z,f)=e} (k_t - \lambda_f a_t) = T_t \tag{25}$$

2. **Collateral Subsidy.** The profit maximization problem of entrepreneurs would be given by:

$$\max_{l_t, k_t} \left\{ e^{z_t} (k_t^{\alpha} l_t^{1-\alpha})^{1-\nu} - w_t l_t - (r_t + \delta) k_t, \quad \text{s.t.} \quad k_t \leq \lambda_f (a_t + \theta) \right\} \tag{26}$$

Moreover, the budget constraint for all agents in the economy would be given by:

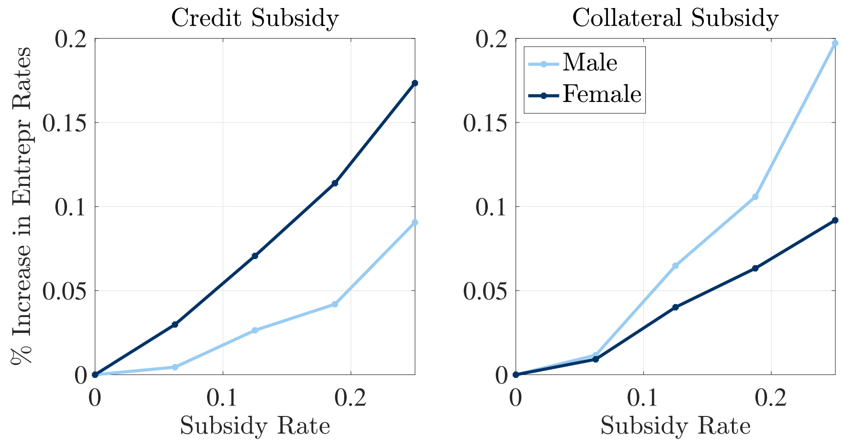
$$a_{t+1} = \max\{\pi_t(a, z, c; r_t, w_t), w_t\} + (1 + r_t) a_t - c_t - T_t \tag{27}$$

Hence, for the resource constraint of the fiscal sector to hold, in each t it must be true that:

$$\int_{o_t(a,z,f)=e} \left(\frac{k_t}{\lambda_f} - a_t \right) = T_t \tag{28}$$

Figure 12 and Figure 13 document the change in the male and female *extensive* and *intensive* margins of entrepreneurship after the introduction of credit and collateral subsidies. For the purpose of the analysis, we create a grid of values for the subsidy θ that ranges from 0 to 25% of the

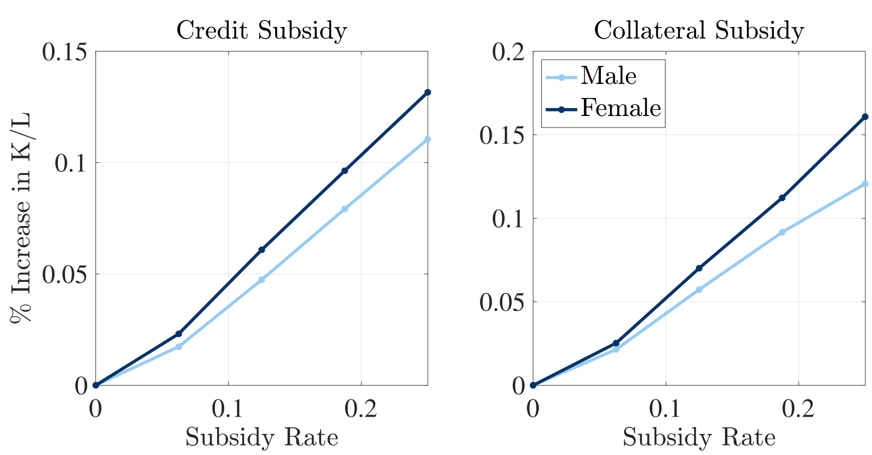
Figure 12: Effect of Entrepreneurial Subsidies on the Extensive Margin



asset base of entrepreneurs in our economy. Unlike the previous exercise, these types of subsidies directly interact with the financial friction and the gender-based wedge present in the model and hence lead to starker differences in the resulting effects across genders.

In particular, both the credit and collateral subsidies involve a relaxation of the borrowing constraint faced by entrepreneurs and thereby ensure higher levels of rented capital. As shown in Figure 13, the increase in the k/l ratio is relatively bigger for female-led firms, whose baseline borrowing limit λ_f is relatively smaller. In addition, Figure 12 illustrates that the credit subsidy fosters female entrepreneurship by relatively more, as government-backed financing is not subject to the tighter borrowing limit that women face on financial markets. On the contrary, the collateral subsidy raises the amount entrepreneurs can pledge to finance capital acquisition, but the subsequent increase in business ownership is higher for male agents, as male-led firms in our calibrated framework can still borrow up to a higher fraction of their collateral compared to female-led ones.

Figure 13: Effect of Entrepreneurial Subsidies on the Intensive Margin



7 Conclusion

Despite the increase in the US share of female entrepreneurs over the past years, pronounced gender gaps in several entrepreneurial dimensions still persist. In this paper, we have attempted to shed light on this issue, by examining both empirically and quantitatively how the allocation of talent and capital, as well as aggregate production, are affected by gender-based financial frictions.

Using micro-level data from a panel of US firms, we have shown that it is more difficult for female-led businesses to access credit, despite the fact that they are neither riskier, nor less profitable compared to male ones. We have also documented that female entrepreneurs have a higher $arpk$, a sign of misallocation of capital across the productive units in our sample, and suggested that the observed gender gap in access to credit may be what is driving the misallocation of capital found in the data. Next, we have rationalized our empirical observations in a standard model of entrepreneurial choice and financial frictions augmented with gender differences in borrowing constraints, which has then been quantified using the available data. Our calibrated model is able to match well both targeted and untargeted moments from the data, and to explain a substantial fraction of the gender heterogeneities in capital utilization and entrepreneurial rates.

Having evaluated the performance of our model, we have quantified the output losses that come from the misallocation of resources among entrepreneurs, and from the misallocation of entrepreneurial talent in the economy. When removing the gender gap in access to credit, female entrepreneurship increases and capital misallocation decreases, leading to a 4% rise in aggregate output. Finally, we have assessed how policy instruments targeting firms can differently affect the *extensive* and *intensive* margins of entrepreneurship of men and women in our model economy. In particular, we have analyzed subsidies to the (i) profits, the (ii) labor costs, the (ii) capital costs, the (iv) credit needs, and the (v) borrowing collateral of male and female entrepreneurs.

We believe our work leaves an important question unanswered: what is driving female entrepreneurs' lower access to credit? How could the theoretical gap in borrowing constraints be microfounded further? Ultimately, how should we think about the deep roots of gender-driven capital misallocation? Our paper opts for an indirect approach, insofar as it documents the presence and extent of gender-driven capital misallocation, links it to the differences in financial frictions, and quantifies its macroeconomic effect through an entrepreneurship model. Yet, many factors could be responsible for female entrepreneurs' impaired access to credit. For example, Restuccia and Rogerson (2017) note that discrimination, culture, and social norms may be potential drivers of misallocation of talent (and resources) across firms. At the same time, gender differences in information frictions or in entrepreneurial networks (see Wallskog (2021) for evidence) could also be important factors to further investigate and quantitatively model. We believe a deeper analysis of these channels could reach more persuasive and relevant conclusions, especially in terms of guiding policy interventions, and certainly constitutes an exciting avenue for future research.

Appendix

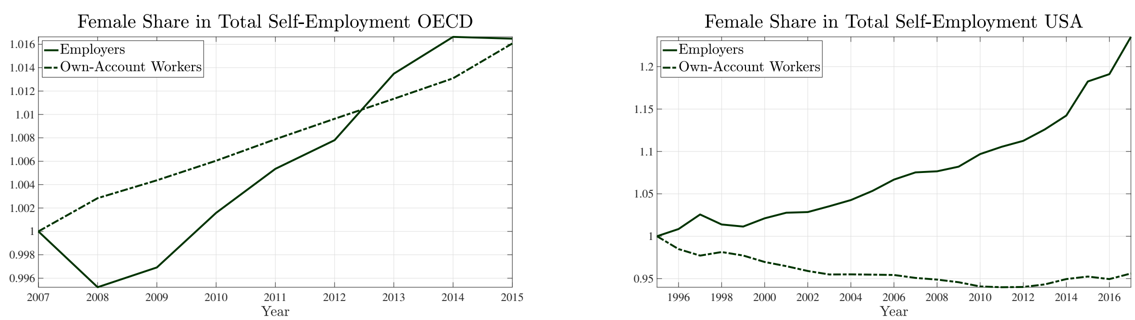
A Data Appendix

A.1 Female Entrepreneurship and Economic Development

Figure A.1: Female Participation Rates and Earning Gaps in the US

Left Panel: Percentage of women among employed, self-employed and entrepreneurial work forces in the US. Note that self-employed workers my include both employers (running businesses with at least one employee) and own-account workers. Source: OECD, 1975-2017. *Right Panel*: Male/Female earning ratios by educational attainment, considering both wages and profits separately. Source: US Current Population Survey, 2004-2011 (wages) and KFS, 2004-2011 (profits).

Figure A.2: Share of Self-Employed Women Over Time



[a]

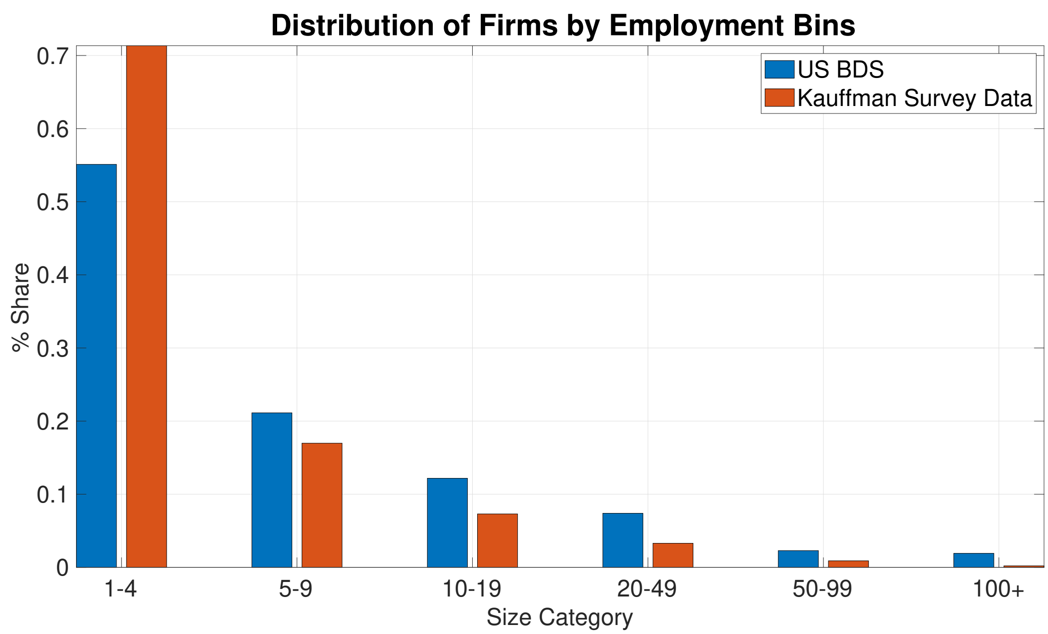
Left Panel: OECD average female share in self-employment between 2005 and 2015. Countries included: Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, and the United Kingdom. *Right Panel*: US average female share self-employment between 1995 and 2017. Shares are normalized to 1 at the beginning of the sample.

[a] According to official statistics, the average fraction of female employers and own-account workers over the total across OECD countries has grown by 3% from 2005 to 2015, whereas in the US, the increase in the fraction of female employers is almost tenfold. Moreover, while it is known that average OECD entrepreneurial rates have been sluggish in the past two decades, and a pronounced decline in business dynamism has been reported for the US economy, the share of female entrepreneurs is nonetheless growing in relative terms. Moreover, according to US statistics, the 1997-2017 variation in female entrepreneurial rates amounts to -10.4%, while male entrepreneurial rates have declined by -32.4% over the same period. It is therefore clear that declining business dynamism is affecting male employers more heavily than female ones. Nonetheless, we focus our attention precisely on the aforementioned *composition* effect, while we leave the investigation of declining business dynamism for future research.

