Female Entrepreneurship and Financial Frictions*

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Abstract

In this project, we investigate and quantify the effect of gender imbalances in access to financial markets on both entrepreneurship and the misallocation of productive inputs. First, using a detailed dataset comprising 5,000 U.S. entrepreneurs, we empirically document the evidence of gender differences in firms' access to credit and in the average product on inputs of production. In particular, female entrepreneurs are 10% more likely to be rejected when applying for a bank loan. Moreover, estimation results show a significant degree of misallocation of capital inputs, with the average product of capital being 12% higher for female entrepreneurs, whereas no differences exist in the average product of labor across genders. Second, we develop a model of entrepreneurial choice under financial frictions that features agents' heterogeneity in wealth, productivity and gender. In our theoretical framework, female entrepreneurs are subject to tighter borrowing constraints that limit their entrepreneurial participation and distort their optimal capital choices. Calibrating the model to the U.S. economy, we show that gender gaps in credit access accounts for the bulk of gender differences in the average product of capital. Moreover, eliminating gender differences in financing has a sizeable positive effect on both the allocation of entrepreneurial talent and the inputs of production in aggregate, and leads to a 5% increase in total productivity. Finally, we explore the appropriateness of fiscal policies in mitigating the effect of gender imbalances in financial markets.

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

JEL Classification: O11 E44 D11

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1 Introduction

Businesses are a crucial engine of economic activity. Over time and across countries, entrepreneurs have played an important role in enhancing aggregate productivity, job creation and innovation, among other factors (see Davis and Haltiwanger (1999)). Understanding the determinants of entrepreneurship is therefore relevant for researchers and policy makers, as fostering entrepreneurial talent is regarded as an effective means of promoting economic growth.[1] However, contrary to this spirit, there are still sizeable gender imbalances in entrepreneurship, which not only precludes the participation of all the most productive agents in entrepreneurial ventures, but also brings distortions in entrepreneurs' optimal choice of inputs of production. Quantifying the effect of one such gender imbalance, namely access to credit, on both talent and capital allocation and aggregate output is the main contribution of our paper.

Using a detailed dataset comprising nearly 5,000 U.S. entrepreneurs, we empirically document the evidence of gender differences in firms' access to credit and in the average product on inputs of production. In particular, after controlling for agents' observable traits, and firms' and industry characteristics, female entrepreneurs are found to raise 35% lower business debt and to be 10% more likely to be rejected when applying for a bank loan. Bank loans are the main source of credit for entrepreneurs in our sample, and an impaired access to such credit is likely to harm the business operations of female producers. Moreover, estimation results show that female entrepreneurs have 12% higher average product of capital with respect to their male counterpart. Following the established literature on misallocation of inputs,[2] we interpret this difference as a clear sign of misallocation of capital across entrepreneurial units. Importantly, no differences exist in the average product of labor across genders, which is consistent with the fact that female entrepreneurs face higher barriers precisely in accessing credit and financing their acquisition of capital.

To rationalize the main findings from the data, we develop a model of entrepreneurial choice under financial frictions that features agents' heterogeneity in wealth, productivity and gender. In our theoretical framework, which is based on Buera and Shin (2013), female entrepreneurs are subject to a tighter borrowing constraint that limit their entrepreneurial participation and distort their optimal capital choices. This imbalance is the key difference across genders, which we can clearly quantify in our data. Calibrating the model to the U.S. economy, we show that gender gaps in credit access accounts for the bulk of gender differences in the average product of capital. We can match very well several targeted and untargeted moments, such as the overall entry rate an the gender differences in entrepreneurial rates, as well as features related to the size and distribution of debt and leverage across producers. Moreover, in our main counterfactual exercise, we first document that eliminating gender differences in financing has a sizeable positive effect on both the

[1] In addition, data from the Global Entrepreneurship Monitor (GEM hereafter) confirms that there is a positive and statistically significant correlation between the level of development of a given country (in terms of GDP per capita) and the share of female entrepreneurs running both small businesses (1-6 employees) and medium-sized establishments (20+ employees). See the Appendix for further details.

[2] See Hopenhayn (2014) for a detailed survey.

allocation of entrepreneurial talent and the inputs of production in the economy, leading to a 16% increase in female entrepreneurial rates and a 30% decrease of female entrepreneurs' *arpk*. Then we show that this leads to 5% increase on total productivity. Finally, we explore the appropriateness of fiscal policies in mitigating the effect of gender imbalances in financial markets.

A good starting point to understand the patterns of female entrepreneurial rates in the U.S. is to observe the share of female entrepreneurs over total entrepreneurs has been growing in recent years, at almost ten times the pace of the average for OECD countries (see Figure A.1).[3] Interpreting this rise as a result of declining gender-based barriers, a recent study by Bento (2020) has quantified the importance of increasing female participation into entrepreneurship for growth in output and welfare in the U.S. between 1982 and 2012.[4] However, there is well-documented evidence of still existing gender barriers in entrepreneurship, and the impact of such gender barriers on both talent and capital allocation and aggregate productivity has received less attention in the macroeconomic literature from a quantitative point of view.

To give an example of the magnitude of the gender gaps in entrepreneurship, one can first focus on the fact that female entrepreneurs make up only slightly more than 35% of the total entrepreneurial pool in the U.S.,[5] suggestive of an imbalance on the *extensive* margin. As shown in Figure 1, gender participation gaps are therefore more severe for entrepreneurs than for employed workers: on the one hand, the fraction of female entrepreneurs lags substantially behind the female share in employed workforce, which is now around 46%. On the other hand, gender gaps in earnings are more severe in entrepreneurship than in the labor markets, with the male/female earning ratio been twice as big as the male/female wage ratio especially for more educated agents. Moreover, data shows that substantial gender differences persist in other dimensions of entrepreneurial activities such as firm financing. For instance, in 2018, women received only 2.2% of total U.S. venture capital funding.[6] This type of asymmetry operates along the *intensive* margin and can be responsible for distortions that affect the optimal allocation of productive inputs across entrepreneurial units.

In this paper, we specifically focus on credit access and quantify the effect of gender differ-

[3] 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 U.S. economy, the share of female entrepreneurs is nonetheless growing in relative terms. Moreover, according to U.S. 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.

[4] Several studies have focused on the aggregate productivity effect of the increasing involvement of women in the labor market (see Heathcote et al. (2017), Goldin (2014), Doepke and Tertilt (2016) among others), and Hsieh et al. (2019) has underlined that labor force diversity enhances economic growth.

[5] U.S. Census Data for 2018: `https://www.census.gov/newsroom/press-releases/2018/employer-firms.html`. Such statistics considers businesses for which the entire ownership is female and is therefore better suited for a comparison between female self-employed and employed labor force. If one focuses on businesses where women are at least 50% of the board, the share of "female" enterprises is more than 40% (see Bento (2020)).

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

Figure 1: Female Participation Rates and Earning Gaps

Left Panel: Percentage of women among employed, self-employed and entrepreneurial work forces in the U.S.. 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: U.S. Current Population Survey, 2004-2011 (wages) and KFS, 2004-2011 (profits).

ences in borrowing constraints on both entry into entrepreneurship and the allocation of capital across productive units. For our empirical analysis, we use the confidential, restricted-access version of the Kauffman Firm Survey (KFS hereafter), a panel of nearly 5,000 nascent entrepreneurs in the U.S. covering the years between 2004 and 2011.[7] In principle, gender imbalances in entrepreneurship may be related to multiple factors that differ across genders such as educational attainment, labor attachment, social background, access to finance, among other aspects.[8] In our work however, we strictly focus on understanding whether significant differences with respect to credit access exist across genders, and how they affect entry into entrepreneurship, the allocation of factors of production, and aggregate productivity. We thus seek to answer the following questions: (1) Do female entrepreneurs face more financial constraints than men? (2) How does this affect aggregate productivity and factor allocation? (3) How much would the U.S. economy gain in terms of aggregate production by mitigating gender gaps in credit access?

First, using the KFS dataset, we find suggestive empirical evidence that credit constraints seem to penalize female entrepreneurs relatively more. Not only do female entrepreneurs report lower levels of business debt, but among those who apply for a loan, women have also a higher probability of being rejected. Thanks to the richness of the KFS dataset, our analysis allows us to control for individuals' socioeconomic and personal traits, as well as firms' and industry characteristics. Moreover, we can further establish that higher rejection rates cannot be empirically explained by higher risk of female-led businesses, or lower profitability of these enterprises.

Second, we find that females have a higher average product of capital (hereafter *arpk*) relative to males, which indicates misallocation of capital. No such differences persist when comparing the average product of labor (hereafter *arpl*) across male and female enterprises. Coupled with

[7] We therefore focus on privately held firms, which are also the most likely ones to be affected by financial frictions. Moreover, it should be stressed that privately held firms are of paramount relevance for the U.S. economy, as they account for over 70% of employment and around 50% of output, see Asker et al. (2015).

[8] A discussion of these factors is presented in the Appendix for this part. Note that throughout the analysis, we always control for relevant individual characteristics in our main regressions of interest.

the evidence on differential credit access, we conclude that there is empirical evidence supporting gender heterogeneities in financial frictions, which could be responsible for a suboptimal allocation of capital. While misallocation alone is often regarded as an indicator of latent heterogeneities in financial constraints, it is important to stress that the richness of our dataset enables us to directly document gender imbalances in credit access.

We then proceed to rationalize the main findings from the data in a model of entrepreneurial choice and financial frictions, where agents are heterogeneous along three dimensions, namely their idiosyncratic productivity, asset holdings and gender. Building on the work of Buera and Shin (2013), agents can choose whether to be workers or to run an enterprise, but we specifically introduce gender-based differences across entrepreneurs in accessing credit. As a result, women constitute a lower share of total entrepreneurs, as they anticipate that they will face tighter financial constraints when running a business. Parallel to that, through the lens of the model, the differences in *arpk* across female and male entrepreneurs derive from gender heterogeneity in access to external funding. Specifically, female entrepreneurs are more financially constrained and as such, operate with lower levels of capital. As explained in Midrigan and Xu (2014), capital misallocation is severe especially if high-productivity female entrepreneurs are frequently credit constrained.

We calibrate the model using U.S. data both from the KFS dataset as well as other commonly used sources, following a similar strategies to Buera and Shin (2013), Midrigan and Xu (2014), and Cagetti and De Nardi (2006). It is important to stress that, despite introducing only one type of heterogeneity across genders, the model produces interesting and different patterns in the choice of inputs of production, relative average product, total output, saving decisions and total factor productivities across genders. Moreover, we are able to match the targeted moments and can replicate extremely well other salient features of the data. In particular, among the untargeted moments, we can explain more than 90% of gender differences in *arpk* and capital-to-labor ratios (hereafter *k/l*) in KFS data, while matching at the same time between 70% and 90% of female and male entrepreneurs' average leverage and distributional properties computed using KFS data. At the same time, having included in the model only gender heterogeneities in financial friction, we are still able to replicate 50% of gender differences in entrepreneurial rates (as reported in the U.S. Census), and 90% of overall entry and exit rates.

Next, we use the model to quantify the effect of gender imbalance in credit access on misallocation, the capital over labor ratio, aggregate production and the allocation of entrepreneurial talent for the U.S. economy. Summarizing the main results of our baseline calibration, gender-based financial frictions alone are sufficient to produce a difference of 28% in entrepreneurial rates across genders. Moreover, female entrepreneurs have roughly 40% higher *arpk* and 20% lower *k/l*, whereas no such differences exist in their respective *arpl*.

Finally, we run policy counterfactuals along two dimensions. First, we consider the case where gender imbalances in financial markets is eliminated. Guaranteeing equal access to credit to both male and female entrepreneurs improves dramatically the allocation of entrepreneurial talent and total production in the economy. Specifically, female entrepreneurial rates increase by 16%. Since marginally more productive agents are able to join the entrepreneurial pool, not only does the allocation of inputs across productive units improves, but total production and aggregate welfare increase by up to 5.18% and 5.32% respectively. Second, in a different set of counterfactuals, we keep the gender gap in credit access but introduce fiscal subsidies, either on the profits, the credit or the rental rate of capital of female-owned businesses. We find that these fiscal schemes all foster female entrepreneurship, but the extent to which the effect of gender imbalance in financial markets can be mitigated efficiently depends on the specific type of subsidy implemented.

Related Literature. This paper relates to the empirical literature that has explored the role of gender in business performance, focusing on access to funding, self-selection into less profitable sectors, gender gaps, and policies related to supporting female entrepreneurship.[9] Within this broad literature, some studies have used the KFS data to examine gender differences in firm financing, profits and size growth (see Coleman and Robb (2009), Coleman and Robb (2010), Robb and Watson (2012)). We add to this vast literature by documenting not only the presence of a gender gap in entrepreneurial financing, but also the dispersion in *arpk* across genders, which is a novel empirical fact. Moreover, we use a sound macroeconomic framework to quantify the effect of such frictions on aggregate output, and the allocation of both entrepreneurial talent and inputs of production in the context of the U.S. economy.