A.2 Size Distribution and Ownership Composition of Firms

The Business Dynamics Statistics (BDS) is a US dataset from Census, providing annual figures for operating establishments and firms, along with measures of firm startups and shutdowns, job creation and destruction. We use the sample covering the period between 1978 and 2014 and compute the average the distribution of firms by employment bins. In Figure A.3 we compare the distribution of firms by employment bins in BDS and KFS data.

Figure A.3: KFS and BDS Comparison



Moreover, we can check the representativeness of the KFS sample in terms of female and male ownership. We use as a comparison the Annual Survey of Entrepreneurs (ASE) from US Census, a dataset that provides information on selected economic and demographic characteristics for businesses and business owners by gender, ethnicity, race, and veteran status. The survey is available for 2014–2016. It includes are all non-farm businesses with paid employees filing Internal Revenue Service tax forms as sole proprietorships, partnerships, or any type of corporation, and with receipts of $1,000$ dollars or more. In Table A1, we verify that the shares of female and male entrepreneurs in the KFS sample resemble closely the ones in the ASE.[1]

Table A1: Entrepreneurial Rates

	Annual Survey of Entrepreneurs (ASE)	Kauffman Firm Survey (KFS)
Female	0.22	0.23
Male	0.62	0.59
Mixed	0.16	0.18

[1] In the ASE, business ownership is defined as having 51% or more of the stock or equity in the business.

A.3 Variable Definitions

Table A2 summarizes the definitions of entrepreneurs' characteristics and other control variables we use in the regressions. Except for the case where we use the gender of the firm's primary owner as our definition of female-owned firms, if the firm has more than one owner, owner characteristics (except for marital status) is taken as the average across all owners.[2] These average measures are directly provided in the confidential KFS data. In the case where we take the gender of the firm's primary owner as our definition of female-owned firms, owner characteristics shown in Table A2 refer to the primary owner's characteristics, regardless of other owners' characteristics if the firm has more than one owner-operator.

A.4 Winsorization

Continuous variables such as assets, business debt, equity, revenues, profits, fixed assets, wage bill and employees are winsorized at 1 and 99th percentile.[3] Furthermore, the risk and profitability measures leverage, sd(ROA), $\frac{Profit}{Assets}$ and $\frac{Profit}{Revenues}$ are also winsorized at 1 and 99th percentile. We do not winsorize $arpk$ and $arpl$ since these are in logarithms already.[4]

A.5 Other Determinants of Entrepreneurship

As mentioned in Section 1, apart from access to finance, entrepreneurial differences across genders can in principle be related to education, age, marital status, experience, labor force attachment, among others. Using the KFS data, we find no significant differences on the education attainment,[5] age and marital status across genders (see Figure A.4). However, males seem to have more work experience in the same industry, and in general (see Figure A.5), and devote more time operating the business compared to females (see Figure A.6), as also documented by Campbell and De Nardi (2009) using the PSED survey. These are factors we control for when we analyze gender-driven misallocation in entrepreneurship. Moreover, we also check the reason why both female and male entrepreneurs in the KFS sample have decided to open their business (see Figure A.6). Women consider self-employment as a source of secondary income and a way to have more time to spend with their family more often than men. In contrast, males seem to prefer self-employment as a way to be their own boss and to earn their primary income.

[2]Moreover, it is important to stress that there is no law in the US that imposes any type of gender quotas in the ownership or board of private companies. Therefore, no firm-level measure of female active ownership is going to be biased by gender-oriented legal regulations, and represents solely the idiosyncratic entrepreneurial choice of the owners themselves.

[3]In the main text, the variables in Table 1 are expressed in terms of logarithms, so they are not winsorized. The time series plot in Figure A.7 contain the winsorized level variables.

[4]We winsorize variables measured in levels to avoid the problem of spurious outliers. Using a logarithmic transformation also mitigates this problem. Since our misallocation measures $arpk$ and $arpl$ are log-transformed, winsorization does not really make any difference.

[5]This result is in line with what is reported by Campbell and De Nardi (2009) using the Panel Survey of Entrepreneurial Dynamics (PSED).

Table A2: Description of Variables

Variable	Description
Age	For firms with more than one owner-operator, it is the average age across owner-operators.
Race	For firms with more than one owner-operator, it represents the share of white owners.
Education	It is a categorical variable measuring the highest level of education attained by owners. The original scale is from 1 (less than 9th grade) to 10 (professional school or doctorate). For firms with more than one owner-operator, it is averaged across owners, thereby making an originally categorical measure into a continuous one. As a result, it provides no meaningful interpretation even though it is not the focus of the analysis nor will regression results materially change. Thus, they are recoded into three levels, namely high school, college level and graduate level. College level refers to education categories "some college, but no degree", "associate's degree" and "bachelor's degree". Graduate level refers to the categories "some graduate school but no degree", "master's degree" and "professional school or doctorate".
Work experience	For firms with more than one owner-operator, it is the average years of work experience of owner-operators in the same industry.
Marital status	It is a binary variable = 1 if at least one owner is married. Considering or not entrepreneurs that cohabitate as married does not alter the results due to the small share of such category in our dataset. Data is available from 2008 to 2011 only.
Number of owners	It is a continuous measure indicating the total number of owners of the firm.
Hours worked	For firms with more than one owner-operator, it is the average number of hours in a week that owner-operators devoted to the business.
Legal status	It is a categorical variable which takes on a different value depending on the legal status of the firm. Categories are sole proprietorship, partnership, limited liability company or corporation.
Business Debt	It is debt obtained under the name of the business. It is the sum of business bank loans, lines of credit, loans from non-financial institutions, business credit card balance, and business loans from various other sources, such as from family, employees, federal agencies, etc.
Personal Debt	It is debt obtained under the name of the owner on behalf of the business. It is the sum of personal and business credit cards issued under the name of the owner, personal bank loans and personal loans from family and other sources.
State FE	It refers to the 50 states of the US.
Sector FE	It refers to the 4-digit NAICS code, except for loan rejection regressions where 2-digit NAICS code is used instead since there is not enough sectoral variation to run probit regressions without encountering optimization failure.

Figure A.4: KFS Owners' Characteristics

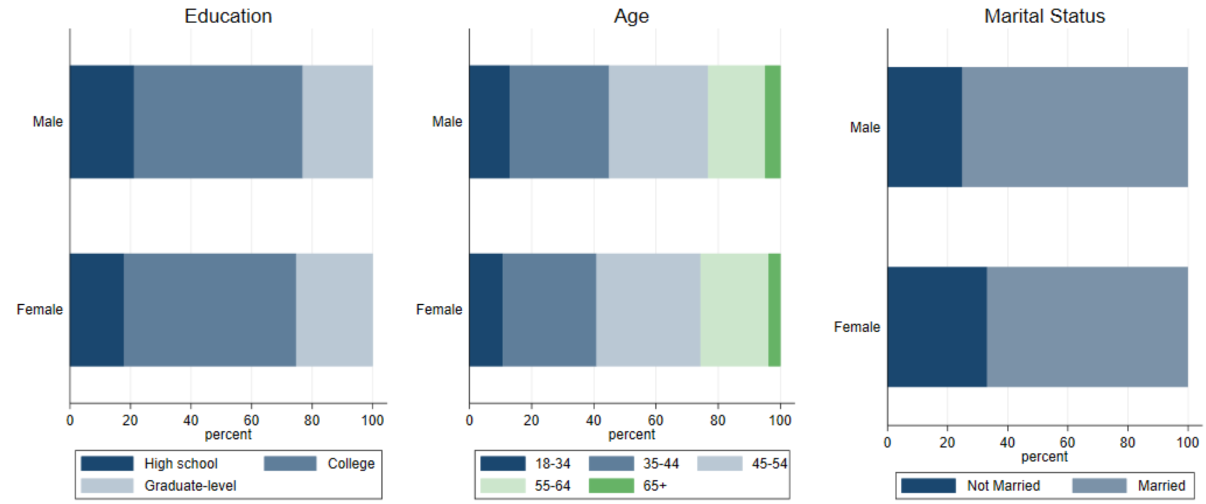


Figure A.5: KFS Owners' Work Experience

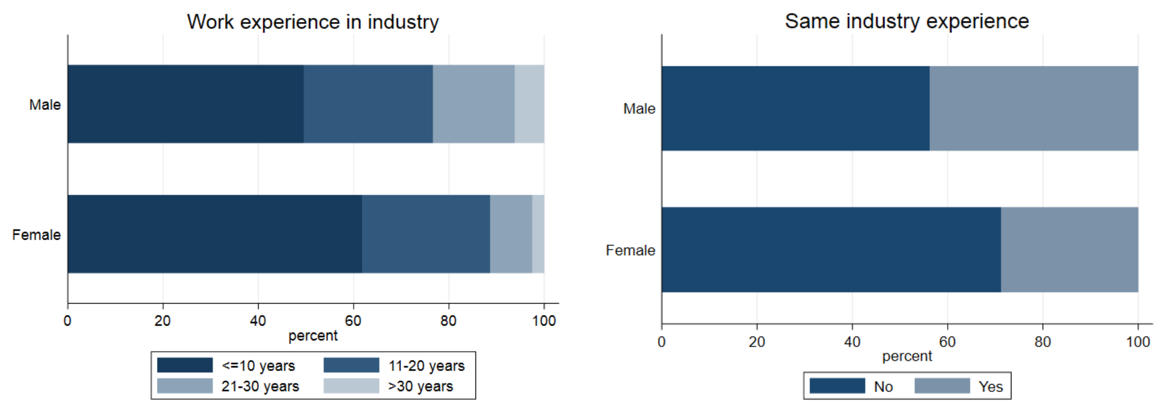
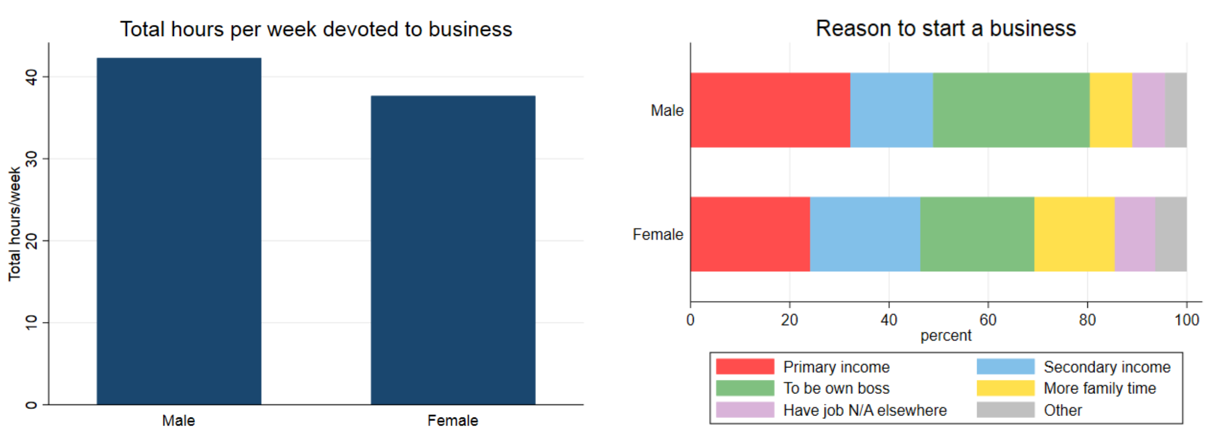


Figure A.6: KFS Number of Hours Worked & Reasons to Open a Business



We also examine the legal status of firms in KFS in more detail. As Table A3 shows, more than half of the total female-owned firms in the sample are organized as sole proprietorship, whereas conversely, around 60% of male-owned firms are corporations and limited liability companies. This implies that substantially more female entrepreneurs assume full responsibility over all the debts or losses that their firm suffers from, relative to male entrepreneurs.

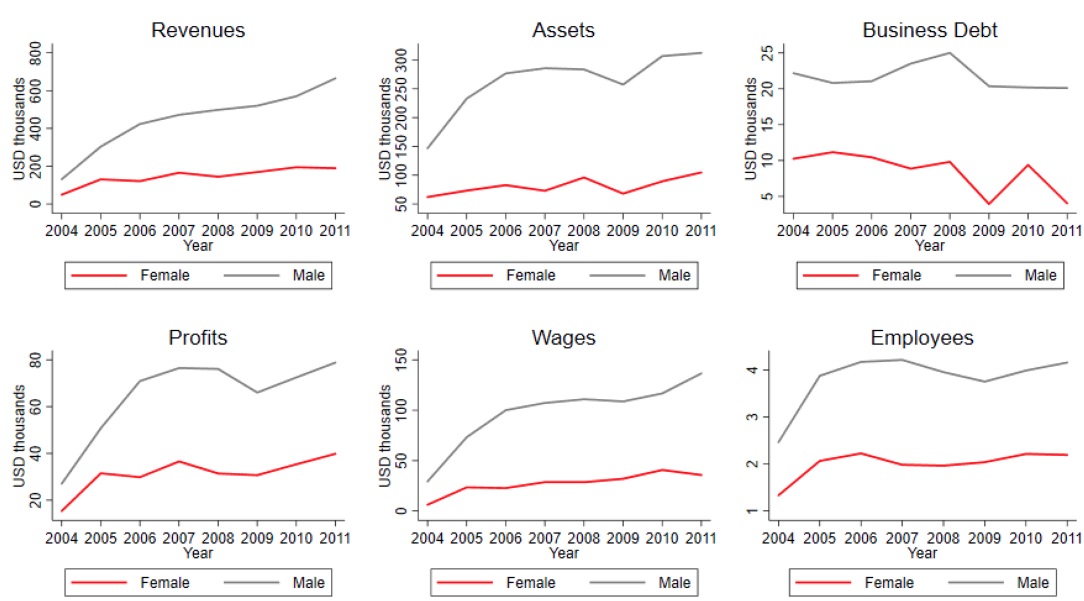
Table A3: Business Legal Types in KFS

	Sole Proprietorship	Partnership	Corporation	Limited Liability Company
Male	35.59%	3.16%	28.74%	32.51%
Female	55.54%	2.89%	19.61%	21.95%
Total	41.15%	3.11%	26.18%	29.57%

A.6 Firm Performance After Entry

In Table 1, we show that on average, females have lower levels of assets, business debt, revenues, profits, wages and number of employees, and these differences are all statistically significant. Here in Figure A.7, we show the evolution of these variables over time. We observe that at every point in time, females on average have lower values of all these variables.

Figure A.7: Behavior of Financial Variables Over Time



In Figure A.8, we show that as a share of the total number of active firms in a given year, there are more male-led active firms and also more of them exiting. The exit rate is computed as the number of firms that have gone out of business in a given year, relative to the total number of active firms in the previous year.

Figure A.8: Active and Exiting Firms Over Time

We estimate a Cox proportional hazard model to examine the correlation between gender and firm closure, controlling for relevant demographic and firm characteristics. As shown in Table A4, there are no statistically significant differences in the likelihood of exit across genders, with or without controlling for size.[6]

Table A4: Cox Proportional Hazard Model for Firm Exit

	(1)	(2)	(3)
Female	0.0173	-0.0114	0.0208
	(0.0796)	(0.0820)	(0.0800)
$\log(assets)$		-0.0583***	
		(0.0096)	
$\log(revenues)$			-0.5447***
			(0.1122)
Controls	Y	Y	Y
Sector FE	Y	Y	Y
Observations	14,774	13,832	14,706

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Survey weights are used. Control variables include the number of owners, number of hours worked per week, legal status and size as measured by $\log(assets)$ or $\log(revenues)$, as well as owners' characteristics such as education, experience, race, and age.

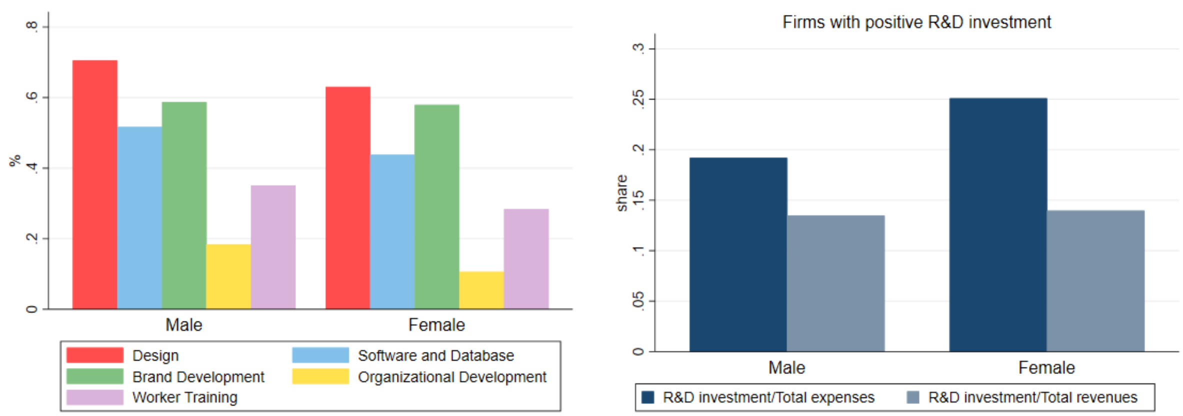
We also examine profitability of businesses using different measures, as shown in Figure A.9. Female-led businesses seem to have slightly higher profitability, when weighted by assets, revenues and equity. That male-led businesses do not have higher profit margins leads us to exclude the possibility that they have higher markups. In Table 4 columns (3) and (4), we show that when we run OLS regressions controlling for factors that may affect profitability of firms across genders, we find further support that female-led firms have higher profitability.

[6]This is consistent with the result in Robb and Watson (2012), who use the KFS data for 2004 to 2008.

Figure A.9: Profitability of Firms

Next, we examine research and development (*R&D*) activities and spending of entrepreneurs. The left panel of Figure A.10 shows the types of *R&D* activities that firms engage in and suggests that there are no systematic differences across genders. For businesses that have non-zero investment in (*R&D*), the right panel of Figure A.10 shows that average *R&D* spending as a share of total expenses and revenues do not differ across genders.

Figure A.10: *R&D* Investment of Firms



A.7 More on Financing of Entrepreneurs

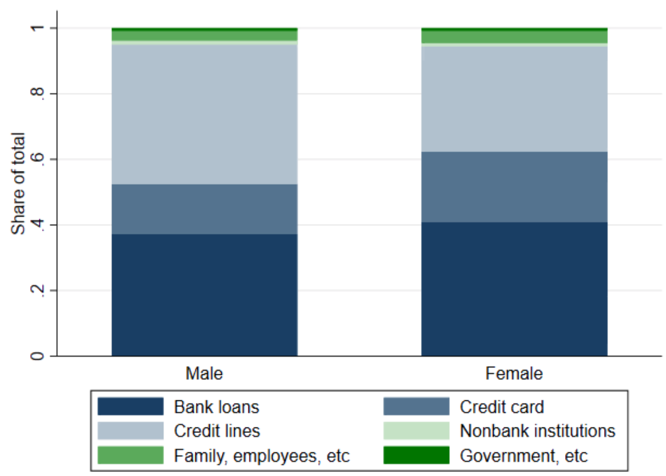
In this subsection, we delve deeper into the details regarding the financing of entrepreneurs. Following the classification procedure of Robb and Robinson (2014), we provide in Table A5 a comprehensive picture of the capital structure decision of nascent male- and female-owned firms. Using the confidential KFS data, Robb and Robinson (2014) has shown that nascent entrepreneurs rely heavily on external debt financing – in particular bank loans – rather than funds from family and friends, to finance startups. Table A5 and Figure A.12 confirm this finding by showing the breakdown of funding sources for both male- and female-owned firms. We also observe that while owner equity is important in the initial year of operations, its role as a financing source diminishes in subsequent years.

Table A5: Gender Differences in Sources of Funding (in USD)

	Male	Female		Male	Female
Initial Year (2004)			**2008–2011**		
Owner Equity	27,596	16,723	Owner Equity	6,841	3,811
Inside Equity	2,081	2,499	Inside Equity	561	115
Outside Equity	26,378	2,957	Outside Equity	11,209	215
Owner Debt	2,329	3,072	Owner Debt	3,344	4,124
Inside Debt	4,310	2,696	Inside Debt	2,194	1,472
Outside Debt	36,257	20,921	Outside Debt	32,300	14,992
2005–2007					
Owner Equity	11,099	6,530			
Inside Equity	1,180	635			
Outside Equity	18,304	6,452			
Owner Debt	3,692	3,399			
Inside Debt	3,104	1,366			
Outside Debt	34,577	20,978			

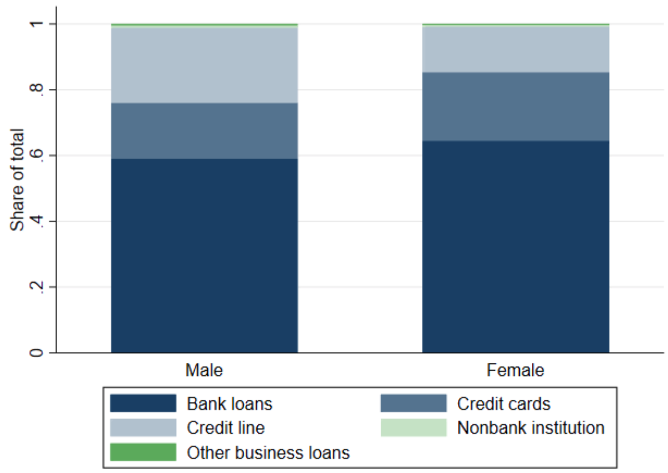
Notes: Inside equity is equity from spouse/family. Outside equity is equity from angel investors, venture capital, government and other entities. Owner debt is from owners' personal credit cards. Inside debt is loans from family, personal loans, and business loans from other owners, family and other employees. Outside debt is composed of personal and business bank loans, business credit card balance, business credit lines and business loans from the government or other external parties.

Figure A.11: Composition of Business Debt of Male and Female Entrepreneurs



Outside debt or debt obtained from formal institutions, which is the most important source of funding for entrepreneurs, is composed of personal and business bank loans, credit lines, loans from nonbank financial institutions, business credit cards and other business loans sourced elsewhere (e.g. federal agencies). As shown in Figure A.12, out of all these different sources of formal debt, bank loans constitute the largest share in dollar amount, irrespective of gender. This is followed by lines of credit and credit cards.

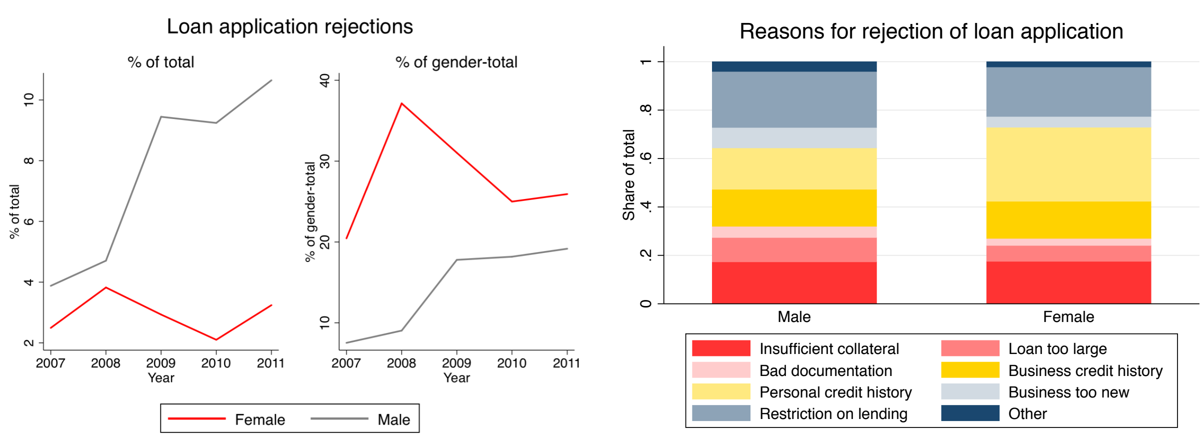
Figure A.12: Composition of Outside Debt of Male and Female Entrepreneurs



If instead we look at the composition of business debt, which takes on a slightly different definition from outside debt, nonetheless we find that (business) bank loans and credit lines are the most important sources of debt financing. Overall, this highlights the importance of bank financing for entrepreneurial startups, as highlighted in Robb and Robinson (2014).

Since bank loans are the main funding source of entrepreneurs, we examine the fraction of loan applications that get rejected and the reasons for this. From the left panel of Figure A.13, it is clear that female entrepreneurs have a higher rate of loan application rejections relative to males, which led to further analysis on this in the main text (see Table 3). Additionally, the right panel of Figure A.13 reveals that the main reason why loan applications by female entrepreneurs get rejected is due to personal credit history. This motivates our analysis in the main text on the riskiness and profitability of female-led enterprises relative to their male counterparts.