In addition to that, our work relates to the vast literature that has analyzed the impact of female labor force participation on U.S. output growth (see Hsieh et al. (2019) and Heathcote et al. (2017) for recent studies). Similar to the recent paper by Bento (2020), we specifically focus on female entrepreneurship, an aspect of the female labor force that has so far been less analyzed by macroeconomic researchers. In particular, we document gender imbalances in entrepreneurial credit access at the micro-level, which are likely to distort the optimal choices of capital, and also find that female entrepreneurs have statistically significant higher *arpk*, which is regarded as an instance of capital misallocation. We subsequently build a model of entrepreneurship à la Buera and Shin (2013), where we introduce gender-based financial constraints, in order to interpret our empirical findings through the lens of a macroeconomic model and quantify the impact of talent and capital misallocation on aggregate output in the U.S.

In particular, Bento (2020) examines the increase in female entrepreneurship from 1982 to 2012 and interprets such trend through the lens of an Hopenhayn (1992) model in which barriers to female entrepreneurship decrease over time. He models gender-based barriers as wedges that affect the cost of entry, cost of hiring labor, cost of acquiring capital, and demand for output from female entrepreneurs and quantifies the contribution of gradually releasing such barriers on aggregate output growth (+12%) and female welfare (+19%) in the U.S. between 1982 and 2012. Moreover, he concludes that female entrepreneurs still face substantial barriers to financing capital expen-

[9] See for example 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. (2019), Naaraayanan (2019), Delecourt and Ng (2020) among others.

ditures relative to men. Despite our significantly different empirical and quantitative approach, we nonetheless see our paper as strongly complementary to his work, insofar as we focus on the still existing gender imbalance in credit access and quantify the effect on both talent and capital allocation and aggregate output.

Moreover, our paper relates to the macroeconomic literature on productivity losses and resource misallocation, especially on the negative effects that can be generated by financial frictions (see Hsieh and Klenow (2009), Buera et al. (2011) and Midrigan and Xu (2014)). Parallel to that, we refer to the literature investigating the importance of personal wealth in determining entrepreneurial choices (see Cagetti and De Nardi (2006)). These models, which feature heterogeneous agents, entrepreneurial choices and financial constraints, are known to perform well in matching the observed income distribution in the data, as they combine both uninsurable income risk and stochastic returns to wealth from entrepreneurial activity. However, unlike these studies, we allow for heterogeneity in access to capital, and assess the quantitative effect of gender gap in credit access on misallocation and productivity in the US.

Finally, as a novel aspect of our approach, we propose and assess fiscal policies aimed at mitigating gender-driven misallocation and foster female entrepreneurship.[10] Our work is different from Li (2002) and Kitao (2008) insofar as we aim to compare different types of subsidies, thereby assessing the validity of each instrument given the specific distortion implied by the model. In addition, we are the first (to our knowledge) to specifically conduct such quantitative analysis in relation to gender-driven financial frictions and implied capital misallocation.

The remainder of this paper is organized as follows. In Section 2, we document empirically gender differences in credit access and *arpk*, which are indicators of gender-based financial frictions and misallocation of capital. In Sections 3–6, we introduce and solve numerically a model of entrepreneurial choices and financial constraints to quantify gender-driven misallocation, and run policy counterfactuals. Finally, in Section 7, we conclude.

2 Empirical Evidence

2.1 Data Description

In this paper, we use the restricted-access version of KFS 2004–2011 data, as well as the U.S. Census Survey of Business Owners 2007, the U.S. Census Annual Survey of Entrepreneurs (ASE) 2014–2016, and the U.S. Census Business and Dynamics Statistics (BDS) 1978–2014. Since we draw most of our empirical evidence on KFS micro data, we proceed to briefly discuss the main characteristics of KFS survey below, while we leave the description of the other datasets, which we use in the calibration of the model, in the Appendix.

[10]We focus on taxes collected on all individuals and redistributed in favor of female entrepreneurs. We therefore do not explore issues related to estate taxation and wealth inequality, further investigated in Cagetti and DeNardi (2009) and Meh (2005).

The KFS sample includes 4,928 new firms in the U.S. that started their operations in 2004, and have been followed until 2011. The survey includes information on the age, gender, race, marital status, education, working/other start-up experience for up to 10 owners, for each firm. It also reports which owners are actively managing their businesses, which we focus on in the current analysis following standard practices in the literature (see for example Cagetti and De Nardi (2006)).[11] At the same time, the survey contains detailed information on the geographical location, industry, wage bill, assets, revenues, and profits, along with data on different types of financing sources (debt and equity). We emphasize two important points in our use of the KFS data throughout the empirical analysis and subsequently when computing salient moments from the data. First, we define a female-led business to have female active owners only, and a male-led business to have male active owners only.[12] Second, we use sample weights to get a representative sample of entrepreneurs.[13] Table 1 provides the summary statistics of the main variables of interest.

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	3.82	9.30	4.15	1.95	0.0000
Loan rejection	0.19	0.39	0.16	0.32	0.0053
Observations	17,824		11,286	3,547	

Notes: Loan rejection is the average probability that loan applications are always rejected. Survey weights are used to compute the averages.

The richness of the KFS sample differentiates it from other commonly used macro datasets that do not contain enough detail at the firm level. Unlike panel surveys, such as NLSY79, that follow individuals over time, the KFS targets entrepreneurs only and covers firm characteristics related to their operations that are crucial to assess quantitatively and extensively business performance.[14]

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

[12] In the Appendix, we consider other definitions of owner's gender and show that the empirical findings presented in the main text hold. In particular, we first distinguish them based on the gender of the primary owner. Then, we use a continuous measure of female ownership and use it in our regressions to show that the more female owners, the stronger the effects on credit constraints and resource misallocation.

[13] We also run the specifications of our main regressions of interest without using sample weights as a robustness check. The sign and statistical significance of the female ownership dummy in Table 3 and Table 5 do not change.

[14] We believe the main limitation related to the nature of the KFS is that it surveys entrepreneurs that have *already*

Finally, we should note that the KFS fairly represents the U.S. entrepreneurial universe (in terms of education, gender, race and other individual characteristics), and can also be compared to the average distribution of firms in the U.S. economy. In particular, the share of female and male entrepreneurs in the KFS sample resembles the one in the Census ASE (see Table A2 in the Appendix). Moreover, we compare the distribution of firms over size bins (measured in terms of employees) in KFS to the one from BDS, as shown in Figure A.2 of the Appendix. BDS is a vastly used dataset in quantitative works, comprising details on the size of more than 3 millions firms per year, between 1977 and 2014. In particular, with respect to BDS, KFS seems to moderately oversample small firms (1-4 employees), whereas there are no other sizeable differences across the two distributions. We discuss the importance of having a representative sample later on when we explain our calibration strategy in Section 4.

2.2 Credit Access

While entrepreneurial differences across genders potentially arise due to various factors, we focus on the financing aspects of entrepreneurship in this section, and discuss other potentially interesting motives in the Appendix. These factors, such as different educational levels or working experience, which have already been studied in other works, are not central to our argument and are always controlled for in our empirical analysis.[15] Since we aim to build an entrepreneurial model enriched with gender-based financial constraint on the amount of credit entrepreneurs can obtain, we proceed by estimating gender differences in funding across the entrepreneurs in our KFS sample. Here, we focus on two main measure of firm's funding: business debt (a commonly used *external* source) and equity (which is regarded to be mostly an *internal* source, especially for not publicly traded firms like the ones in the KFS sample).

In Table 2, we find that female entrepreneurs operate with lower business debt, regardless of the size of their business, their industry sector, their geographical location, and their relevant personal traits. Moreover, we find that they are not compensating such lower levels of debt with higher levels of equity.[16] Furthermore, as reported in Figure A.11, bank loans and credit lines make up for most of the business debt across firms in the KFS sample. In line with these findings, we concentrate our attention on loan financing and provide additional evidence on tighter borrowing constraints for female entrepreneurs. In particular, this serves the purpose to match directly the empirical evidence with the theoretical modeling of gender-based differences in credit access.

The fact that female entrepreneurs on average have lower levels of business debt is potentially driven by an interplay of both supply and demand factors. On the one hand, the lower debt levels may be due to the fact that women find it more difficult to access credit (supply-side constraint).

started a firm. This comes at the expense of not being able to clearly disentangle all the important forces that drives agents into entrepreneurship.

[15] Robb and Watson (2012) provides an excellent discussion on how these factors can affect entrepreneurial outcomes.

[16] 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 A4 that indeed, female-owned firms hold lower levels of debt and this is not compensated with more equity financing.

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 $\log(\textit{revenues})$.

On the other hand, it may also be that women deliberately decide to seek less external funding and rely more on their own resources (demand effect).[17] To partially control for the demand channel, we turn our attention to loan rejections, and focus on the subsample of entrepreneurs who actually applied for loans. KFS provides data on loan application outcomes for 2007–2011. In our sample, 22% of loan applicants get a rejection from financial institutions, with the average rejection rate being higher for female entrepreneurs (32%) compared to male entrepreneurs (16%). We proceed to estimate the likelihood of loan rejections for the male and female entrepreneurs in our sample. Specifically, we run the following probit regression:

$$Pr(Reject_{isrt} = 1) = F\left(\beta_0 + \beta_1 \mathbb{1}_{female} + \delta' \mathbf{\Gamma}_{isrt} + \alpha_t + \eta_s + \nu_r\right) \tag{1}$$

where $Reject_{it}$ is a binary variable that takes on a value of 1 if loan applications are always rejected, and 0 if loan applications are always approved. 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 100% male-owned. The regressions include a set of controls $\mathbf{\Gamma}$, which captures various factors apart from gender that may affect whether a loan application gets rejected or not (e.g. age, race, education, previous experience, firms' leverage and personal debt), as well as sector, region and year fixed effects (η_s, ν_r and α_t respectively).[18]

As reported in Table 3, female ownership strongly correlates with higher probability of loan rejections, suggesting that women face more constraints in accessing credit. In particular, female entrepreneurs face a 10% higher probability of having their loan application rejected.[19] It is cru-

[17] Nevertheless, in Table A6 in the Appendix we also document that there is no robust difference in the likelihood of applying for a loan across genders.

[18] We report results from robustness checks using linear probability model regressions in Table A7 in the Appendix.

[19] We note that our results show a gender imbalance in the likelihood of obtaining credit, but we cannot identify the type of discrimination female entrepreneurs face. The data is not suited for analysis that will make this distinction clear-cut. In principle, this may be due to a Becker-type of discrimination, where women experience more loan rejections by virtue of their gender despite not being riskier borrowers. Or alternatively, this may be driven by statistical discrimina-

Table 3: Loan Application Rejections

	(1)	(2)	(3)	(4)
Female	0.1011***	0.1166***	0.1048***	0.1196**
	(0.0512)	(0.0609)	(0.0511)	(0.0593)
Controls	Y	Y	Y	Y
Leverage	N	Y	N	Y
Personal debt	N	N	Y	Y
Sector FE	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	622	461	598	448
Pseudo-R^2	0.218	0.241	0.248	0.271

Notes: Estimates are marginal effects at the average. 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 always rejected, and = 0 if loan applications are always approved. Controls for the number of owners, and for individual characteristics such as education, experience, race, and age are included.

cial to stress that female entrepreneurs' lower probability to obtain a loan is likely to have a strong impact on the business's ability to fund its operations, as the main source of financing for entrepreneurs in the KFS sample, regardless of gender, is precisely bank loans.