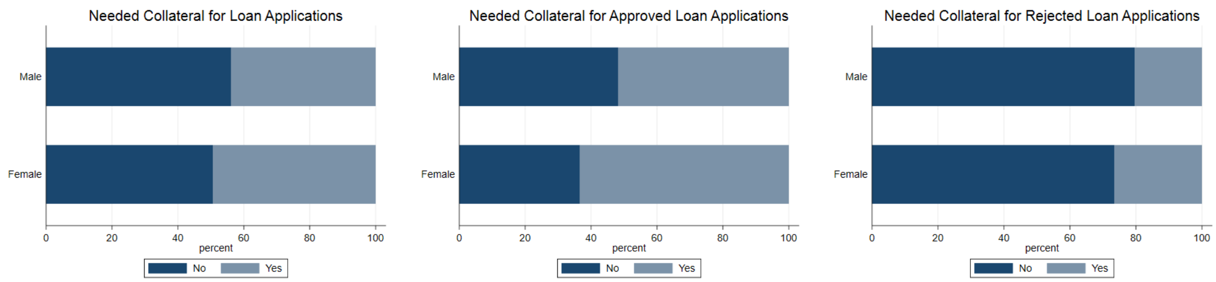
Figure A.13: Loan Application Rejections[a]



[a]These plots are constructed using publicly-available KFS data.

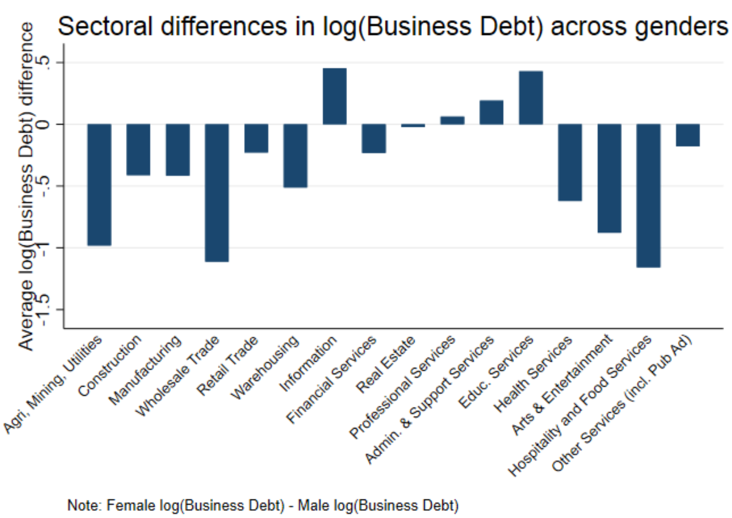
In addition, we also look at whether owners are required to provide collateral when applying for loans. We find that on average, slightly more females are asked for collateral, regardless of whether the loan applications get approved or not (see Figure A.14).

Figure A.14: Collateral in Loan Application



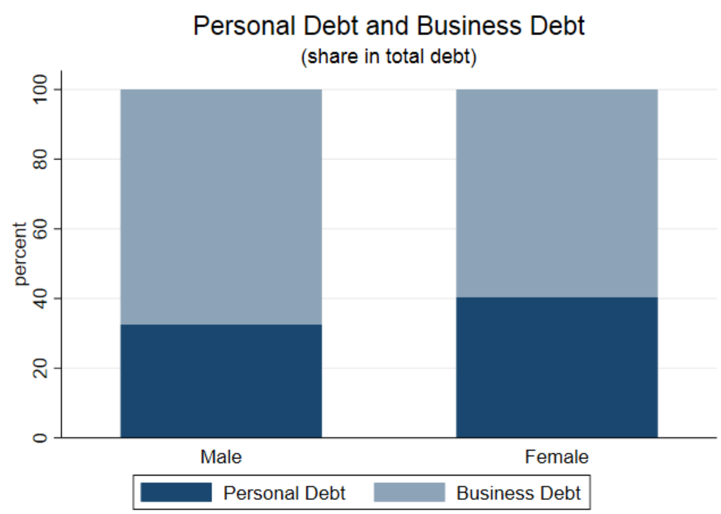
In Figure A.15 we report the residuals from the regression in Table 2 across industries to show that female-owned firms hold lower amount of business debt across most sectors, a sign that the result is not driven by one specific sector only.

Figure A.15: Gender Differences in Business Debt Across Industries



Finally, Figure A.16 shows the composition of total debt for female and male-owned firms. Female-owned firms have a slightly higher share of personal debt in total debt for their entrepreneurial activities. This reflects higher *unlimited* liability on the part of female entrepreneurs, which relates to the type of enterprise that they operate, namely sole proprietorship (see Table A3).

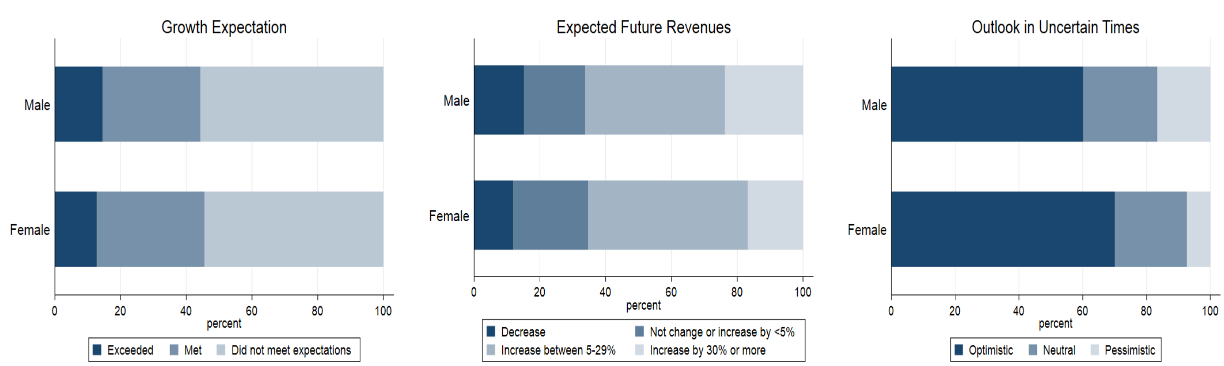
Figure A.16: Composition of Total Debt



A.8 Risk Aversion

In Table A6, we follow the approach used in Fairlie et al. (2020) to examine in further detail the gender differences in attitudes towards acquiring debt from formal institutions (mainly from banks), namely on loan applications, loan application outcomes and aversion towards applying for loans.[7] When we do not control for any relevant firm or owner's trait, slightly less female entrepreneurs apply for loans. However, conditional on applying, their loan applications have a lower probability of always getting approved,[8] regardless of whether they are deemed to be risky or not. Finally, we find that there is no difference in the overall fraction of female and male entrepreneurs that did not apply for a loan due to fear of being rejected, except for the lowest risk class.

Figure A.17: KFS Owners' Expectations and Outlook



Next, in Table A7, we show that there is no robust evidence that female entrepreneurs are less likely to apply for a loan. After controlling for relevant owner and firm characteristics, we find

[7]In Fairlie et al. (2020), they examine this in the context of race, comparing outcomes of black versus white entrepreneurs, across different credit risk classes.

[8]This is just analogous to female entrepreneurs facing a higher probability of rejections on their loan applications.

Table A6: Gender Differences in Attitudes on Formal (Outside) Debt

		Credit Risk Score		
	Overall	Below 25^{th}	Below Median	Above Median
Applied for a Loan				
Male	0.12	0.17	0.13	0.11
Female	0.09	0.14	0.09	0.07
Loan approved				
Male	0.67	0.75	0.72	0.64
Female	0.59	0.65	0.63	0.53
Did Not Apply For Fear of Rejection				
Male	0.18	0.13	0.13	0.19
Female	0.19	0.17	0.15	0.17

Notes: Credit risk scores are given on a scale of 1 to 5, where 1 represents the lowest risk class and 5 is the highest risk class. Applied for a loan is a binary variable = 1 if firm applied for a loan, and =0 otherwise. Loan approved is a binary variable = 1 if loan application is approved, and =0 if loan application is sometimes or always rejected. Did not apply for fear of rejection is a binary variable = 1 if respondent did not apply for a loan in anticipation that it will be rejected, and =0 otherwise.

that female entrepreneurs are not less likely to apply for loans as male entrepreneurs under our baseline definition (columns 1 and 2) and alternative definition based on primary ownership (see Section A9 for details). Overall, our results suggest that there seems to be not enough supporting empirical evidence from KFS to conclude that female entrepreneurs are robustly and consistently more risk averse than male entrepreneurs in our sample. Moreover, we conduct a similar analysis using SCF data and confirm the same conclusion. We refer the reader to Section A10 for further details on this.

Table A7: Applied for a Loan

	100% male/female		Primary owner		Share of female owners	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0009	0.0063	0.0042	0.0113	-0.0059	-0.0002
	(0.0123)	(0.0124)	(0.0109)	(0.0111)	(0.0119)	(0.0122)
Controls	Y	Y	Y	Y	Y	Y
Personal Debt	Y	Y	Y	Y	Y	Y
Credit risk score	N	Y	N	Y	N	Y
Sector/Region/Year FE	Y	Y	Y	Y	Y	Y
Observations	6,338	6,196	7,575	7,409	7,715	7,543
Pseudo-R^2	0.141	0.150	0.120	0.132	0.129	0.138

Notes: Estimates are average marginal effects. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Survey weights are used. The dependent variable is a binary indicator = 1 if a firm applied for a loan, and = 0 if a firm did not apply for a loan. Control variables include the number of owners, legal status of the firm, number of hours worked per week and size as measured by $\log(revenues)$, as well as owners' characteristics such as education, experience, race, and age.

A.9 Robustness Checks

In this part of the paper, we examine alternative definitions of owners' gender that allow for a gender mix of the owner-operators of businesses. Recall that in the main text, our analysis is centered on the comparison between 100% female-owned versus 100% male-owned firms. Here, we look at (1) the gender of the firm's primary owner, defined as the owner with the highest percentage of firm ownership, as an alternative binary measure of the owner's gender and (2) ownership share – the share of female owners in the total number of owner-operators of the firms. These measures are provided in the confidential KFS data and they significantly overlap with our benchmark definition. In particular, 98% (99%) of firms that have a female (male) primary owner are also 100% female-owned (100% male-owned). Also, as noted in Table A1, only 18% of the firms have mixed ownership, and thus the remaining 82% are either 100% female-owned or 100% male-owned.

A.9.1 Loan Application Rejections

In the main text, we use a non-linear model to compare the probability of loan application rejection of males and females. In Table A9, we also present results using the linear probability model, and confirm the same findings.

Table A8: Loan Application Rejections Using Other Definitions of Owner's Gender

	Primary Owner		Share of female owners	
	Probit FE	LPM	Probit FE	LPM
Female	0.1113**	0.1177**	0.1510***	0.1563***
	(0.0395)	(0.0534)	(0.0455)	(0.0576)
Controls	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	667	636	552	649
R^2	0.307	0.349	0.271	0.368

Notes: For Probit FE models, estimates are average marginal effects. Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Survey weights are used. The dependent variable is a binary indicator = 1 if loan applications are rejected, and = 0 if loan applications are approved. Control variables include the number of owners, legal status of the firm, number of hours worked per week, size as measured by log(*revenues*), leverage, personal debt and credit risk score, as well as owners' characteristics such as education, experience, race, and age. In column (1), leverage is not included due to optimization failure.

Given the aforementioned alternative definitions of the owner's gender, it is important to control for the number of owners for firms with more than one active owner. This is because for such firms, if one of them is male, then the male owner of the firm can be sent to the bank to apply for a loan, and the concern about the gender gap in credit access will not arise as a result. Including the number of owners as a control variable in the regressions rules out this possible story.

Table A9: Loan Application Rejections – Linear Probability Model

	(1) Full Sample	(2) Full Sample	(3) Full Sample	(4) Excluding Personal Credit History
Female	0.1095*	0.1069*	0.1377**	0.1314**
	(0.0604)	(0.0552)	(0.0602)	(0.0570)
Controls	Y	Y	Y	Y
Leverage	Y	N	Y	Y
Personal debt	N	Y	Y	Y
Credit risk score	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	573	686	507	476
R^2	0.321	0.296	0.398	0.397

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Survey weights are used. The dependent variable is a binary indicator = 1 if loan applications are rejected, and = 0 if loan applications are approved. Control variables include the number of owners, legal status of the firm, number of hours worked per week and size as measured by $\log(\mathit{revenues})$, as well as owners' characteristics such as education, experience, race, and age.

In Table A8, we find the same conclusions as in the main text – female owners have higher probability of having their loan applications rejected. Specifically, if the primary owner of the business is female, the firm faces a higher probability of loan application rejection (see columns 1 and 2). Similarly, for firms with a higher share of female owners, they also face a higher probability of rejection in loan applications (see columns 3 and 4).

A.9.2 Risk and Profitability

In Table A10, we show that under the alternative definitions of owner's gender, female-led firms are neither riskier nor less profitable than male-led firms.

Table A10: Measures of Risk-Taking and Profitability Using Other Definitions of Owner's Gender

	Primary Owner				Share of female owners			
	leverage	sd(ROA)	$\frac{Profit}{Assets}$	$\frac{Profit}{Revenues}$	leverage	sd(ROA)	$\frac{Profit}{Assets}$	$\frac{Profit}{Revenues}$
Female	0.0228	0.0700	0.2321**	0.0083	0.0080	0.1881	0.3802***	0.0264**
	(0.0226)	(0.1199)	(0.1146)	(0.0107)	(0.0227)	(0.1232)	(0.1012)	(0.0102)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y	Y	Y
Region FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	9,484	5,580	7,038	6,916	9,600	5,629	7,102	6,987
R^2	0.083	0.132	0.098	0.326	0.082	0.127	0.100	0.335

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Survey weights are used. Control variables include the number of owners, legal status of the firm, number of hours worked per week and size as measured by $\log(\mathit{revenues})$, as well as owners' characteristics such as education, experience, race, and age. Regressions on sd(ROA) also include leverage as a control variable, following Faccio et al. (2016).

A.9.3 Misallocation

In Table A11, we show that under the alternative definitions of owner's gender, *arpk* is higher for female-led businesses, indicating misallocation of capital. In particular, *arpk* is higher if the primary owner of the business is female (see columns 1 and 2) and if firms have a higher share of female owners (see columns 3 and 4).

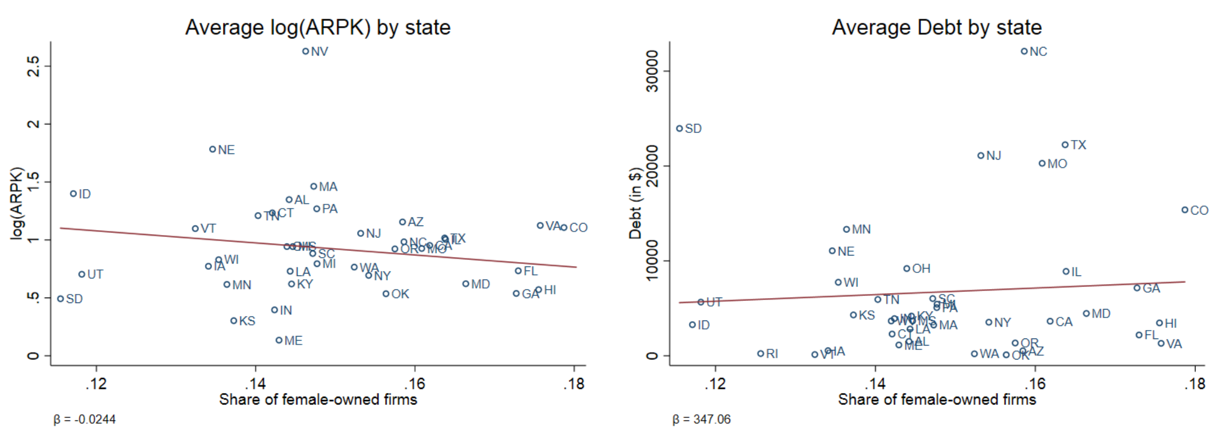
Table A11: *arpk* and *arpl* across genders

	Primary Owner		Share of female owners	
	arpk	*arpl*	*arpk*	*arpl*
Female	0.0954**	0.0516	0.0931**	0.0526
	(0.0441)	(0.0442)	(0.0466)	(0.0488)
Controls	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	9,468	7,309	9,571	7,380
R^2	0.229	0.171	0.229	0.164

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Survey weights are used.Control variables include the number of owners, legal status of the firm, and number of hours worked per week, as well as owners' characteristics such as education, experience, race, and age.

Next, Figure A.18 shows the breakdown by state of Figure 3 using the average instead of residual female *arpk* and debt and without grouping geographic locations by similar female entrepreneurial rates.

Figure A.18: Female *arpk* and Debt Across States



Note: Average *arpk* and debt level of female-owned firms versus the share of female-owned firms across states.

In Table 6, we documented a strong interplay between credit (business debt and personal debt) and capital misallocation using our baseline definition of female-owned firms. Table A12 and Table A13 show that our results hold for alternative definitions based on primary ownership and share of female owners.

Table A12: *arpk* and Debt – Primary Owner

	Business Debt	Personal Debt
	arpk	*arpk*
	revenues>\$10,000	revenues>\$10,000
$\text{Female}_{primary\ owner}$	0.1881***	0.2160***
	(0.0581)	(0.0642)
log(Debt)	-0.0061	-0.0152***
	(0.0043)	(0.0041)
Female × log(Debt)	-0.0327***	-0.0190**
	(0.0092)	(0.0083)
Controls	Y	Y
Sector FE	Y	Y
Region FE	Y	Y
Year FE	Y	Y
Observations	6,333	6,920
R^2	0.275	0.276

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Survey weights are used. Control variables include the number of owners, legal status of the firm, and number of hours worked per week, as well as owners' characteristics such as education, experience, race, and age. Results for the entire sample available upon request.

Table A13: *arpk* and Debt – Share of Female Owners

	Business Debt	Personal Debt
	arpk	*arpk*
	revenues>\$10,000	revenues>\$10,000
Share of Female Owners	0.1135*	0.2189***
	(0.0614)	(0.0679)
log(Debt)	-0.0093**	-0.0132***
	(0.0046)	(0.0045)
Female × log(Debt)	-0.0147	-0.0216**
	(0.0104)	(0.0093)
Controls	Y	Y
Sector FE	Y	Y
Region FE	Y	Y
Year FE	Y	Y
Observations	6,397	6,984
R^2	0.269	0.273

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Survey weights are used. Control variables include the number of owners, legal status of the firm, and number of hours worked per week, as well as owners' characteristics such as education, experience, race, and age. Results for the entire sample available upon request.

A.10 Robustness Checks Using SCF Data

Whenever possible, we cross-check our main results of interest from the empirical exploration of the KFS using other datasets. Here in particular, we report robustness checks using the Survey of Consumer Finances, a triennial cross-sectional survey of US families conducted by the Federal Reserve Board. Data from the SCF are widely used in macroeconomic works, as it includes information on families' balance sheets, pensions, income, and demographic characteristics. Moreover, even if the survey does not exclusively target entrepreneurs, business owners are well represented and constitute roughly 20% of the total sample, which is the main reason why SCF has been frequently used in macroeconomic papers on entrepreneurship (see Cagetti and De Nardi (2006) for example). The section containing questions related to the businesses owned by the respondents contains details on revenues, profits, employees, business debt and equity, as well as information related to the industry, the legal status and the funding date of firms, how the business was initially started and funded, the ownership share of the respondent and their working hours.

For our analysis, we use the 2010-2019 combined sample, for which we have 17,837 business owners interviewed, actively managing their businesses, between 18 and 65 years old, and reporting at least 1 employee, including the owner. The final sample spans a different period compared to the KFS, which is good for testing the validity of our results, and lacks the panel component. In terms of gender representativeness of the SCF sample, 94% of the entrepreneurs are male and 6% are female: this constitute a major difference from the KFS sample, whose gender composition is definitely more in line with official census statistics on female business ownership (see Table A1). Accordingly, we always use survey weights in the following regressions, but we nonetheless believe that the small female representation in the SCF sample of entrepreneurs calls for interpreting the estimated coefficients with caution. We also make sure to include controls as close as possible to the ones used in analogous regressions using KFS data. Importantly, since we only observe one owner – namely the survey respondent – our $female$ dummy will reflect the gender of the only owner we observe, as opposed to reflecting the gender of all the owners of the firm.

Table A14: Business Legal Type in SCF

	Partnership	Sole-Proprietorship	Corporations	Limited Liability Company
Male	8.54%	22.39%	28.68%	40.39%
Female	6.22%	46.94 %	13.17%	33.67%
Total	8.40%	23.87%	27.74%	39.98%

Table A14 shows the businesses we focus our attention on belong to different legal types, and give a balanced representation of the entrepreneurial landscape in the US. In particular, SCF entrepreneurs are more likely to own corporations than other types of businesses, and, in this sense, it is clear that we are not capturing only very small businesses. Moreover, we note that female entrepreneurs are twice more likely to own sole-proprietorship firms and twice less likely to own corporations compared to males. This feature resembles closely the findings in KFS (see Table A3).

Table A15: How the Business Originated in SCF

	Bought	Started	Inherited	Joined/Became a Partner	Other
Male	18.59%	67.59%	4.24%	9.13%	0.45%
Female	14.01%	75.79%	4.17%	5.57%	0.46%
Total	18.32%	68.09%	4.23%	8.91%	0.45%

Next, Table A15 reports how the businesses considered in the SCF sample were initiated. Most entrepreneurs personally started their businesses, and especially so for female entrepreneurs. Crucially, 32% of male business owners report that their spouse also participate in the managing of the business, compared to just 3% of female business owners reporting having their husband involved in their business activities. This is important in ruling out the possibility that female entrepreneurs in the SCF sample may be actually leaving important managing responsibilities to their spouses, and in ensuring that the effects documented in our analysis are indeed to be attributed to the gender of the owners.

Table A16: First Source of Funding to Start Business in SCF

	Savings	Credit Card	Personal Debt	Business Debt	Other
Male	57.20%	5.18%	12.68%	14.28 %	10.65%
Female	60.56%	12.48%	5.66%	7.29%	14.01%
Total	57.42%	5.65%	12.23%	13.84%	10.87%

Moreover, we report in Table A16 the first source of funding to start a business. Most business owners initially use their savings, but the use of business debt is more likely for male entrepreneurs as opposed to female entrepreneurs. This gender difference persists when reporting other main sources of business funding. Importantly, the 2016 and 2019 survey included a question regarding preferences towards financial risk. Table A17 shows that female entrepreneurs are neither more nor less risk averse than male entrepreneurs, once we control for relevant demographic characteristics. This evidence, paired with analogous analysis in KFS, leads us to exclude gender differences in the risk aversion parameter in our main model specification.

Table A17: Attitudes Towards Risk in SCF

	Preference Towards Financial Risk
Female	-0.1272
	(0.1661)
Controls	Y
Sector FE	Y
Year FE	Y
Observations	9,180
R^2	0.2700

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Survey weights are used, but unweighted regressions also holds. Controls include age, race, education, home-ownership status, business equity, and working hours of the owner, as well as legal status of the firm and business founding date. Results are robust to including business profits, size or revenues as controls. Risk preference reflects the answers given to the SCF question survey asking respondents to indicate how much they love risk from 1 to 10.

Note that since the SCF questionnaire does not contain questions related to business assets and wage bills, it is not possible to assess the presence and extent of input misallocation. Nonetheless, SCF contains some information regarding business funding and business loan applications, which we can use to verify and cross-check the main empirical findings in terms of differential credit access by gender, as reported in Section 2 using KFS data. Importantly, throughout the analysis, we focus our attention to entrepreneurs reporting at least 10K revenues (in dollars), which is a restriction held in place in order to drop extremely small businesses with abnormally low business sales. We note that these observations are anyway less than 6% of the total.

Table A18: Business Debt in SCF

	(1) Business Debt	(2) Business Equity
Female	-0.7069***	0.0517
	(0.1430)	(0.1546)
Controls	Y	Y
Sector FE	Y	Y
Year FE	Y	Y
Observations	3,794	3,794
R^2	0.6881	0.6738

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Survey weights are used, but unweighted regressions also holds. Controls include age, race, education, home-ownership status, and working hours of the owner, as well as legal status of the firm, business size, business funding date and business equity in (1) or business debt in (2). Robust to also control for profits or sales instead of business size. We consider firms with at least 10K yearly revenues.