The correlation between female ownership and the likelihood of being denied credit access is relevant and statistically significant also when different definitions of female ownership are considered (see Table A8 in the Appendix). Moreover, it is important to note that crucial control variables in our regression strategy are the leverage of the firm and the personal debt burden of business owners themselves. This is particularly relevant since entrepreneurial and business risk are often regarded as key determinants of loan application approval. In fact, if female entrepreneurs were to run riskier businesses compared to their male counterpart, this could be a candidate reason for their higher rejection rates on loan applications.[20]

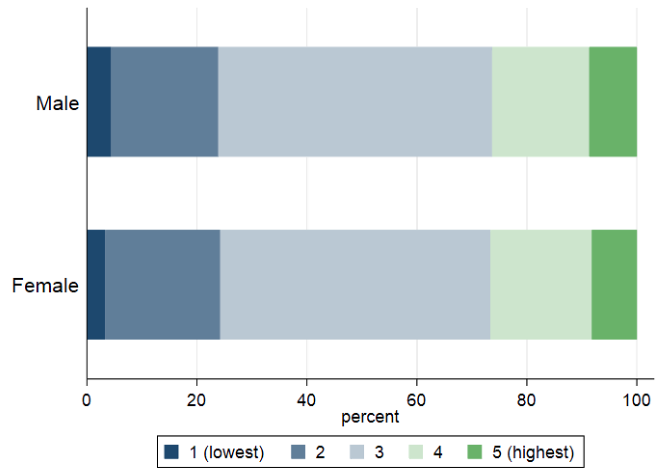
To further provide evidence on the specific risk profile of female-owned firms as opposed to male-owned ones, we first examine official credit risk scores assigned by the Dun & Bradstreet rating agency to female and male-owned firms in our sample. Figure 2 shows that female entrepreneurs are not rated as riskier than male entrepreneurs in our KFS sample. Parallel to that, we can also focus specifically on the entrepreneurs that have filed an application for a loan. The average credit score of businesses with *accepted* loan requests is 2.59 (numbers closer to 1 refer to low credit risk). A break down by gender shows that male entrepreneurs' average credit risk score is 2.62 whereas for female entrepreneurs, it is 2.44. Moreover, the average credit score of businesses with *rejected* loan requests is 3.10. Again, breaking down this sample by gender, we

tion, where loan officers use information from the applicant's group to gauge the applicant's creditworthiness, rather than his or her own credit history. We provide a more detailed discussion of this issue in the Appendix.

[20] If this was indeed the case, then in principle, we should find no significant differences in rejection rates across genders after controlling for credit risk scores. However, as we document in Table A9, even after we control for credit risk scores, female-owned firms nonetheless face a higher probability of rejection in loan applications.

can check that male entrepreneurs' average is 3.22 and the female entrepreneurs' one is 2.87. This means that female entrepreneurs' businesses have better credit risk profiles among both *accepted* and *rejected* loan applications.[21]

Figure 2: 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.

Second, to complement the analysis, we construct and examine two well-established measures of risk, namely leverage and volatility of return on assets, following Faccio et al. (2016). Leverage is defined as business debt over assets, while volatility on the return on assets is measured as standard deviation of profit over assets. As shown in Table 4 columns (1) and (2), there is no statistically significant difference between the leverage and volatility of returns across genders. In conclusion, the empirical evidence gathered seems to suggest that female entrepreneurs are not riskier clients for banks.

We then examine the profitability of businesses. One could in principle question whether female and male-owned businesses are equally profitable, after controlling for individuals' observables and other well-known determinants of firms' profitability. Standard measures of profitability include the return on assets $\frac{Profit}{Assets}$, and the profit margin $\frac{Profit}{Revenues}$, which we compute for both female and male entrepreneurs in the KFS sample. From Table 4 columns (3) and (4), we can see that female-led businesses are not less profitable compared to their male counterparts.[22]

In summary, we find suggestive evidence of heterogeneities in financial frictions along the gender dimension. Female entrepreneurs face tighter constraints to credit access in the sense that they have a higher probability of facing rejections on their loan applications, despite not being

[21] Table A5 in the Appendix further analyzes differences in gender attitudes towards external financing, with a break down by credit risk score. Interestingly, 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.

[22] This is consistent with the findings of Robb and Watson (2012), where they use KFS data from 2004 to 2008 to show that after controlling for relevant individual and firm characteristics, there is no difference in the performance between female- and male-owned businesses.

riskier nor less profitable compared to male-led businesses.[23]

Table 4: Measures of Risk-Taking and Profitability

	(1)	(2)	(3)	(4)
	leverage	sd(ROA)	$\frac{Profit}{Assets}$	$\frac{Profit}{Revenues}$
Female	0.0302	-0.0301	0.2758**	0.0064
	(0.0201)	(0.1554)	(0.1096)	(0.0109)
Controls	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	11,034	6,510	7,851	7,717
R^2	0.079	0.142	0.094	0.300

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 $\log(revenues)$.

2.3 Misallocation

In what follows, we explore gender differences in average returns to inputs of production, which is a common method to verify and quantify any misallocation of resources across producers of any given good (see Hsieh and Klenow (2009)). To conceptualize the notion of misallocation, one can imagine an economy where output is produced by heterogeneous producers that differ in their individual levels of 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. Absent misallocating forces, there should be a unique choice for the inputs producers should operate with, and relative to how labor and capital should be allocated across them in order to maximize total output.

However, as explained by Restuccia and Rogerson (2017), misallocation across heterogeneous producers arises whenever productive inputs do not flow to producers according to their respective productivity A_i. Moreover, recent works summarized in Hopenhayn (2014) have argued that misallocation of productive inputs can precisely stem from frictions that constrain some entrepreneurs, such as borrowing constraints. It is important to note that we differentiate from this standard approach in that we focus on financial frictions that affect female entrepreneurs more than their male counterpart (see Goraya (2020) and Bento (2020) for other examples of such approach). This type of misallocation is likely to also negatively impact the optimal flow of inputs to productive units and, as a consequence, aggregate productivity and economic growth.

[23] Also related to the analysis of the profitability of firms in the KFS dataset, we check whether and how much entrepreneurs invest for the progress of their businesses through research and development (*R&D*) activities. Such activities may be related to worker training, product/service design, brand, software and organizational development, and their relevance for business performance has been widely documented (see Corrado et al. (2009) for example). As reported in Figure A.9, even if female-owned businesses are on average smaller and hence spend less on *R&D* in absolute terms, there are no gender differences in the resources devoted by businesses to *R&D* as a share of total expenses and revenues.

To document misallocation empirically, we first note that empirical differences in the average products of inputs are a good indication of misallocation of resources across producers. This is due to the fact that capital-constrained firms may run their operations with lower than average levels of capital, resulting in higher average product of capital. Hence, to measure misallocation across producers of different genders, we compute the average return to capital and labor as follows:[24]

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

where the variable Y_{it} is revenues, k_{it} is capital, measured using fixed assets, and l_{it} is labor input, measured as wage bill. We use the wage bill instead of employment as a measure of labor input, following Hsieh and Klenow (2009), to control for differences in labor quality and actual hours worked across firms. Fixed assets is computed as the sum of all non-current asset categories in the KFS dataset.[25] This includes inventory, equipment and machinery, land and buildings, vehicles and other properties.[26] We run the following regression:

$$y_{isrt} = \beta_0 + \beta_1 \mathbb{1}_{female} + \delta' \mathbf{\Gamma}_{isrt} + \alpha_t + \eta_s + \nu_r + \varepsilon_{isrt} \tag{2}$$

where $y_{isrt} = \{arpk_{isrt}, arpl_{isrt}\}$. 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 100% male-owned. The regressions include a set of controls $\mathbf{\Gamma}$, which captures various factors apart from gender that may affect how firms allocate their inputs of production, as well as sector, region and year fixed effects.

As shown in Table 5, female-owned businesses are associated with 8-12% higher *arpk*, depending on the preferred regression specification. This clearly suggests the presence of gender-driven misallocation of capital across firms, with female entrepreneurs operating with lower levels of capital compared to their male counterpart. Coupled with the evidence shown earlier on the presence of gender heterogeneities 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. Moreover, Table 5 documents that there is no statistically significant difference between the *arpl* of male and female-owned firms. Importantly, this finding is consistent with Bento (2020), who also documents that gender differences in firms' *arpl* have lost relevance and significance in recent years as opposed to the 1980s.

As a further validation of such hypothesis, the left panel of Figure 3 shows the relationship of female *arpk* and the share of female-owned firms across U.S. states. To compute the share of

[24]Note that without implying any specific form for the production function, it is possible to compute *average* returns to inputs of production. Dispersion in *average* returns is in fact a clear indicator used in the literature to signal the instance of misallocation without imposing any specific production function on the data.

[25]For another example of how to compute *arpk* using KFS data see Kochen and Guntin (2020).

[26]In the KFS dataset, the remaining asset categories, which we consider as current assets, are cash and accounts receivable.

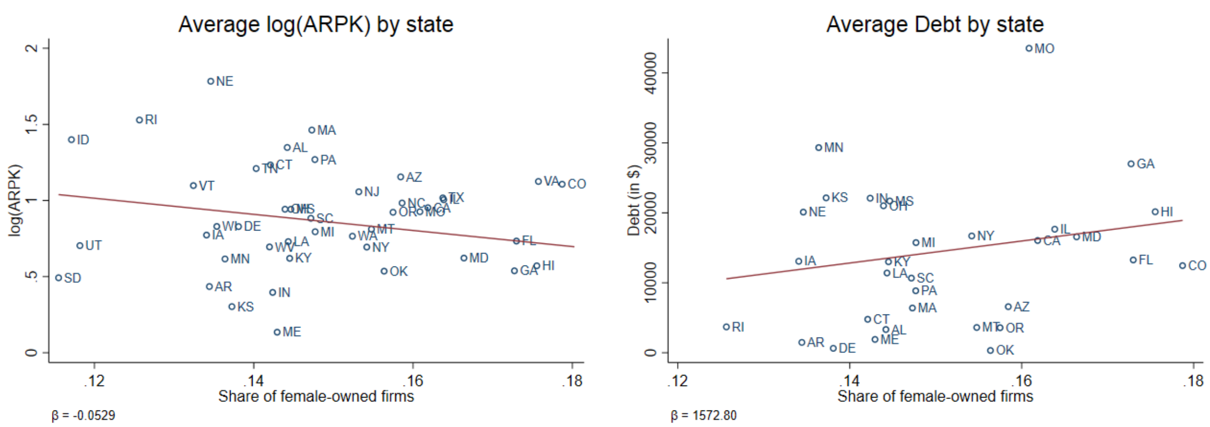
Table 5: *arpk* and *arpl* across genders

	(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. Controls for individual characteristics include education, experience, race and age. Other controls include the number of owners, legal status of the firm and number of hours worked per week.

female-own enterprises for each state, we use national Census statistics from SBO for the year 2007.[27] In states where women are more represented among the entrepreneurial forces, female *arpk* is lower, implying lower capital misallocation. Similarly, in the right panel of Figure 3, we document that the average debt level of female-own enterprises is higher in states where women are more represented among entrepreneurs. Consequently, even if we do not take a stand on the specific source of gender gaps in credit access, we can nevertheless observe that whenever female entrepreneurial representation is stronger, capital misallocation across genders will be lower.[28]

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 in each state.

To strengthen our results, we also run the regressions on a subsample of firms with empirically

[27] SBO Census statistics for the entrepreneurial universe in the U.S. 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.

[28] This effect can be due to the fact that female entrepreneurship is higher in states where female face less barriers to entrepreneurship, may they be related to cultural norms, federal laws, less gendered-stereotypes, among other factors.

relevant levels of revenues per year and confirm the same findings (column (3) and (4) in Table 5). Moreover, while our main specification refers to firms where all owners are female or male, our result is robust to restricting our attention to primary owners of firms. Finally, when using a continuous measure of female ownership as our main regressor of interest, the coefficient keeps being positive and statistically significant (results are reported in Table A12 in the Appendix). In the quantitative section of the paper, we compute the model-equivalent counterparts of these two empirically relevant measures – *arpk* and *arpl*– and show that an entrepreneurship model featuring assets, productivity and gender heterogeneities and enriched with gender-based borrowing constraints, can precisely deliver gender differences in *arpk*: female entrepreneurs have significantly higher *arpk* than male one, while having the same *arpl* as their male counterpart.

3 Theoretical Framework

The empirical evidence we provide suggests that financial frictions may be causing distortions in the optimal level of capital with which female entrepreneurs decide to operate their businesses. On the one hand, female entrepreneurs have higher *arpk* than male entrepreneurs, whereas no such differences can be found when computing the *arpl*. On the other hand, we find that female entrepreneurs seem to have more difficulties in accessing credit. Our goal is precisely to model and quantify the effect of gender differences in the degree of financial constraints, which can lead to distortions on both the *extensive margin* (i.e. entrepreneurial participation) and the *intensive margin* (i.e. optimal allocation of resources).

In our theoretical framework, which is built on Buera and Shin (2013), agents of different genders and asset base can decide whether to be workers or entrepreneurs. Entrepreneurs are heterogeneous in their idiosyncratic productivity, and produce using both labor and capital, but the amount of capital that they can borrow depends on their stock of assets.[29] Such limit is gender-based and constrains female entrepreneurs to borrow less compared to male entrepreneurs with similar wealth and productivity. In particular, on the *extensive margin*, tighter financial frictions cause women to face higher barriers in starting a business,[30] while on the *intensive margin*, it can influence their optimal choice of capital, leading to consequent losses in aggregate production and misallocation of inputs of production. We specifically aim to build a parsimonious model where gender gaps in credit access are the only element of heterogeneity across female and male agents, in order to bridge our empirical evidence and the quantitative predictions on this structurally identified and relevant margin.[31]

[29] Goraya (2020) uses a similar setup of the model to examine caste-driven misallocation in India.

[30] Therefore, only the very skilled and productive ones manage to become entrepreneurs. This phenomenon is called *self-selection* and it will be discussed in further detail in the following paragraphs.

[31] Such modeling strategy leaves open the possibility of introducing other gender differences such as differential risk aversions, wage gaps, heterogeneities in entrepreneurial productivities and/or in operational costs, which we abstract from in the current analysis. While we believe these margins may bring the model even closer to a complete representation of labor and entrepreneurial markets dynamics, we instead show that a simple model of entrepreneurship and financial frictions, enriched with gender heterogeneities in credit access, matches well salient features of the data.

3.1 Model Primitives

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

Occupation: At every point in time, agents choose their occupation $o(z,a,g)$, based on their wealth a and productivity z. They can either choose to be entrepreneurs e or workers w. Entrepreneurs own a firm and earn business profits π. Workers inelastically supply one unit of labor and earn for a wage w. For simplicity, we assume that w is independent of agents' individual characteristics and is indeed the same for agents of different genders.[32]

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 $d\Xi(z'|z)$.[33] Therefore, our model features (uninsurable) idiosyncratic shocks to entrepreneurial productivity, while there is no source of aggregate uncertainty in the economy as a whole.

Preferences: Agents have a strictly increasing concave utility function that satisfies standard Inada conditions. The coefficient of risk aversion is denoted by γ and is assumed to be the same across genders. This assumption can in principle be relaxed without changing the nature of our results.[34] Moreover, agents discount the future at a rate β, and maximize their utility over the following stream of present and future 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 decreasing returns to scale production function that combines capital and labor[35] and is given by:

[32]While there is corroborated evidence of a gender wage gap in U.S. labor markets, this specific issue is not the focus of the present work, and our results do not hinge on this particular simplifying assumption.

[33]Other works in the literature use a Pareto distribution for entrepreneurial skills, see for example Buera and Shin (2013). Our main results do not hinge on any specific choice in this regard, as we are able to calibrate both the persistence ρ_z and volatility σ_ϵ to match the same salient moments from the data used in Buera and Shin (2013) among others.

[34]We could assume, for example, that female agents are more adverse to risk. A higher risk aversion would further discourage women to become entrepreneurs and amplify the channel already present in our baseline specification. In that case, our current results would be a more conservative estimate of both gender-driven misallocation of talent and productive inputs and aggregate output loss. Empirically, we cannot support such difference in our available data, as explained further in Appendix, therefore we abstract from including different γ by genders.

[35]The production function is increasing in all the arguments, and it is strictly concave in capital and labor. Moreover, the production function shows decreasing returns, allowing for a non-degenerate distribution of the enterprise size.

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

where $1-\nu$ is the span of control as in Lucas (1978). Importantly, both capital and labor are static input and therefore are rented at each point in time by the entrepreneurs.[36]

3.3 Financial Markets

There is a perfectly competitive intermediary sector that receives deposits from savers and lends these funds to entrepreneurs, without intermediation costs. The rental rate of capital is given by $r_t + \delta$, where δ captures depreciation and r_t is the deposit rate. Financial markets are incomplete insofar as entrepreneurs can only borrow up to a fraction of their assets a_t. At each point in time, capital constraints take the following form:

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

where $a_t \geq 0$ (any intertemporal borrowing for consumption smoothing is ruled out) and λ_g measures the degree of the constraints, which varies by gender. In particular, 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. Specifically, female entrepreneurs in the model can borrow less than the males, which amounts to assuming that $\lambda_m - \lambda_f > 0$.[37] We refer to such difference in borrowing constraints as a wedge τ such that $\tau = \lambda_m - \lambda_f > 0$, and give a more detailed characterization of its impact in the paragraph below.

3.4 Profit Maximization

Entrepreneurs maximize revenues net of capital renting costs and labor costs, with the only gender difference being in the tighter borrowing constraint female entrepreneurs face when renting

[36] It will not be unrealistic to assume that female and male entrepreneurs may also be subject to different operational or entry costs as in Bento (2020). Indeed, we cannot precisely pin down their empirical relevance using the KFS sample and this is the reason why we abstract from them in this paper. However, if we were to introduce a gender-specific cost that is higher for female entrepreneurs, it will strengthen our mechanism, leading to even higher self-selection, capital misallocation and output losses. Our results in this paper will be hence a more conservative estimate with respect to that theoretical variant.

[37] To justify this specific theoretical choice, we have shown empirically that loan rejections are more likely for female entrepreneurs, controlling for many individual, firm, industry and geographical characteristics. We are certainly not the first to document discriminatory treatments with respect to financing. See for example Cavalluzzo et al. (2002), Bellucci et al. (2010), Aristei and Gallo (2016), De Andres et al. (2019) and Montoya et al. (2020) on the topic of loan requests and Hebert (2020) and Ewens and Townsend (2020) on external funding. Many other works have documented gender differences in interest rates paid on loans (see Coleman (2000) and Alesina et al. (2013)), as well as in the frequency/size of collateral requested to the entrepreneurs (see Calcagnini et al. (2015) and Xu et al. (2016)). Using our data, we can also document that female entrepreneurs are asked more frequently to provide collateral when asking for a loan, compared to men (see Figure A.13). While there is great empirical evidence and consensus that gender differences in credit access exist, in this paper we do not take a precise stand on where differences between λ_m and λ_f are originating from, leaving a more refined micro-foundation for future investigation. However, in the Appendix, we include some suggestive evidence on the possible instances of both taste-based and statistical discrimination using our available KFS data, which can give a further interpretation to the observed gender differences in credit access.

capital. Since output price is normalized to one, profit maximization can be written as:

$$\pi_t = \max_{l_t, k_t} \left\{ e^{z_t} (k_t^{\alpha} l_t^{1-\alpha})^{1-\nu} - w_t l_t - (r_t + \delta) k_t, \quad \text{s.t.} \quad k_t \leq \lambda_g a_t \right\} \tag{3}$$

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

3.4.1 Understanding Gender-Driven Misallocation

An intuitive way to appreciate the effective mechanism of gender heterogeneities in financial frictions is to derive the profit maximization for a female entrepreneur and compared it to the one of any male entrepreneur. We have assumed in this analysis that $\lambda_f = \lambda_m - \tau > 0$, where τ is interpreted as a wedge on the capital input that distinguishes female profit maximization from the male in each t. Thus, for a female entrepreneur, we have:

$$\max_{l_t, k_t} \left\{ e^{z_t} (k_t^{\alpha} l_t^{1-\alpha})^{1-\nu} - w_t l_t - (r_t + \delta) k_t - \mu_t \left(\frac{k_t}{\lambda_m - \tau} - a_t \right) \right\} \tag{4}$$

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

$$l_t^{opt} = \left(\frac{(1-\nu)(1-\alpha) e^{z_t} (k_t^{\alpha})^{1-\nu}}{w_t} \right)^{\frac{1}{1-(1-\alpha)(1-\nu)}} \tag{5}$$

$$k_t^{opt} = \left(\frac{(1-\nu)\alpha e^{z_t} (l_t^{1-\alpha})^{1-\nu}}{r_t + \delta + \frac{\mu_t}{\lambda_m - \tau}} \right)^{\frac{1}{1-\alpha(1-\nu)}} \tag{6}$$

Gender differences in borrowing constraints do not affect female entrepreneurs' optimal choice of labor l_t^{opt}, while they do negatively impact 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) reduces k_t^{opt} for a female entrepreneur relative to her male counterpart. In fact, one should note that the presence of borrowing constraints in the economy (captured by μ_t) distort all entrepreneurs' decisions with respect to their chosen level of capital, but the different borrowing limit across genders τ further biases downwards women's k_t^{opt} with respect to men's k_t^{opt}.[39] If one thinks of the firms for which constraints are more likely to

[38] We also able to check that female entrepreneurs in our sample do not pay lower wages to their employees with respect to their male counterpart, which further justifies our choice to only focus and model gender gaps in credit access, which are responsible of differences in the optimal capital and *arpk* across genders.

[39] Similarly, any proportional increase in both financial constraints λ_m and λ_f results in a release of financial constraints: since agents expect financial constraints to be less often binding, the entrepreneurial productivity cutoff of both genders decreases, leading to higher entry into entrepreneurship, lower average entrepreneurial ability and higher output produced across all entrepreneurs. However, as long as the increase in λ_m and λ_f is proportional, gender differences in credit access are preserved and, as a consequence, the relative business performance differences between men

bind – for example young or small ones – female-owned firms of such kind would be more often constrained relative to male-owned ones, which may not only create distortions in their business operations but also limit their growth and expansion.

To give a direct counterpart to the misallocation measures computed empirically in the KFS sample and discussed in Section 3, we proceed to compute 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. $\frac{\partial D_k}{\partial \tau} = \frac{\mu_t \lambda_m^2}{((\lambda_m - \tau)\lambda_m)^2} > 0$
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 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 gender differences in financial constraint τ. Gender imbalances in credit access produce heterogeneity in the average product of capital of female and male entrepreneurs in the model, which links to the empirical evidence presented in Section 3. Therefore, the quantitative purpose of this paper is precisely to estimate such τ and assess how much this gender wedge can impact on the allocation of talent and capital, as well as aggregate productivity. As a final remark, one can note that, if $\tau = 0$, then for a female entrepreneur, the *k/l* ratio is the same as for the male counterpart and it is given by:

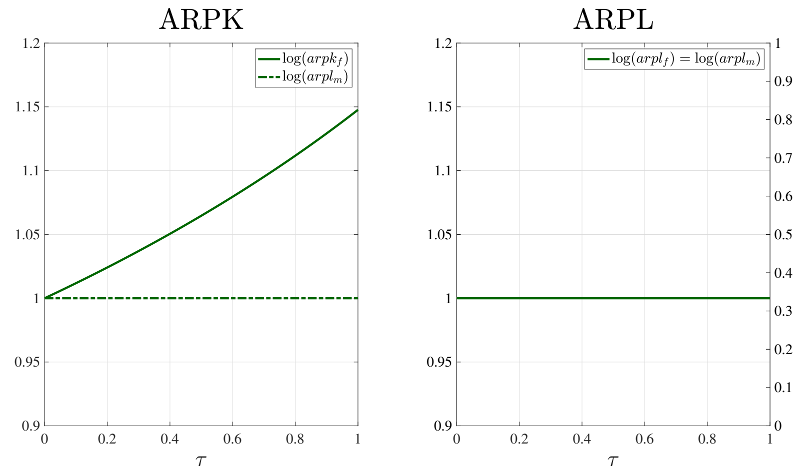
$$\frac{k_t}{l_t} = \frac{w_t(1-\alpha)}{\alpha(r_t + \delta + \frac{\mu_t}{\lambda_m})}$$

Otherwise, if $\tau \neq 0$:

$$\frac{k_t}{l_t} = \frac{w_t(1-\alpha)}{\alpha(r_t + \delta + \frac{\mu_t}{\lambda_m - \tau})}$$

and women remain unaffected.

Figure 4: Proposition 1



and the *k/l* ratio is inefficiently low for female entrepreneurs. On the one hand, gender-specific borrowing constraints can generate gender imbalances in entrepreneurial rates by discouraging women from becoming entrepreneurs. On the other hand, they can lead to distortions in the optimal choice of capital, implying resource misallocation across productive units. These effects can be reconciled with U.S. aggregate evidence on lower female entrepreneurial rates, and with the gender differences in the level of financial constraints and *arpk* computed in the KFS dataset.

3.5 Individual's Problem

At each time t, agents maximize their expected utility for a given set of factor prices $\{w, r\}$, their assets a, and their productivity z, such that the budget constraint always binds. The value function that agents maximize is:

$$V(a,z,g) = \max\{V^w(a,z,g), V^e(a,z,g)\} \tag{7}$$

The workers' value function is given by:

$$V^w(a,z,g) = \max_{c,a' \geq 0} \; u(c) + \beta \int V(a',z',g) dY(z'|z) \tag{8}$$

$$s.t. \quad c + a' \leq w + (1+r)a \tag{9}$$

The entrepreneurs' value function is given by:

$$V^e(a,z,g) = \max_{c,a' \geq 0} \; u(c) + \beta \int V(a',z',g) d\Xi(z'|z) \tag{10}$$

$$s.t. \quad c + a' \leq e^z (k^\alpha l^{1-\alpha})^{1-\nu} - wl - (r+\delta) + (1+r)a \tag{11}$$

$$k \leq \lambda_g a \tag{12}$$

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:

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

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

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

4 Quantitative Results

This section of the paper quantifies the role of gender gap in access to credit in explaining the across-gender dispersion in the *arpk*, and evaluates the TFP losses due to resource misallocation generated by asymmetries at the *extensive* and *intensive* margin. We first begin by estimating the model on the U.S. economy using various sources of data, and analyze the main quantitative predictions of our exercise in terms of aggregate economic losses due to gender-based financial asymmetries. Next, we run several counterfactuals to assess the positive effect of removing gender differences in credit access on the allocation of entrepreneurial talent and capital, as well as aggregate output and welfare in the economy.