Not only do female entrepreneurs have lower debt levels – which they do not compensate with higher levels of equity – but they also have higher probabilities of rejection when applying for a business loan (see Table A18 and Table A19). Interestingly, there are no gender differences in the likelihood of applying for a business loan, only in acceptance rates, just as in the KFS sample.

This could signal that lower external funding of female-owned businesses in both samples are most likely related to *supply-side* effect, rather than *demand-side* reasons. In particular, we control for relevant demographic factors, business characteristics (including profitability), year and sector fixed effects. Moreover, in Table A20 we further confirm that female entrepreneurs seem not to have lower profitability (per dollar revenues of employees) compared to male entrepreneurs, as also found using the KFS sample.

Table A19: Loan Applications in SCF

	(1) Prob of Applying	(2) Prob of Acceptance
Female	-0.0051 (0.0149)	-0.1112*** (0.0516)
Controls	Y	Y
Sector FE	Y	Y
Year FE	Y	Y
Observations	16,320	4,663
R^2	0.1585	0.4799

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Survey weights are used, but unweighted regressions also holds. Controls include age, race, education, home-ownership, and working hours of the owner, as well as legal status of the firm, business funding date, owner's equity and profits. Results are robust to include risk preferences as controls, which however shorten the sample period to the years 2016/2019 only. We consider firms with at least 10K revenues per year.

Table A20: Profitability in SCF

	$\frac{Profits}{Revenues}$
Female	0.2006*** (0.0582)
Controls	Y
Sector FE	Y
Year FE	Y
Observations	17,673
R^2	0.2263

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Survey weights are used, but unweighted regressions also holds. The dependent variables are in log, hence coefficients can be interpreted as percentage effects. Controls include age, race, education, home-ownership status, and working hours of the owner, as well as legal status of the firm. We consider firms with at least 10K revenues per year.

B Additional Quantitative Analysis

B.1 Interpreting differences in λ in the Model

Using the KFS data, we have provided evidence of gender gaps in credit access, which have been embedded later on in the model as differences in the borrowing limit that affects female and male entrepreneurs. We emphasize that it is not within the scope of our analysis to microfound the reasons behind the observed gender-driven imbalance in the credit market, which we leave for future research. Exploring plausible reasons that drive the wedge between λ_m and λ_f is important in providing a rationale and a guide for policy interventions.

Existing literature has noted three forms of discrimination, namely (1) statistical discrimination, (2) taste-based discrimination and (3) implicit discrimination. Papers such as Alesina et al. (2013) and De Andres et al. (2020) have ruled out statistical discrimination as a reason why there is a gender gap in credit access. According to Alesina et al. (2013), female-owned firms are not more opaque relative to male-owned firms, ruling out the idea that lenders are able to observe some risk factor that otherwise cannot be observed by the econometrician. Similarly, Ongena and Popov (2016) suggested that if female-owned firms do not underperform male-owned firms (e.g. in sales growth), this effectively alleviates the concern of statistical discrimination. In light of this latter argument, we do find in our data that female-owned firms are more profitable (or at least not less profitable) relative to male-owned firms, which lends support to the idea that statistical discrimination is not the main driver of the observed gender gap in credit access in the KFS data.

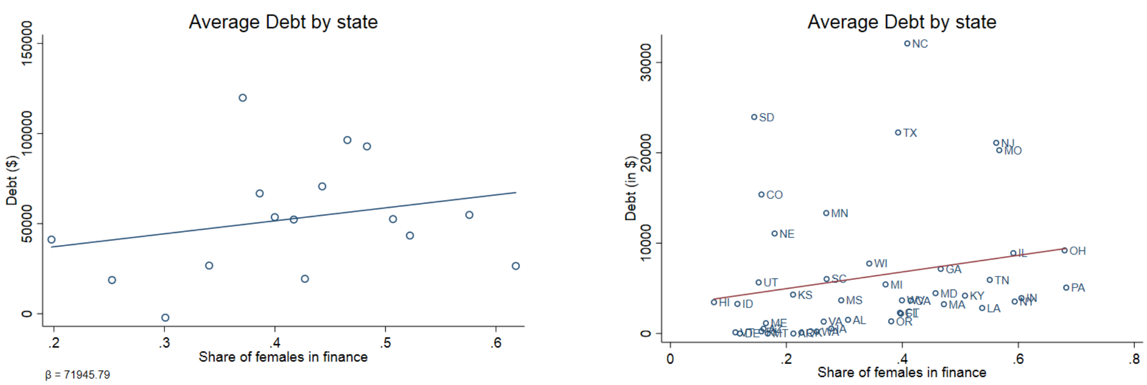
One plausible explanation would be due to taste-based discrimination. In this case, one could imagine that female entrepreneurs in the KFS sample receive less credit due to a gender bias in loan officers' preferences (see Montoya et al. (2020) for experimental evidence on this). Alesina et al. (2013) suggests this as a potential explanation of the observed higher interest rates charged on female-led firms. Our dataset does not report information on the side of loan institutions or officers and hence makes it difficult to infer a clear instance of taste-based discrimination. What we can control for however, is the specific reason entrepreneurs are given by loan institutions when their loan application is rejected. As shown in the right panel of Figure A.13, female entrepreneurs are more often rejected on the basis of personal credit history, which is the only reason among the possible choices that refers specifically to entrepreneurs themselves and not the business they run.

It is important to note that, in order to control for the personal credit situation of the respondent, we include personal debt in our controls when assessing the probability of loan rejection for male and female owned businesses. Moreover, female entrepreneurs in our sample do not show higher levels of personal debt, and tend to have on average higher credit balances on both personal and business credit cards (on business credit cards specifically, they show 15% higher balance than their male counterpart). While we cannot assess undoubtedly the existence of taste-biased discrimination in the sample of entrepreneurs we work with, this simple analysis reveals that female entrepreneurs are more often rejected on the basis of personal credit reasons that cannot be clearly confirmed empirically using our available information. Coupled with the analysis presented in Section 2.3 on the fact that female-owned businesses seem equally risky and profitable relative to male ones, this opens up the possibility of further investigating whether female entrepreneurs are denied equal access to credit on the basis of taste-based discrimination.

Finally, another explanation is based on implicit discrimination, as suggested in Alesina et al. (2013) and De Andres et al. (2020). In Alesina et al. (2013), they noted that women might get better loan deals when they deal with banks run by women.[9] One check we do along this direction is to document that the debt of female-owned firms (both the raw average and after controlling for other factors) is higher in states where women are more represented in the financial sector (see Figure B.1). This may relate to the idea that in states where there is greater representation of females in the financial sector jobs, female entrepreneurs face less difficulty in accessing loans. De Andres et al. (2020) finds that female-owned firms faced greater difficulty in securing a loan relative to male-owned firms in the founding year, but that this credit access gap disappeared after two years, effectively ruling out taste-based discrimination. And because this credit access gap is present in female-owned firms that are less likely to go into default, this also rules out statistical discrimination in favor of implicit discrimination. This may suggest that the cost of screening is high, thereby leading banks to use gender as an imperfect proxy for creditworthiness.

Figure B.1: Average Debt of Female Entrepreneurs and Share of Females in Finance Across States

(a) Bin scatter plot (b) Scatter plot



Note: Debt of female-owned firms versus the share of females in the financial sector in each state.

While we do not find conclusive evidence in favor of a specific type of discrimination, the more plausible ones that our data can lend support to are either taste-based or implicit discrimination on the credit supply side of the economy, which motivates modelling the differential access to business funding as a gender gap in the borrowing constraints λ_m and λ_f. Either form of discrimination is inefficient and leaves room for policy intervention.

B.2 Computing TFPR in the Model

Computing TFPR one way to conceptualize misallocation, as misallocation of inputs across productive units typically results in differences in their marginal value. To think about it in the case of DRS technology $Y = e^z(K^\alpha L^{1-\alpha})^{1-\nu}$ note that:

$$Pe^z = \frac{PY}{(K^\alpha L^{1-\alpha})^{1-\nu}} = P\left(\frac{Y^\alpha}{K^{\alpha(1-\nu)}}\frac{Y^{(1-\alpha)}}{L^{(1-\alpha)(1-\nu)}}\right) = P\left(\frac{MRPK}{\alpha(1-\nu)}\right)^\alpha \left(\frac{MRPL}{(1-\alpha)(1-\nu)}\right)^{(1-\alpha)} (K^\alpha L^{1-\alpha})^\nu$$

[9] They do not find conclusive evidence along this angle because banking is a male-dominated industry in Italy.

Rearranging, we get:

$$\frac{Pe^z}{(K^\alpha L^{1-\alpha})^\nu} = \frac{PY}{K^\alpha L^{1-\alpha}} = P \underbrace{\left(\frac{MRPK}{\alpha(1-\nu)}\right)^\alpha \left(\frac{MRPL}{(1-\alpha)(1-\nu)}\right)^{1-\alpha}}$$

If there are no distortions, the bracketed term will be equalized across firms. If there are distortions, then $\frac{e^z(K^\alpha L^{1-\alpha})^{1-\nu}}{K^\alpha L^{1-\alpha}}$.

B.3 Wage per unit worker

In our baseline model, we focus on the gender gap in credit access and assume that male and female entrepreneurs pay the same wages to their employees. In Table B1, we empirically document that after controlling for relevant individual and firm characteristics, we do not find robust statistically significant differences in wages per unit worker across female and male-owned firms. That the continuous measure is showing a negative and statistically significant coefficient implies that the result is being driven by mixed ownership firms, which we do not consider in our model. This provides additional justification for our parsimonious modelling strategy.

Table B1: Log of wage per unit worker across genders

	100% male/female	Primary Owner	Share of female owners
Female	-0.1779	-0.0014	-0.6524***
	(0.1476)	(0.1302)	(0.1370)
Controls	Y	Y	Y
Sector FE	Y	Y	Y
Region FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	6,470	8,225	8,337
R^2	0.341	0.296	0.310

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Survey weights are used. Control variables include the number of owners, legal status of the firm, number of hours worked per week and size as measured by log(*revenues*), as well as owners' characteristics such as education, experience, race, and age. We consider firms with more than one employee.

B.4 Calibration

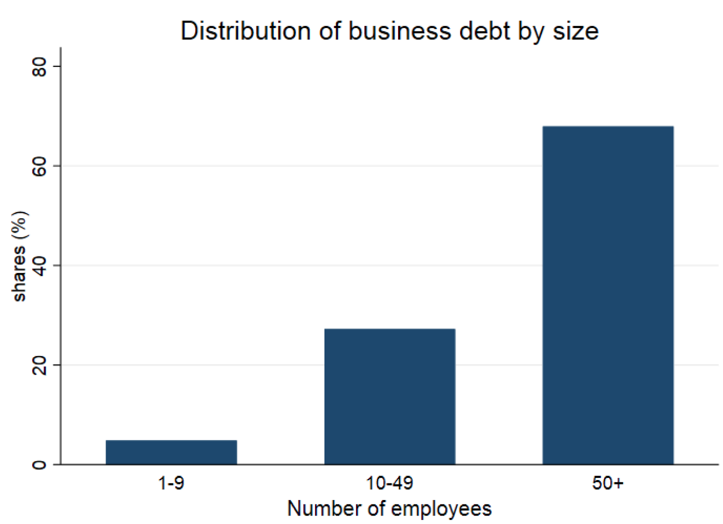
B.4.1 Moments from the KFS Data

As in the empirical part of the paper, k is measured using fixed assets and l is measured using wages. Entrepreneurial borrowing $b := k - a$ is measured using business debt. The k/l ratio is computed as fixed assets over wages. The exit rate is defined as the number of firms that have gone out of business in a given year, relative to the total number of active firms in the previous year. The exit rate for male-owned and female-owned firms is calculated in a similar fashion. The serial correlation of wage bill for males and females are computed using an AR(1) model as follows: $\log(wages)_{it} = \rho \log(wages)_{i,t-1} + \varepsilon_{it}$. Table B2 summarizes the moments computed using the KFS data. Finally, Figure B.2 shows the distribution of business debt across size groups. As noted in the main text, larger firms have higher average debt.