4.1 Structural Estimation

In what follows, we present our calibration strategy, which is based on Buera and Shin (2013) and Midrigan and Xu (2014), and summarized in Table 6. A model period is one year. Of the nine parameters we need to estimate, three are fixed outside the model, for which we pick common values chosen by most works in the literature (see Cagetti and De Nardi (2006) for example). In particular, we set the coefficient of risk aversion $\gamma = 1.5$, the capital share $\alpha = 0.33$, and the depreciation rate $\delta = 0.08$.[40]

With respect to the six remaining parameters, we aim to match six relevant empirical moments for the U.S. economy that we will explain in full detail below. First, $\beta = 0.9235$ is picked to to match an average annual interest rate $r = 4.5\%$ for the U.S., as in Buera and Shin (2013).[41] Moments related to demographics and income distribution in the population are computed using U.S. Census data. Specifically, the span of control parameter ν is fitted such that the income share

[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).

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

Table 6: 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	0.08	Capital Depreciation (Annual)	Clementi & Palazzo (2016)
Fitted			
β	0.9235	Discount factor	
$1-\nu$	0.83	Span of control	
σ_ϵ	0.305	Std. deviation idiosyncratic shock	
ρ_z	0.93	Persistence idiosyncratic productivity	
λ_m	3	Borrowing constraint male	
λ_f	1.93	Borrowing constraint female	

of the bottom 90% of agents is the same in the data and in the model as in Buera et al. (2011): this procedure is motivated by the fact that $1-\nu$ regulates firms' scale of operations and, subsequently, the profits of the entrepreneurs, which are likely to be at the top deciles of the earnings distribution. Our final value $1-\nu = 0.83$ is very much in line with the one estimated for the U.S. by several papers on entrepreneurial choice such as Buera and Shin (2013), among others.[42] Moreover, to identify the volatility of entrepreneurial skills σ_ϵ, we target the top 10% largest firms' employment share in BDS, given that 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 firms.[43] Our final value $\sigma_\epsilon = 0.305$ is in line with productivity estimates for the U.S. by Lee and Mukoyama (2015) using the Annual Survey of Manufactures dataset from the U.S. Census Bureau for the period 1972–1997.

Next, we use two moments from the data to identify the two main parameters of interest that govern gender-based financial frictions, namely λ_m and λ_f. We first compute the average size of KFS female and male entrepreneurs' business debt, and then target their relative ratio. We choose to target the relative debt ratio (and not the absolute values for each gender) given the focus of our paper on relative differences in accessing credit across genders. Second, we target the average non-financial corporate debt over GDP for the U.S. for the period 1970–2014, which is 0.37.[44] We

[42]In quantitative macroeconomic works based on the U.S., 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 already by Hsieh and Klenow (2009), a lower span of control reduces the (negative) implied impact on output stemming from misallocation: if one runs a counterfactual exercise in which $1-\nu$ is exogenously lowered, gender differences in *arpk* and *k/l* ratio become less severe. At the same time, a lower span of control worsens the (negative) impact on output stemming from changes in the total number of firms. In fact, a lower $1-\nu$ negatively affect 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 gender imbalance in credit access on aggregate production.

[43]Size is measured in terms of total employees. This is also the strategy adopted in Buera and Shin (2013) and Midrigan and Xu (2014), which nonetheless assume that entrepreneurial skills follow a Pareto distribution.

[44]Using credit to non-financial sector instead of total debt constitutes the only significant difference in our calibration strategy with respect to the one by Buera and Shin (2013). Our choice is motivated by the fact that general measure of total debt over GDP for the entire U.S. economy tend to aggregate together household and corporate debt and consequently cannot be mapped correctly to our theoretical framework, see Kochen and Guntin (2020) for an example

obtain the series from the Federal Reserve Bank of St. Louis.[45]

Finally, we use KFS data to compute the average serial correlation of employment across entrepreneurial units. This is done to identify the persistence in the entrepreneurial productivity process ρ_z. In particular, we estimate an AR(1) process on total wage bill for both female-owned and male-owned KFS firms, getting an estimated value for persistence in wages for the entire sample. We then calibrate $\rho_z = 0.93$ in the model to generate the same persistence ratio in the model and in the data. In the Appendix, we report the results using a different strategy that targets the persistence in revenues instead of the wage bill. [46]

The estimation procedure uses a standard minimum distance criterion to minimize the weighted distance between the moments in the data and in the model. For arbitrary values of the vector of parameters to be estimated, we first solve the recursive competitive equilibrium of the model and evaluate the stationary distribution $H(z, a, g)$. Using this distribution, we compute the equilibrium interest rate, the income distributions, employment distributions, credit-to-output ratios and female and male entrepreneurs' total debt, such that they match their data counterpart outlined above. Then, we draw from the stationary distribution to simulate the economy and construct a balanced panel of firms to compute the serial correlation of employment in the same spirit of the empirical counterpart. Denoting the simulated moments by $\Omega(X)$ and those computed from the data as $\hat{\Omega}$, we estimate the fitted parameters $\hat{X}$ using a minimum distance criterion given by:

$$L(X) = \min_X (\hat{\Omega} - \Omega(X))' W (\hat{\Omega} - \Omega(X))$$

We set the weighting matrix W = I and use grid search to find the minimum.

4.2 Results

4.2.1 Targeted Moments

It is important to stress again that, on top of gender differences in credit access captured by λ_m and λ_f, we do not have to add any additional gender heterogeneity in the parameters to be able to replicate salient features of the data. In fact, our parsimonious calibration strategy enables us to match very well the targeted empirical moments that are summarized in Table 7.

Our model can replicate fairly well the debt/output ratio for the overall entrepreneurial force (female and male), for which we have targeted the average non-financial corporate debt over GDP for the U.S. for the period 1970–2014. Moreover, as mentioned before, we measure the overall debt

of a similar strategy. Moreover, we conduct two robustness checks. First, we use the debt and output reported by the entrepreneurs in our KFS sample. Interestingly, the average debt/output for our sample of firms between 2004 and 2011 is 0.49, which is close to the credit to non-financial corporate sector/GDP reported by the FED for the same period (about 0.42). Second, we compute 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 very close to the average credit to non-financial sector over GDP ratio we chose to target.

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

[46] 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.

Table 7: Targeted Moments

	US Data	Model
Internally Targeted		
Interest Rate	0.045	0.045
Earnings Share of Top 10% Individuals	0.47	0.46
Employment Share of Top 10% Firms	0.67	0.67
Average Persistence in Firms' Employment	0.73	0.8
Credit(Non-Financial Private Sector)/GDP	0.38	0.37
$\frac{Debt_f}{Debt_m}$	0.5	0.5

of female and male entrepreneurs and compute their ratio both in the KFS sample and in the model. In KFS data, women take on 50% less debt with respect to men, which we match perfectly with our calibration. Together with debt/GDP, this moment enables us to fully identify the two main parameters of interest — λ_f and λ_m — which govern the degree of gender-based imbalance in credit access. In particular, the model identifies λ_m to be roughly 56% higher than λ_f. Later on in Section 6, we remove such differences and quantify the impact on aggregate production and the allocation of resources.

Second, in calibrating the dispersion in the productivity process σ_ϵ, we are able to match the employment share of the top 10% largest firms. Bigger values of σ_ϵ imply greater dispersion in the productivity process (by means of thicker tails in the distribution) and greater employment generation by large firms. As a robustness check, we also compute the average employment shares by firms' size using BDS data for the 1978–2014 period (it covers more than 3 millions firms per year). As previously mentioned in Section 3, the KFS sample is representative of U.S. firms' distribution, and the distribution of firms over size bins implied by KFS and BDS overlay particularly for larger firms. In fact, in both in BDS and in KFS data we find that the employment share of the top 10% largest firms is roughly 0.67, very close to what found by Buera and Shin (2013).

Moreover, we follow recent papers by Batty et al. (2019) and Zucman (2019), which estimate that the top 10% richest Americans make up for almost 47% of total earnings in the economy.[47] We can replicate this feature in our model remarkably well, by calibrating the span of control parameter. In particular, the parameter $1 - \nu$ regulates firms' scale of operations and, subsequently, the profits of the entrepreneurs, who are substantially represented among top income-earners. It is therefore clear that the value of the span of control directly map into the income distribution of agents, as pointed out by Buera and Shin (2013).[48]

Finally, we target the persistence in employment of our sampled firms in order to calibrate the persistence in the entrepreneurial productivity process ρ_z. In the data, the average persistence of employment is 0.73. Simulating our model, we slightly over predict the persistence of

[47] In the period between 1997 and 2017, they report that the top 10% income share oscillates between 45% and 50%.

[48] As a robustness check, instead of using the top 10% earnings share, we can alternatively calibrate $1 - \nu$ to match the share of entrepreneurial wealth in aggregate wealth, which is know to be around 35-40% in the U.S..[49] Accordingly, the share of entrepreneurial wealth in aggregate wealth in our model is 0.38.

employment. This could be due in principle to two reasons: on the one hand, there could be a measurement error in our empirical estimation, due to the fact that the firms in our panel started their operations in 2004 and we have observations only until 2011. On the other hand, firms in our sample are very young and this may exacerbate the volatility of their business performance.[50]

4.2.2 Untargeted Moments

To further validate the performance of our framework, we assess how well the model is able to replicate other relevant moments from the data that are not targeted during the calibration. We are able to explain a substantial share of relevant across-gender differences in untargeted moments that are listed in Table 8 and explained in full detail below.[51]

First, and most importantly, we can explain very well the gender differences in *arpk* and the capital/labor (hereafter *k/l*) ratio. Using the KFS sample, as extensively explained in Section 3, female entrepreneurs are found to have higher *arpk*. This result suggests that women run their business with lower amounts of capital, and a possible reason for that can be related to tighter financial constraints for female entrepreneurs. While gaps in credit access is not the only reason that could lead to gender differences in the *arpk* and the *k/l* ratio, it is the one we are able to clearly estimate in the data and the only one that we model theoretically. It is therefore remarkable that the heterogeneity in the degree of financial constraints, captured by λ_f and λ_m in the model, can alone explain more than 90% of gender differences in both the *arpk* and the *k/l* ratio.

Table 8: Untargeted Moments

	Data	Model
Capital		
% difference $\log(arpk_{fem})$ vs $\log(arpk_{male})$	0.12	0.11
$\frac{Female}{Male}\ k/l$	0.91	0.90
Leverage and Debt		
Female Leverage	0.36	0.48
Male Leverage	0.39	0.67
Debt Share of Top 10% Firms	0.87	0.79
Business Dynamism		
Average Entrepreneurial Rate	0.06	0.07
$\frac{Female}{Male}$ Entrepreneurial Rate	0.35	0.8
Wealth Distribution		
Wealth Share in Top 10%	0.7	0.68

Parallel to that, we also compute other unconditional moments in the data that are related to the leverage of female and male entrepreneurs. Leverage reflects a firm's ability to take on debt,

[50]Importantly, another possibility would be to fix ρ_z using more precise available estimates for the U.S., such as the ones reported in Lee and Mukoyama (2015) or in Clementi and Palazzo (2015). This strategy, while appealing and easier for us to adopt, would make use of external estimates that might have been drawn on sample of firms partially different from the ones included in the KFS dataset.

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

making it an important measure to check in order to assess the performance of the model. In the absence of gender differences in borrowing constraints, larger and/or older firms should be able to take on more debt.[52] However, in the data, female entrepreneurs are more financially constrained and tend to run smaller businesses, and, as a result, their leverage is lower than the one of men. Our model can between 75% and 60% of the empirical leverage of male and female entrepreneurs respectively, as measured in the KFS data.[53] Finally, we are able to replicate successfully not only mean values but also distributional properties: our model can match up to 90% of the debt share of the top 10% largest firms.[54]

Turning to participation into entrepreneurship, we are able to match the overall entrepreneurial rate in the U.S.[55][56] Moreover, the results from our baseline specification show that the gender gap in credit access can account for almost 40% of the observed gender differences in entrepreneurial rates. The fit of gender differences in entrepreneurial rates is less precise due to two main reasons: according to data from the U.S. ASE, 25% of business owners are female, 60% are male, while 15% of the businesses present a mixed ownership.[57] Since we do not allow for mixed ownership in our model, this is likely to prevent a more precise fit of the empirical relative entrepreneurial share across genders. Moreover, the gap in credit access is potentially not the only reason behind gender heterogeneities in entrepreneurial rates: in the Appendix we explore a different specification of the model in which we allow for the presence of an *operational cost* that only affects female entrepreneurs. To calibrate the value of such fixed cost, we target precisely the relative differences in exit rates across genders. This specification, by introducing an extra element that makes entrepreneurship even less viable for women (by reducing their profits) strengthens the mechanism of *self-selection* of women into entrepreneurship. Consequently, it allows us to match more precisely the entrepreneurial shares of females relative to males. Since this is not the primary focus of this project, we leave further considerations for future research.

4.3 The Effect of Gender Gap in Credit Access

In this section, we quantify the effect of gender-based financial frictions on aggregate outcomes using our calibrated model. As explained in the previous sections, such distortions will impact

[52] We can verify this prediction in our KFS sample (see Figure B.2 in the Appendix)

[53] In KFS data, the average entrepreneurial leverage is 0.37. Note that, using a different dataset, namely the Survey of Consumer Finances, Kochen and Guntin (2020) find an average entrepreneurial leverage of 0.35.

[54] Aside from matching the distributional properties of KFS data, we also compare the debt distribution (over size) obtained in our model with the one from Compustat. Again, our model is able to match 89% of the debt shares of the top 10% largest firms, which further strengthens our results.

[55] In the last 20 years, the fraction of entrepreneurs, including men and women, out of the total U.S. labor force is estimated to be around 6%, see `https://data.oecd.org/entrepreneur/self-employed-with-employees.htm#indicator-chart.`

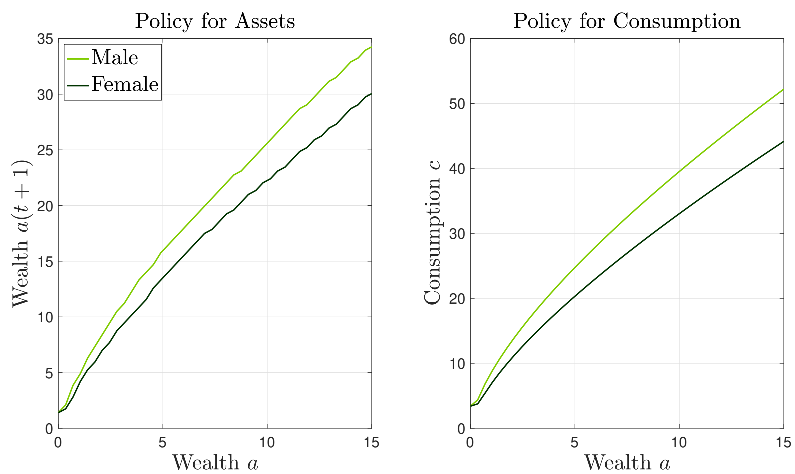
[56] We do not specifically focus on exit rates in our main exercise. However, the turnover of enterprises in our simulation is 10%, which resembles quite closely its empirical counterparts. In fact, the average exit rate in KFS is 10.43%, in line with the exit rate of 10% estimated by Buera and Shin (2013) using U.S. data from BDS.

[57] We find similar results in the KFS sample, 23% of business owners are female, 59% are male, while 18% of the businesses present a mixed ownership.

both the entrepreneurial composition and the optimal choices of entrepreneurs in terms of inputs of production. In turn, this will have repercussions on aggregate activity and thereby lead to an inefficient outcome.

First, we look at consumption and savings policies. Figure 5 plots the optimal choices in terms of assets (left panel) and consumption (right panel) against current individual wealth. We take as a reference two equally productive agents, one male and one female. The graphs show that male agents accumulate more wealth and sustain higher levels of consumption. This is because males face lower financial frictions, and so have higher entrepreneurial profits.

Figure 5: Consumption and Savings Policies



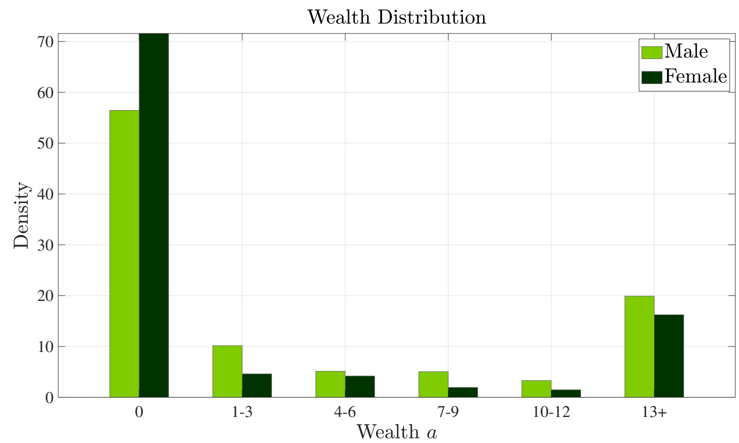
Parallel to that, differences in wealth accumulation are reflected in the distribution of wealth across genders. As Figure 6 documents, for female agents in the economy, the distribution of wealth is more skewed to the left. There are two reasons for this: first, as underlined in the previous graphs, women are able to accumulate less assets due to lower entrepreneurial profits. Second, since accumulating assets is particularly crucial for entrepreneurs because it helps overcome financial frictions, women have marginally lower incentives to do so because they anticipate that entrepreneurship will be a harder choice for them than for their male counterpart.[58]

Moreover, as shown in Table 9, wealth is heavily concentrated, which is a general property of the entrepreneurial models we have built on (see Cagetti and De Nardi (2006)). In particular, recent works by Zucman (2019) have shown that the top 10% of U.S. wealthiest agents accounts for over 70% of aggregate wealth in the economy, which we can replicate fairly well in our model.

Second, we analyze the individual choice of becoming an entrepreneur. Such decision is a function of both idiosyncratic productivity z and wealth a, but it also depends on the gender of the agent. Specifically, higher productivity and/or greater levels of assets have a positive effect on agents' decision to become an entrepreneur. However, since women face relatively more obstacles in carrying on entrepreneurial activities (i.e. tighter financial constraints), the probability of

[58]It is well-known that the wealth distribution in models of this type are very skewed to the left. Saving is crucial mainly for entrepreneurs, represented by the upper tail of the wealth distribution.

Figure 6: Wealth Distribution



become an entrepreneur is lower for a female agent, ceteris paribus. This results in a lower share of female entrepreneurs in the population, as reported in the first column of Table 9.

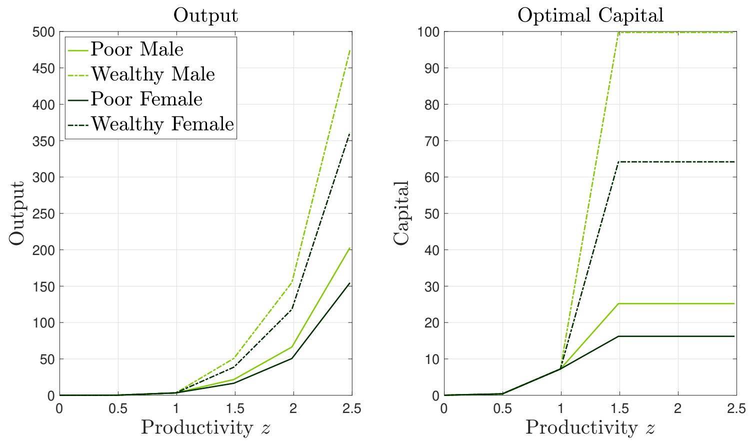
Table 9: Simulation Results

	Entrepreneurial Rates	$arpk$	k/l	$arpl$	tfp
Female	0.058	0.567	1.702	3.395	3.926
Male	0.073	0.410	1.889	3.395	3.583

We now turn to the choices of capital and labor inputs and the subsequent effects on aggregate output and the allocation of resources. Figure 7 shows the choice of capital (left side) and the implied output (right side) as a function of entrepreneurial idiosyncratic productivity z. We take as a reference four different types of individuals: a poor and a rich male, measured based on their current wealth, and a poor and a rich female entrepreneur, similarly measured. Within both wealth categories, female entrepreneurs choose lower levels of optimal capital, which in turn impacts the quantity of final output produced by each respective type of entrepreneur. Effectively, the fact that female agents face tighter financial constraints is able to influence their participation rate into entrepreneurship, their saving decisions and the entrepreneurial outcome, without requiring any extra assumption on gender differences.

Nevertheless, the main result of interest regards the *arpk*, as shown in Figure 8 and further summarized in the second column of Table 9. Interestingly, female have a higher *arpk*, as they operate with lower capital, whereas there are no such differences between the *arpl* of female and male entrepreneurs (see the fourth column in Table 9). This reconciles our model results with the evidence gathered from the data and presented in Section 3. Consistent with this fact, the *k/l* ratio is lower for female entrepreneurs, as further reported in the third column of Table 9. Both the heterogeneities in the *arpk* and the *k/l* ratio disappear or diminish for higher levels of entrepreneurial productivity. Moreover, as shown in Figure B.4 in the Appendix, log differences in *arpk* of female and male entrepreneurs decrease with the decrease in log differences in business size. In fact, as

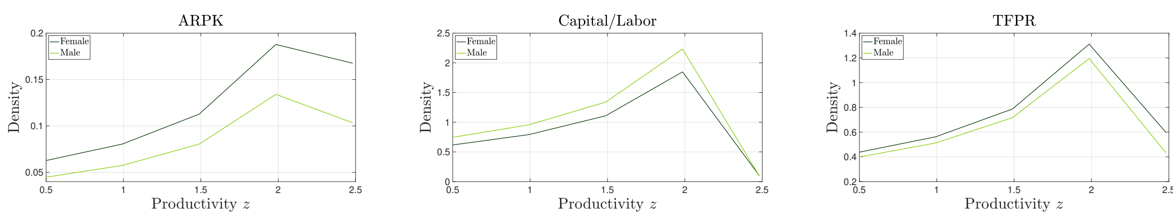
Figure 7: Optimal Capital and Total Output



female-led businesses grow in size, they are able to eventually accumulate enough wealth and operate at their optimal scale, bridging the differences with respect to their male counterpart.

Finally, female entrepreneurs have higher total factor productivity (hereafter *tfpr*),[59] as reported in the last column of Table 9, which is the result of stricter self-selection of women into the entrepreneurial pool. In fact, entrepreneurship is a more difficult choice for women, due to higher operational costs and tighter financial frictions. Consequently, this implies that the marginal female entrepreneur will be relatively more productive than the male one, because only very productive female individuals can operate businesses in a profitable way.

Figure 8: *arpk*, *tfpr* and *k/l* ratio

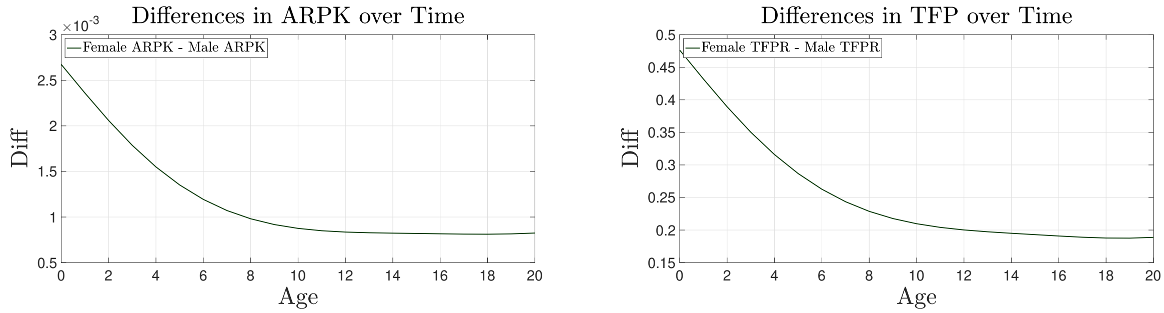


Interestingly, simulation results reported in Figure 9 show that differences in both *arpk* and *tfpr* decreases over time as the firms grow older. This is due to the fact that, as time passes, female entrepreneurs are able to accumulate wealth and progressively overcome the tighter financial constraints that they face.[60] As a consequence, they are able to rent higher levels of capital, which leads to lower *arpk* and *tfpr*. In 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 both female and male business owners.

[59] A discussion of how *tfpr* is calculated in case of decreasing returns to scale functions is provided in the Appendix. We also validate such theoretical prediction in our data by computing the model-implied *tfpr* and regressing it on the same set of variables as in Table 5, and find that female entrepreneurs have statistically significantly higher $tfpr$ relative to males.

[60] The relationship between the age of a business and the progressive release of financial constraints has been made in several other contexts, see for example Davis and Haltiwanger (1999).

Figure 9: *arpk* and *tfpr* over Firms' Age



5 Counterfactual: Removing Gender-Based Financial Frictions

In this section, we quantify the effect of removing gender-based financial constraints. Counteracting gender-based imbalances in credit access can have a major impact on what we have already defined as the *extensive margin*, fostering female participation in entrepreneurship. The economy as a whole benefits from a better allocation of entrepreneurial talent insofar as marginally more productive agents become entrepreneurs and crowd out the less talented ones. Moreover, it generates a more efficient allocation of resources across productive units, reducing capital misallocation and bringing therefore relevant improvements along the *intensive margin*.