Table B2: Moments from the KFS Data

	Data
$(k/l)_{male}$	6.01
$(k/l)_{female}$	5.54
$(\text{average assets}/\text{average revenues})_{male}$	0.62
$(\text{average assets}/\text{average revenues})_{female}$	0.55
Employment share of Top 10% Firms	0.65
Exit rate	0.10
Exit rate$_{female}$	2.41%
Exit rate$_{male}$	6.86%
$\rho_{wages,female}$	0.75
$\rho_{wages,male}$	0.71
$\frac{\sigma(Profits_{fem})}{\sigma(Profits_{male})}$	0.59
$debt/revenues$	0.49

Figure B.2: Distribution of Business Debt



B.4.2 Introducing an Operational Cost for Female Entrepreneurs

In Table B3, we present an alternative model specification and related calibration strategy for the case in which, on top of the discussed gender differences in credit access captured by λ_f and λ_m, we introduce an operational cost κ_f that only female entrepreneurs are subject to. Such cost, being additive and fixed, does not further distort their optimal choices in terms of inputs of production, but it nonetheless reduces the net entrepreneurial profits of women, making entrepreneurship a less viable choice for women in the model. To calibrate κ_f, we target the ratio between the average exit rates of female and male entrepreneurs as computed in the KFS sample. Since we have introduced another margin that further discourages female agents from entering entrepreneurship, this version of the model is able to match more precisely the relative ratio of female and male entrepreneurs, as illustrated in Table B4.

Table B3: Alternative Calibration

Parameter	Value	Description	Reference	
Fixed				
γ	1.5	Coefficient of risk aversion	(see text)	
α	0.33	Physical capital share	(see text)	
δ	0.08	Capital Depreciation (Annual)	(see text)	
Fitted		Target	US Data	Model
β	0.9255	Interest Rate	0.045	0.046
$1-\nu$	0.835	Earnings Share of Top 10% Individuals	0.47	0.47
σ_ϵ	0.305	Employment Share of Top 10% Firms	0.67	0.68
ρ_z	0.93	Average Persistence in Firms' Employment	0.73	0.8
λ_m	3	Credit(Non-Financial Private Sector)/GDP	0.36	0.37
λ_f	2.025	$\frac{Debt_f}{Debt_m}$	0.55	0.55
κ_f	0.4	pp difference $ExitRate_f$ vs $ExitRate_m$	4.45	4.00

Note, however, that gender heterogeneities in the degree of borrowing constraints already generate differences in exit rates across female and male entrepreneurs. In particular, due to the stronger process of selection into entrepreneurship for women, female business owners are on average more productive, which leads to lower exit rates in equilibrium. To be more precise, the p.p. difference in entrepreneurial exit rates across genders in the baseline economy is 3.61, against an empirically estimated value of 4.45. Therefore, our baseline version featuring differences in λ_f and λ_m only can fit up to half of the empirically estimated differences in exit rates, while including disparities in operational costs (κ_f here) can improve this margin.

Table B4: Entrepreneurial Rates

	Data	Baseline Model	Model with Fixed Cost κ_f
$\frac{Female}{Male}$ Entrepreneurial Rate	0.35	0.44	0.42

B.4.3 Introducing Gender Differences in the Entrepreneurial Span of Controls

In Table B5, we present an alternative model specification and related calibration strategy for the case in which, on top of the discussed gender differences in credit access captured by λ_f and λ_m, we allow for the *span of controls* of male entrepreneurs and female entrepreneurs to be different. The *span of control* parameter mostly governs production and affects the dispersion of entrepreneurial profits and the thickness of the tail in the profit distribution. Consequently, the respective values $1-\nu_m$ and $1-\nu_f$ will be calibrated to match both the earnings share of the top 10% richest individuals, as in the baseline case, and the ratio between the standard deviation of profits of female and male owned firms, which we can compute using the KFS data. Note that female entrepreneurs in the KFS sample are found to have a lower dispersion in profits with respect to male entrepreneurs (see Table B2).

Table B5: Alternative Calibration

Parameter	Value	Description	Reference	
Fixed				
γ	1.5	Coefficient of risk aversion	(see text)	
α	0.33	Physical capital share	(see text)	
δ	0.08	Capital Depreciation (Annual)	(see text)	
Fitted		Target	US Data	Model
β	0.9225	Interest Rate	0.045	0.046
$1-\nu_m$	0.8385	Earnings Share of Top 10% Individuals	0.47	0.45
$1-\nu_f$	0.8165	$\frac{\sigma(Profits_{fem})}{\sigma(Profits_{male})}$	0.59	0.62
σ_ϵ	0.305	Employment Share of Top 10% Firms	0.67	0.67
ρ_z	0.93	Average Persistence in Firms' Employment	0.73	0.8
λ_m	2.85	Credit(Non-Financial Private Sector)/GDP	0.36	0.36
λ_f	1.95	$\frac{Debt_f}{Debt_m}$	0.55	0.53

Our baseline economy with gender differences in credit access only already implies a lower standard deviation for profits of female entrepreneurs, due to their stronger process of selection in entrepreneurship. However, by introducing gender heterogeneities in the span of control parameter, we can fit the ratio $\frac{\sigma(Profits_{fem})}{\sigma(Profits_{male})}$ better (from 0.78 in the baseline to 0.62, closer to the empirical 0.59). Moreover, since producing at a lower scale discourages female agents from entering entrepreneurship and decreases their output, this version of the model is able to match more precisely the relative ratio of female and male entrepreneurs, and still replicates the % differences in female and male $arpk$, as illustrated in Table B6.

Table B6: Entrepreneurial Rates

	Data	Baseline Model	Model with ν_{male} and ν_{fem}
% difference Female $arpk$ vs Male $arpk$	0.12	0.13	0.08
$\frac{Female}{Male}$ Entrepreneurial Rate	0.35	0.44	0.42

B.4.4 Introducing Gender Differences in Risk Aversions

In Table B7, we present an alternative model specification and related calibration strategy for the case in which, on top of the discussed gender differences in credit access captured by λ_f and λ_m, we allow for the *risk aversion* of male and female individuals to be different. The γ parameter affects the preferences of male and female agents in our economy and hence their likelihood of choosing entrepreneurship over salaried work. In particular, if female entrepreneurs were to be more adverse to risk, this could contribute to lower female entrepreneurial rates above and beyond the fact that the differential access to credit in our baseline economy already discourages female agents from opening a business. Consequently, the respective values γ_m and γ_f will be calibrated so that the former is normalized to the standard value of 1.5, while the latter is set to match the relative share of female entrepreneurs in the US economy, which is 0.35.

However, we want to stress once more that our empirical analysis could not clearly point out evident and statistically significant gender differences in risk aversion, which is why we do not include them in our baseline economy. Female and male entrepreneurs in the KFS sample do not have different growth expectations or desires for their businesses, and do not show a different likelihood of applying for credit and taking on financial risk. Therefore, we encourage the reader to take this exercise as a further exploration of the mechanisms at play in the model, while we leave a sounder investigation of this issue for future research.

Table B7: Alternative Calibration

Parameter	Value	Description	Reference	
Fixed				
γ_m	1.5	Coefficient of risk aversion	(see text)	
α	0.33	Physical capital share	(see text)	
δ	0.08	Capital Depreciation (Annual)	(see text)	
Fitted		Target	US Data	Model
β	0.90	Interest Rate	0.04	0.04
γ_f	4	$\frac{Entr_{fem}}{Entr_{male}}$	0.35	0.35
$1-\nu$	0.84	Earnings Share of Top 10% Individuals	0.47	0.43
σ_ϵ	0.335	Employment Share of Top 10% Firms	0.67	0.60
ρ_z	0.895	Average Persistence in Firms' Employment	0.73	0.77
λ_m	3.3	Credit(Non-Financial Private Sector)/GDP	0.36	0.31
λ_f	2	$\frac{Debt_f}{Debt_m}$	0.55	0.56

Crucially, raising the value of γ_f deters the entrance of female entrepreneurs more if the persistence of the productivity process is lowered with respect to the baseline economy (down to a value 0f 0.895 from the original 0.93). This is because a lower persistence in the entrepreneurial productivity rises the risks implied in opening and running a business, and hence gets particularly discounted by female agents whenever their risk aversion is higher.

B.5 Alternative Model Specification: Introducing a Corporate Sector

In an alternative version of the model, we include an unconstrained sector that contributes to the total production in equilibrium. We do this to check that our results are not driven by the fact that the baseline economy has only one productive sector which is constrained and in which a sizable gender gap in access to credit show up. In particular, following Cagetti and De Nardi (2006), we augment the economy with a corporate sector, where firms have the same productivity (normalized to 1) and produce using capital and labor. To obtain a well-defined measure of corporate firms, we further assume that corporate firms operate according to a decreasing returns to scale technology with span of control parameter ν_c.

$$f(z,k,l) = e^z (k^\alpha l^{1-\alpha})^{1-\nu_c}, \quad \text{with} \qquad 0 < 1-\nu_c < 1$$

In each period t, corporate firms rent capital and hire labor at the equilibrium input prices $r_t + \delta$ and w_t, always determined in GE. Their profits are then distributed lump-sum to all households in the economy. In essence, corporate firms will differ from entrepreneurial businesses in two dimensions. First, their span of control parameter will be allowed to differ from the one of the entrepreneurial sector to reflect size differences across entrepreneurial businesses and corporations. Second, corporate firms will not face a borrowing limit when renting capital using financial markets. Thus, we modify our calibration strategy to be so that the value assigned to ν_c imply that the share of employment of the corporate sector is 29%, as estimated for the US based on Compustat firms (see Davis et al. (2006)). Results from the estimation procedures are presented in Table B8:

Table B8: Alternative Calibration

Parameter	Value	Description	Reference	
Fixed				
γ_m	1.5	Coefficient of Risk Aversion	(see text)	
α	0.33	Physical Capital Share	(see text)	
δ	0.08	Capital Depreciation (Annual)	(see text)	
Fitted		Target	US Data	Model
β	0.95	Interest Rate	0.045	0.045
$1-\nu$	0.8175	Earnings Share of Top 10% Individuals	0.47	0.46
$1-\nu_c$	0.9175	Employment Share of Corporate Sector	0.29	0.29
σ_ϵ	0.305	Employment Share of Top 10% Firms	0.67	0.65
ρ_z	0.935	Average Persistence in Firms' Employment	0.73	0.80
λ_m	2.7	Credit(Non-Financial Private Sector)/GDP	0.41	0.41
λ_f	1.9	$\frac{Debt_f}{Debt_m}$	0.55	0.55

Moreover, we report how this alternative version of the model performs on untargeted dimensions in Table B9. The fit of untargeted moments is close to the one of the baseline model, especially in relation to *arpk* and entrepreneurial differences across genders. The main discrepancy with respect to our baseline case is that this alternative version of the model reduces the skewness of the wealth distribution, and therefore has a harder time matching the wealth share of the top 10% richest individuals that is observed in the data.

Table B9: Untargeted Moments

	Data	Model
Capital & Debt		
% difference Female $arpk$ vs Male $arpk$	0.12	0.13
Female k/l relative to Male k/l	0.91	0.85
Female Capital-to-Output	0.55	0.66
Male Capital-to-Output	0.62	0.79
Debt Share of Top 10% Firms	0.87	0.74
Business Dynamism		
Female Relative Entrepreneurial Rate	0.35	0.44
Average Entrepreneurial Rate	0.06	0.07
Average Exit Rate	0.10	0.10
Wealth Distribution		
Wealth Share in Top 10%	0.70	0.38
Entrepreneurial Wealth Share	0.30	0.23

We then run the counterfactual exercise of removing the gender differences in the borrowing constraints λ_f and λ_m, and compute output gains and improvements in female entrepreneurial participation and capital allocation. Importantly, since we have augmented the model with yet another unconstrained sector that contributes to the production of output, one should expect the productivity gains in the counterfactual economy to be scaled downwards, which is what we can observe in Table B10. Output gains shift from a +3.82% in our baseline economy, to a +1.73%, which is still a considerable figure when thinking about the aggregate US economy (note that the welfare gains also decrease significantly). Moreover, improvements along both the extensive and intensive margin of female entrepreneurship are instead very comparable to the ones obtained in our baseline counterfactual. This is because adding another unconstrained productive sector shrinks in relative terms the importance of the entrepreneurial firms, but does not crucially affect the estimated gender imbalances within the entrepreneurial sector.