Furthermore, if female entrepreneurs are able to rent higher levels of capital, as a consequence, they produce more output. As such, we show that guaranteeing equal access to credit across genders not only improves the allocation of entrepreneurial talent and productive inputs, but also generates substantial gains for the whole economy in terms of higher aggregate production and welfare. We run this first counterfactual by removing the difference between λ_m and λ_f. Recall that in the baseline calibration, λ_f is almost 56% lower than λ_m, and constitutes the only difference across entrepreneurs of opposite gender. In Table 10, we present the quantitative implications of lowering this difference to λ_f being 20% lower than λ_m and removing it completely until $\lambda_f = \lambda_m$.

Relaxing the tighter credit constraint that female entrepreneurs face increases their participation in the entrepreneurial pool and their *k/l* ratio of up to 16.7% and 33.7% respectively when $\lambda_f = \lambda_m$. Female entrepreneurs can operate their businesses with higher levels of capital and as a result, their *arpk* decreases by 29.8% when $\lambda_f = \lambda_m$. As shown in the left panel of Figure 10, the mean of distribution of female entrepreneurs' *arpk* substantially decreases when shifting from the baseline to the counterfactual case. Parallel to that, an easier access to credit for female agents allows for a better allocation of entrepreneurial talent, as more marginally productive female entrepreneurs will find profitable to enter entrepreneurship and start a business. As illustrated in the right panel of Figure 10, this implies a leftward shift in the mean of female entrepreneurs' productivity, as the productivity cutoff for women to become entrepreneurs decreases.

Table 10: Policy Simulation Results

	Total Output	Total Welfare	Female $ARPK$	Female K/L Ratio	% Female Entrepreneurs
$\lambda_f = 0.85 * \lambda_m$					
Increase wrt Baseline	+ 3.46%	+ 3.8%	- 20.1%	+ 21.3%	+ 10.9%
$\lambda_f = \lambda_m$					
Increase wrt Baseline	+ 5.18%	+ 5.32%	- 29.8%	+ 33.7%	+ 16.7%

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. It is crucial to stress again that female entrepreneurs are now able to choose a higher level of capital, and as a result, the allocation of inputs across productive units stabilizes in a positive way for the economy as a whole. Consistent with this, the positive effect of relaxing gender-based differences in financial constraints is evident when computing total output for the whole economy. The increase in aggregate output with respect to the baseline case reaches a maximum of 5.18%. Using U.S. GDP of 2019 as a reference,[61] this could represent an increase of more than 1 trillion U.S. dollars. The fact that marginally more productive female agents can enter the pool of entrepreneurs and produce with their optimal level of capital has a direct effect on the quantity of output that is ultimately produced in the economy due to a better allocation of entrepreneurial talent and productive inputs.

It is important to mention that through a general equilibrium effect, higher female participation into entrepreneurship raises the demand of both labor and capital and increases the equilibrium level of input prices r and w. As a consequence, this process crowds out some of the marginally unproductive male entrepreneurs from the entrepreneurial pool and partially offsets the gain in aggregate output achieved by higher female participation in the entrepreneurial pool. In fact, if we were to perform this exact same counterfactual in a partial equilibrium setting, namely, without recomputing for the aggregate equilibrium input prices r and w, the achieved increase in aggregate production and in female entrepreneurial rates would be higher (by 1.5 and 10 percentage points respectively). This is precisely due to the fact that the rise in the equilibrium level of input prices r and w acts as a dampening force for entry into entrepreneurship and production by increasing business costs and reducing entrepreneurial profits.

Finally, it should be stressed that such policy 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 economies and compare it to the one obtained in the baseline case. When $\lambda_f = \lambda_m$, aggregate welfare increases by 5.32% (when $\lambda_f = 0.85 * \lambda_m$ the increase amounts to 3.8% with respect to the baseline case).[62] Removing gender-based imbalance in finan-

[61] See https://fred.stlouisfed.org/series/GDP.

[62] This substantial increase in welfare is mainly due to removing the gender gap in credit access and the distortions in allocation of talent and productive inputs that come with it. However, general equilibrium dynamics amplify this

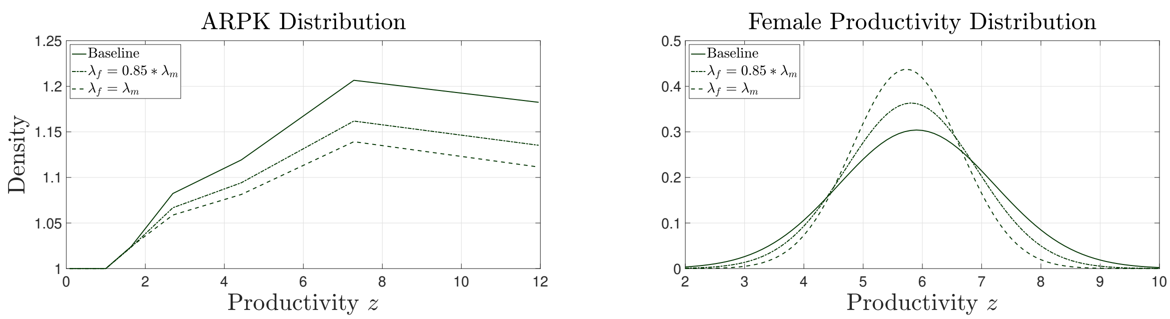
Table 11: Aggregate Welfare Gains (left) and Output Gains (right) in Counterfactuals

		λ_f		
		1.93	2.55	3
	1.93	*- 7.1%*	*- 3.9%*	*+ 0%*
λ_m	2.55	*- 3.9%*	*+ 1%*	*+ 3.8%*
	3	*baseline*	*+ 3.8%*	***+ 5.32%***

		λ_f		
		1.93	2.55	3
	1.93	*- 3.2%*	*+ 3.7%*	*+ 0%*
λ_m	2.55	*+ 3.7%*	*+ 2.5%*	*+ 3.5%*
	3	*baseline*	*+ 3.5%*	***+ 5.18%***

cial markets is thus not only a desired measure to increase and foster productive activities, but it is also a *welfare improving* policy from which all agents, entrepreneurs and workers, benefit in terms of higher consumption levels.

Figure 10: Female *arpk* and *tfpr* in Counterfactuals



As a final consideration, note that we have performed the exercise of increasing the borrowing constraint of female entrepreneurs to equal the one of their male counterpart. We can also verify how much increase in aggregate welfare and output we would obtain by doing the opposite exercise and lowering the borrowing constraint of male entrepreneurs to make it equal to the one of their female counterpart. Table 11 illustrates the welfare gains and output gains (with respect to the baseline economy in which $\lambda_f = 1.93$ and $\lambda_m = 3$) of several combinations of values for λ_f and λ_m. It can be verified that indeed the best outcome for the economy as a whole is the one in which female and male entrepreneurs are able to borrow under the same constraint – namely $\lambda_f = \lambda_m = 3$. Intuitively, it is not beneficial in terms of both aggregate welfare and productivity to lower the borrowing constraint of male entrepreneurs until it reaches the one of their female counterpart. Moreover, a middle-ground case in which λ_f is raised by say 85% and λ_m is lowered to be equal to λ_f, is sub-optimal with respect to the case in which $\lambda_f = \lambda_m = 3$.

effect: since more productive female agents become entrepreneurs and crowd out marginally more inefficient male entrepreneurs, both the demand of capital and labor in the economy increase. In particular, rising equilibrium wages benefits the workforce, ensuring higher levels of consumption. Moreover, the modest rise in interest rates leads to higher wealth accumulation and positively impact consumption (this positive effect is more than proportional than the negative externality on rising entrepreneurial capital costs). In fact, if we were to 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 1.79% instead of +5.32%.

6 Fiscal Policies

In this final section, we explore and evaluate the appropriateness of fiscal policies aimed at reducing the distortions created by gender gaps in credit access. Around the world, there are examples of initiatives to sustain female entrepreneurs especially in matters related to funding and credit access. To name a couple, the Government of Canada allocated $20 million of their 2018 budget to the Women Entrepreneurship Fund to fund over 200 projects. Women-led businesses across Canada can receive up to $100,000 in federal funding to help them grow and reach new markets. This plan is part of a broader strategy that has the potential of adding $150 billion in incremental GDP by 2026 and reach its goal of doubling the number of majority women-owned businesses by 2025 (currently roughly 16% of total businesses). Moreover, in Germany, the Federal Ministry for Economic Affairs and Energy launched a fund in 2013 that provides small and young enterprises with equity of up to €50,000 to improve their credit ratings and increase their chances of securing new loans. While open for all business starters, women and people with migrant background are given priority access. Turning to the developing world context, one example would be the Isivande Women's Fund (IWF) that was established by the South African government to exclusively support funding needs of women-owned businesses.[63] This fund 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.[64]

Focusing on the U.S., the Small Business Administration (SBA) is the governmental unit that has put forward few programs to facilitate the funding of business owners, both male and female. In this regard, one of the programs aimed at helping businesses is the SBA 7(a) Loan Program.[65] In this case, the SBA agency does not lend money directly to business owners, but instead sets guidelines for loans made by its nationwide network of partnering lenders and micro-lending institutions. In addition, it guarantees loans between $500 and $5.5 millions that can be used for most business purposes, including long-term fixed assets and operating capital. In so doing, SBA reduces risk for lenders and makes it easier for them to access credit.[66] More specifically related to female entrepreneurs, the SBA sponsors around 100 Women's Business Centers across the country to assist women entrepreneurs with access to capital and business development. Some of these centers, for example the California Capital Financial Development Corp., directly lend out money, while others help female entrepreneurs find small-business loans and grants. Other training programs are established by the Office of Women's Business Ownership and several funding

[63] http://www.investmentincentives.co.za/enhancement-competitiveness/women-economic-empowerment-incentives/isivande-women-s-fund

[64] https://www.inventiva.co.in/stories/government-schemes-for-women-entrepreneurs-to-kickstart-their-business/

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

[66] A related initiative is the 8(a) Business Development Program, which aims to provide a level playing field for small businesses owned by socially and economically disadvantaged people or entities. In this case, the SBA agency limits competition for certain federal contracts and tries to guarantee the representation of minority-owned small businesses.

opportunities are held in place by separate private entities and organizations.[67]

Using our setup, we aim to carry out a quantitatively estimate the size of aggregate output gains and improvements in female entrepreneurs' performance that fiscal policies can induce. In our exercise, we consider fiscal policies in the form of subsidies targeting either the profits, the credit needs or the capital costs of female-owned firms, which are financed through lump-sum taxation on all the households. In theoretical frameworks where some frictions are present, it has been shown that fiscal policies can be welfare improving for the economy.[68] Specifically, in our model, the key friction we have focused our attention on is the gender-specific borrowing constraint, which implies that female entrepreneurs have a lower borrowing capacity than their male counterpart. We therefore aim to assess if fiscal policies that target female entrepreneurs can improve female entrepreneurial rates and business performance, while also benefiting aggregate productivity, as in our previous counterfactual exercise. We take as a reference our baseline economy and also compare the resulting improvements from fiscal policies to the the counterfactual economy without gender-based financial constraints as described in the previous section.

6.1 Subsidizing Female Entrepreneurs' Profits

The first fiscal policy exercise we do is to hold in place a lump-sum tax that is levied on all agents and subsequently rebated as a subsidy θ on the profits of female entrepreneurs. Note that we allow for the baseline gender imbalance in credit access: $\lambda_m > \lambda_f$ by 56%, as in our baseline calibration. Thus, we can assess by how much fiscal policy alone is able to counteract gender imbalance in credit access. While there are no changes in the problem of a male entrepreneurs, the maximization problem for a female entrepreneur is now given by:

$$\max_{l_t, k_t} \left\{ (1+\theta)(e^{z_t}(k_t^{\alpha} l_t^{1-\alpha})^{1-\nu} - w_t l_t - (r_t+\delta)k_t), \quad \text{s.t.} \quad k_t \leq \lambda_f a_t \right\} \tag{13}$$

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

$$a_{t+1} = \max\{\pi_t(a, z, c; r_t, w_t), w_t\} + (1+r_t)a_t - c_t - T_t \tag{14}$$

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

$$\int_{o_t(a,z,f)=e} \theta \pi_t = T_t \tag{15}$$

We create a grid of possible values for the subsidy, raging from 0 to 1. Within this grid, a subsidy rate $\theta = 0.15$ achieves an increase of 10.56% in female entrepreneurial rates, and a decrease of 7.29% in their *arpk*. However, such policy comes at the expense of aggregate output, which decreases by 3.18%. Such result is due to GE effects: a subsidy on female entrepreneurs' profit only

[67] A (partial) list of other programs funded by private entities and organizations to foster female entrepreneurship in the U.S. is available at `https://www.fundingcircle.com/us/resources/resources-for-female-entrepreneurs/`.