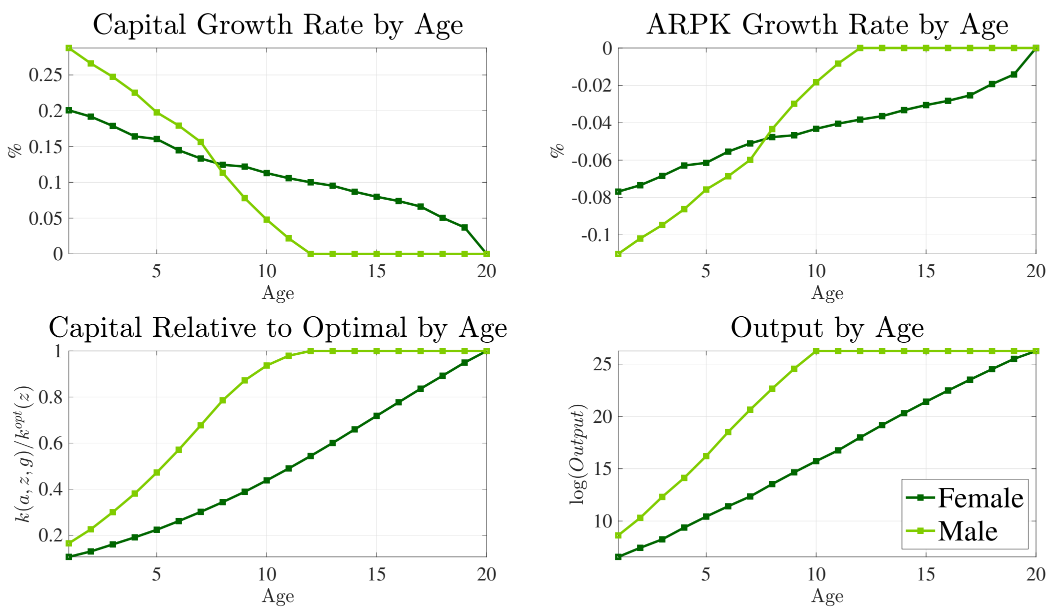
Table B10: Policy Simulation Results

$\lambda_f = \lambda_m$	Total Output	Total Welfare	Female $ARPK$	Female K/L Ratio	% Female Entrepreneurs
Increase wrt Baseline	+ 1.73%	+ 0.5%	-11.56%	+ 19.26%	+ 13.99%

B.6 Quantitative exercise

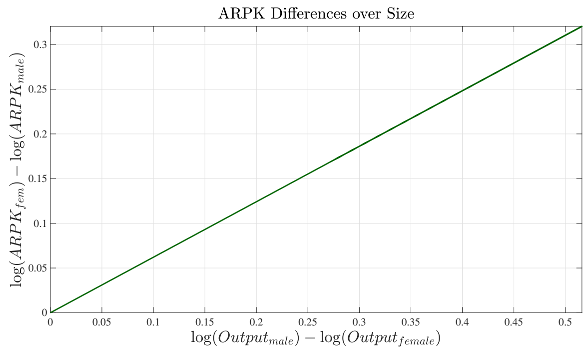
In Figure B.3, we plot illustrative evidence of firms' performance evolution over time. For the sake of exposition, we consider one female and one male entrepreneur that start their respective business at time t and are followed for 20 periods after. We further assume that their initial wealth a and productivity z are identical, and we do not allow z to change over time.

Figure B.3: Firms' Performance over Age



We first compute capital and *arpk* growth rates. Capital grows faster when firms are younger (and presumably smaller) and its growth slows down over time. Moreover, it takes time for firms to reach the optimal level of capital for their given productivity z due to the presence of financial frictions. At the same time and with a comparable speed, *arpk* decreases as the firms are able to accumulate capital. Capital in the female-led business grows more slowly initially (and the *arpk* decreases more slowly): this is due to the fact that, as female entrepreneurs face tighter borrowing constraints, they cannot borrow as much as their male counterpart especially when the enterprise is young and small. This gap is bridged over time, thanks to female entrepreneurs' accumulation of own wealth. As a complementary analysis, Figure B.4 shows that the log differences between female and male *arpk* decrease when the log difference between male and female output decreases.

Figure B.4: Firms' ARPK over Size



C Fiscal Policies

C.1 Policies Supporting Female Entrepreneurship

Around the world, several initiatives have been established to sustain the credit access of female entrepreneurs. In advanced economies, the Government of Canada allocated \$20 millions of their 2018 budget to the Women Entrepreneurship Fund to finance over 200 projects, as a component of a broader strategy that has the potential of adding \$150 billions in incremental GDP by 2026 and reaching the goal of doubling the number of majority women-owned businesses by 2025 (currently roughly 16% of the total). Similarly, in 2013 the German government launched a fund that provides small and young firms, especially those led by women, with equity up to €50,000 to improve their credit ratings and increase the chances of securing loans. Turning to the US, the SBA sponsors around 100 Women's Business Centers to assist women with access to capital and business development, helping them secure loans and grants.[10] In the developing world context, one example would be the Isivande Women's Fund (IWF) that was established by the South African government to support funding needs of women-owned businesses,and that allows women to secure loans of up to 2 million rands. Another example would be India, whose government has put forth several funding schemes for female entrepreneurs, which includes collateral-free loans, concessions on the interest paid on loans, extended loan repayment duration, among others.

In this section, using our model calibrated on the US economy, we explore and evaluate the appropriateness of fiscal policies aimed at reducing the distortions created by the gender gap in credit access. We consider subsidies targeting either the profits, the credit needs or the capital rental costs of female-owned firms, which are financed through lump-sum taxation on all the households. The aim is to assess if policies that target female entrepreneurs can improve female entrepreneurial rates and business performance, while also benefiting aggregate productivity. We take our baseline economy as a reference, and also compare the resulting improvements from fiscal policies to the counterfactual scenario in which gender-based financial constraints are removed.

[10] A related initiative is the 8(a) Business Development Program, in which the SBA agency limits competition for certain federal contracts and tries to guarantee the representation of minority-owned small businesses.

C.2 Subsidizing Female Entrepreneurs' Profits

In our first exercise we introduce a lump-sum tax levied on all agents and subsequently rebated as a subsidy θ on the profits of female entrepreneurs. Note that we allow for λ_f to be 30% lower than λ_m, as in our baseline economy, and assess if the proposed fiscal policy can possibly counteract the gender gap in borrowing constraints. While there are no changes in the profit maximization problem of a male entrepreneur, the one of any female entrepreneur is now given by:

$$\max_{l_t,k_t} \left\{ (1+\theta)(e^{z_t}(k_t^{\alpha} l_t^{1-\alpha})^{1-\nu} - w_t l_t - (r_t+\delta)k_t), \quad \text{s.t.} \quad k_t \leq \lambda_f a_t \right\} \tag{29}$$

Moreover, the budget constraint for all agents in the economy is given by:

$$a_{t+1} = \max\{\pi_t(a,z,c;r_t,w_t), w_t\} + (1+r_t)a_t - c_t - T_t \tag{30}$$

Hence, for the budget constraint of the fiscal sector to hold, in each period t it must be true that:

$$\int_{o_t(a,z,f)=e} \theta \pi_t = T_t \tag{31}$$

We create a grid of values for the subsidy, raging from 0 to 1. A subsidy rate $\theta = 0.15$ increases by 1.74% and 7.39% aggregate output and female entrepreneurial rates, and reduces by 4.94% capital misallocation, by affecting women's decision to become entrepreneurs but not directly biasing their optimal inputs choices. Female agents find entrepreneurship more accessible, which raises their average earnings and savings: since they are able to increase the wealth against which to borrow in financial markets, capital misallocation decreases. Moreover, by raising the number of entrepreneurs in the economy, such policy induces a boost in the demand for labor and capital. Higher input costs, however, reduce entrepreneurial profits and therefore depress the increase in aggregate output. A summary of the results is reported in Table C11.

Table C11: Percentage Change Relative to Baseline

	Subsidy Rate	Output	Welfare	Female $arpk$	Female Entrepreneurs
Profit Subsidy	$\theta = 0.15$	+ 1.74%	- 3.11%	- 4.94%	+ 7.39%
Credit Subsidy	$\theta = 0.33$	+ 2.97%	- 4.75%	- 4.44%	+ 1.88%
Capital Subsidy	$\theta = 0.40$	+ 3.01%	- 2.44%	- 4.20%	+ 2.88%

C.3 Subsidizing Female Entrepreneurs' Credit Needs

The second experiment we conduct is to introduce a lump-sum tax that is levied on all agents and subsequently rebated as a credit subsidy θ in favor of female entrepreneurs. The subsidy is such that it increases the maximum amount female business owners are able to borrow to finance their capital, without changing their specific borrowing limit parameter λ_f. The capital constraint of female entrepreneurs hence becomes $k_t \leq \lambda_f * a_t + \theta$. Under such modification, female entrepreneurs' wealth constitutes only one part of the collateral for their debt, while the rest is actually covered by the government. As in the previous policy exercise, we allow for λ_f to be 30% lower than λ_m, which is our baseline calibration. While there are no changes in the problem of male entrepreneurs, the maximization problem for a female entrepreneur is now given by:

$$\max_{l_t,k_t} \left\{ e^{z_t}(k_t^{\alpha} l_t^{1-\alpha})^{1-\nu} - w_t l_t - (r_t + \delta)k_t, \quad \text{s.t.} \quad k_t \leq \lambda_f a_t + \theta \right\} \tag{32}$$

Moreover, the budget constraint for all agents in the economy is given by:

$$a_{t+1} = \max\{\pi_t(a, z, c; r_t, w_t), w_t\} + (1 + r_t)a_t - c_t - T_t \tag{33}$$

Hence, for the resource constraint of the fiscal sector to hold, in each period t it must be true that:

$$\int_{o_t(a,z,f)=e} (k_t - \lambda_f a_t) = T_t \tag{34}$$

Table C11 shows the composite effect of a government subsidy increasing by roughly 30% the effective amount that constrained female entrepreneurs can borrow to finance capital. In particular, we find that such policy raises aggregate output by 2.97%, decreases female *arpk* by 4.44% and increases female entrepreneurial rates by 1.88%. The subsidy on female entrepreneurs' credit needs succeeds in enlarging the asset base of female owners by increasing the amount they can borrow to finance capital, without changing their specific borrowing constraint. In so doing, it makes entrepreneurship more profitable for female agents and helps marginally more productive women become entrepreneurs, despite the tighter financial constraints they face.

C.4 Subsidizing Female Entrepreneurs' Capital Renting Cost

The third experiment we run is to keep in place a lump-sum tax that is levied on all agents and then rebated as a subsidy θ on the cost of capital renting for female entrepreneurs ($r_t + \delta$ in the model). Specifically, female entrepreneurs targeted by such policy bear a portion $1 - \theta$ of their capital costs, while the government covers the rest. Note that we allow for λ_f to be 30% lower than λ_m, as in our baseline calibration. Thus, we try to assess by how much a fiscal policy entailing an interest rate subsidy for female entrepreneurs is able to counteract the gender gap in credit access, while possibly improving aggregate output. While there are no changes in the profit maximization problem of a male entrepreneur, the one of any female entrepreneur is now given by:

$$\max_{l_t,k_t} \left\{ e^{z_t}(k_t^{\alpha} l_t^{1-\alpha})^{1-\nu} - w_t l_t - (1-\theta)(r_t + \delta)k_t, \quad \text{s.t.} \quad k_t \leq \lambda_f a_t \right\} \tag{35}$$

Moreover, the budget constraint for all agents in the economy is given by:

$$a_{t+1} = \max\{\pi_t(a, z, c; r_t, w_t), w_t\} + (1 + r_t)a_t - c_t - T_t \tag{36}$$

Hence, for the budget constraint of the fiscal sector to hold, in each period t it must be true that:

$$\int_{o_t(a,z,f)=e} \theta(r_t + \delta)k_t = T_t \tag{37}$$

We create a grid of possible values for the subsidy rate, raging from 0 to 1: a subsidy rate $\theta = 0.40$ increases output by 3.01%, decreases female *arpk* by 4.20% and increases female entrepreneurial rates by 2.88%. On the one hand, the subsidy on female entrepreneurs' capital renting costs makes entrepreneurship relatively more profitable for female agents and helps marginally more productive women become entrepreneurs, despite the tighter financial constraints. Moreover, by affecting their optimal choice of capital, such subsidy directly raises the level of capital used in production, which further contributes to the decrease in female entrepreneurs' *arpk* and capital misallocation in the economy. On the other hand, by decreasing the capital rental rate paid by all female entrepreneurs, this policy actually benefits both constrained and unconstrained female entrepreneurs, which amplifies the positive effects on aggregate output.

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