[68] See Moll (2014), Li (2002) and Kitao (2008).

affects women's choice to become entrepreneurs – the *extensive* margin – and does not change their optimal choices of productive inputs (the *intensive* margin). Female agents find entrepreneurship more accessible and therefore are able to raise their average earnings and their savings, which helps them increasing their asset base. The positive effect of reducing female *arpk* comes therefore from the fact that women are able to save more and expand the wealth against which they borrow in financial markets, not because gender-specific borrowing constraints are lowered. Moreover, by raising the number of entrepreneurs in the economy, such policy induces an increase in the demand of labor and in the equilibrium wage. Higher labor costs harm entrepreneurial profits of both males and females, and decrease therefore aggregate output. A summary of the results is reported in Table 12.

Interestingly, there is no value for the subsidy rate θ that can generate at the same time both the increase in aggregate output and female entrepreneurs-specific improvements achieved by removing gender differences in credit access as in the previous section. In contrast to that, when choosing θ within a grid of possible values between -1 and 0 (making it a tax and not a subsidy to entrepreneurs' profits), one can obtain improvements in aggregate output, but at the expenses of worsening female entrepreneurial performance. Hence, the tax on entrepreneurs' profits makes entrepreneurship even less profitable for female agents, and adds to the barriers created by gender-based gap in credit access.[69]

6.2 Subsidizing Female Entrepreneurs' Credit Needs

The second experiment we conduct is to have 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 they are able to borrow in order to finance their capital without changing their specific borrowing constraint parameter: the capital constraint of female entrepreneurs shifts hence from $k_t \leq \lambda_f a_t$ to $k_t \leq \lambda_f a_t + \theta$. Under this modification of the financial constraint, female entrepreneurs' wealth thus constitute only one part of the collateral for their debt, while the rest is covered by the government. As in the previous policy exercise, we stick to the baseline calibration where the gender gap in credit access is present: $\lambda_m > \lambda_f$ by 56%. While there are no changes in the problem of a male entrepreneurs, the maximization problem for

[69]In this regard, Itskhoki and Moll (2019) discusses examples of optimal policies in a standard growth model with financial frictions that involve taxing entrepreneurs. In our GE framework, taxing entrepreneurial profits entails lowering entrepreneurial rates and, subsequently, the labor demand and the wage in equilibrium. At the margin, a fraction of wealthy/productive agents will still find preferable to become entrepreneurs over being workers, as average entrepreneurial profits are more likely to be higher than the equilibrium wage. The redistribution towards workers, who have the highest marginal utilities, produces welfare gains in the economy. Moreover, entrepreneurs will produce facing lower labor costs. However, such sequence of effects penalizes relatively more female agents who face already a severe barrier in entering entrepreneurship due to tighter borrowing constraints. Seeing their potential profits been lowered by a tax, and anticipating they will face tighter financial constraints than their male counterpart, less female agents will find desirable to become entrepreneurs and will prefer being workers. This composition effect worsens the under-representation of women into entrepreneurship and their business outcomes.

a female entrepreneur is now given by:

$$\max_{l_t, k_t} \left\{ e^{z_t} (k_t^{\alpha} l_t^{1-\alpha})^{1-\nu} - w_t l_t - (r_t + \delta) k_t, \quad \text{s.t.} \quad k_t \leq \lambda_f a_t + \theta \right\} \tag{16}$$

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

$$a_{t+1} = \max\{\pi_t(a, z, c; r_t, w_t), w_t\} + (1 + r_t) a_t - c_t - T_t \tag{17}$$

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

$$\int_{o_t(a,z,f)=e} (k_t - \lambda_f a_t) = T_t \tag{18}$$

We create a grid of possible values for the subsidy, raging from 0 to 2: to give a concrete example, a total subsidy $\theta = 1$ represents an increase of 20% in the average asset base of female entrepreneurs.[70] We find that a total subsidy $\theta = 0.5$ – corresponding to an increase in the asset base of female entrepreneurs of 10.5% – will bring an increase in aggregate output of 0.45%. At the same time, female *arpk* would decrease by 1.03% and female entrepreneurial rates would increase by 0.7%. A summary of the results is reported in Table 12.

Such subsidy on female entrepreneurs' credit needs succeeds in enlarging the asset base of female entrepreneurs by effectively increasing the amount they can borrow to finance capital, without changing their specific borrowing constraint. In so doing, the subsidy to female entrepreneurs' credit makes entrepreneurship relatively more profitable for female agents and helps the marginally more productive women become entrepreneurs, despite the tighter financial constraints. It therefore represents an improvement in both the *extensive margin*, as more marginally productive female agents become entrepreneurs. Moreover, the credit subsidy generates as well improvements on the *intensive margin*, as female entrepreneurs can rent higher levels of capital and hence lower their *arpk*. Both these channels dominate any other GE effect related to input prices and hence grant an increase in aggregate output as well.

6.3 Subsidizing Female Entrepreneurs' Capital Renting Cost

The third experiment we test 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).[71] Specifically, targeted female entrepreneurs need only bear a portion $1 - \theta$ of their debt, while the rest is covered by the government. Note that we allow for the baseline gender imbalance in credit access: $\lambda_m > \lambda_f$ by 56%, as in our baseline calibration. Thus, we try to assess by how much a fiscal

[70] In the model, the average asset base a_t of female entrepreneurs is 4.8.

[71] A similar exercise in spirit has been done by Li (2002), in order to analyse the appropriateness of SBA programs that involve interest subsidies to entrepreneurs. He targets θ to match the fact that, for example, between 1984-1998 SBA subsidies lowered borrower payments by 7.2 percent on average. However, he does not distinguish by the gender of the entrepreneurs, and we rather look at the value of θ that will lead to the highest increase in aggregate output while improving specifically female entrepreneurial performance.

policy entailing interest subsidies for female entrepreneurs alone is able to counteract the gender gap in credit access while possibly improving aggregate welfare. While there are no changes in the problem of a male entrepreneurs, the maximization problem for a female entrepreneur is now given by:

$$\max_{l_t,k_t} \left\{ e^{z_t}(k_t^{\alpha} l_t^{1-\alpha})^{1-\nu} - w_t l_t - (1-\theta)(r_t+\delta)k_t, \quad \text{s.t.} \quad k_t \leq \lambda_f a_t \right\} \tag{19}$$

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

$$a_{t+1} = \max\{\pi_t(a,z,c;r_t,w_t), w_t\} + (1+r_t)a_t - c_t - T_t \tag{20}$$

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

$$\int_{o_t(a,z,f)=e} \theta(r_t+\delta)k_t = T_t \tag{21}$$

We create a grid of possible values for the subsidy rate, raging from 0 to 1: a subsidy rate $\theta = 0.6$ will bring an increase in aggregate output of roughly 1.8%. At the same time, female *arpk* would decrease by 5.21% and female entrepreneurial rates would increase by 4.6%. On the one hand, the subsidy on female entrepreneurs' capital renting makes entrepreneurship relatively more profitable for female agents and helps the marginally more productive women become entrepreneurs, despite the tighter financial constraints. In so doing, it represents an improve in both the *extensive margin* – more female agents become entrepreneurs– as well as the *intensive margin* – female entrepreneurs can rent higher levels of capital and hence lower their *arpk*. On the other hand, it is important to mention that, by decreasing the capital rental rate paid by all female entrepreneurs, this policy benefits both constrained and unconstrained female entrepreneurs. If we were to subsidize the capital renting costs of constrained female entrepreneurs only, the optimal subsidy rate θ would be 17% higher.[72]

Table 12: Percentage Change Relative to Baseline

Policy	Rate	Output	Female *arpk*	Female Entrepreneurs
Profit Subsidy	$\theta = 0.15$	- 3.18%	- 7.29%	+ 10.56%
Credit Subsidy	$\theta = 0.5$	+ 0.45%	- 1.29%	+ 0.71%
Capital Subsidy	$\theta = 0.6$	+1.79%	- 5.21%	+ 4.60%

Comparing the different policies proposed, it is clear that removing the gender gap in credit access of female entrepreneurs, as done in the counterfactual exercise of the previous section, is the most effective way to counteract the distortion in the optimal choice of capital due to tighter financial constraints for women. Such policy achieves a substantial increase in aggregate welfare

[72]Moreover, the implied changes in female entrepreneurial performance and aggregate output would be similar: aggregate output would still increase by roughly 1.8%, female *arpk* would decrease by 9.17% and female entrepreneurial rates would increase by 5.48%. In practice however, it may be difficult to distinguish female entrepreneurs that are financially constrained or not when granting more favourable interest rates on loans from female applicants.

(+5.32%), aggregate output (+5.18%), and it is effective in promoting female entrepreneurship, reducing female entrepreneurs' *arpk* by increasing their *k/l* ratio. The fiscal policies considered in this section – subsidies on profits, credit and capital renting costs – generate improvements in female entrepreneurial performance and aggregate output, but such positive effects are substantially smaller compared to the ones achieved in the counterfactual exercise of removing the gender-gap in credit access. Hence, although they represent a good starting point, they do not manage to completely tackle the severe imbalances in the entrepreneurial composition and allocation of productive inputs, while at the same time increasing aggregate productivity.

7 Conclusion

Despite an increase in the share of female entrepreneurs in recent years, the gender gap in entrepreneurship still persists, yet its macroeconomic implications have not received much attention in the literature. In this paper, we shed light on the issue and examine how the allocation of talent and capital, as well as aggregate productivity are affected by this phenomenon.

First, we have shown that it is more difficult for female entrepreneurs to access credit and that they have a higher $arpk$ relative to males, signifying misallocation of capital inputs, whereas we do not find such differences in $arpl$ across genders. We interpreted these findings as suggesting that this gender imbalance in access to credit may be what is driving the observed misallocation of capital in the data. Next, we have rationalized these findings in a standard model of entrepreneurial choice and financial frictions and introduce gender differences in borrowing constraints. Motivated by our empirical finding of tighter access to credit by females, we specifically assume a tighter borrowing constraint for female entrepreneurs. We calibrate the model to the U.S. economy and show that our model matches very well salient features of the data.

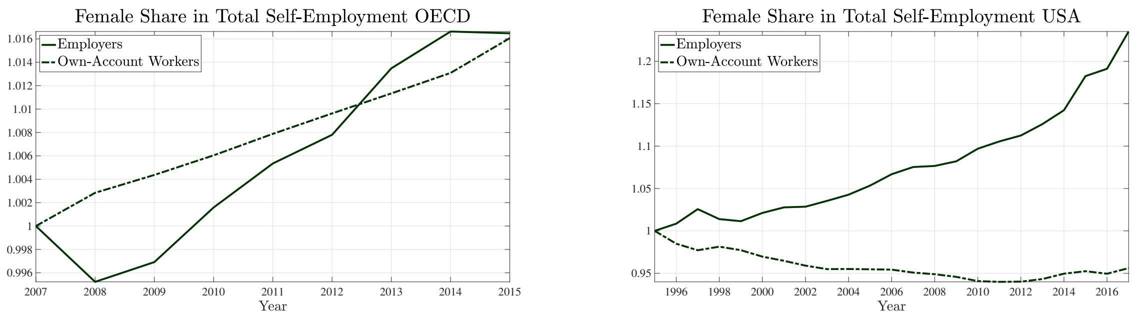
Then, having evaluated the performance of our model, we quantify output losses that come from the misallocation of resources among entrepreneurs, and the misallocation of entrepreneurial talent in the U.S. economy. In removing gender-based differences in access to credit, we find an overall output gain of 5.18% in the economy, coming from the improved allocation of capital, and of entrepreneurial talent. In particular, since females now have better access to credit, they are now able to produce at the optimal level of capital, whereas the improved allocation of talent stems from the fact that the marginally more productive female agents can participate in entrepreneurial activities. Finally, we propose several policy instruments to mitigate the distortionary effects of the gender gap in credit access. We assess the impact of policies such as a subsidy on female entrepreneurs' profits, a subsidy on their credit needs and a subsidy on female entrepreneurs' capital renting cost, on female entrepreneurial rates, production outcomes and optimal choice of inputs. Overall, we find that while all these policies female entrepreneurial participation and capital allocation, and are generally associated with aggregate output gains, the resulting positive effects are smaller compared to removing gender differences in borrowing constraints.

Appendix

A Data Appendix

A.1 Female Entrepreneurship and Economic Development

Figure A.1: Share of Self-Employed Women Over Time



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*: U.S. average female share self-employment between 1995 and 2017. Shares are normalized to 1 at the beginning of the sample.

We also consider how the relative importance of female-led businesses changes with economic development. We use data from the Global Entrepreneurship Monitor (GEM), a cross-country entrepreneurial survey covering over 100 countries, for 2005–2015. GEM contains information on owner characteristics such as gender, which is key to our analysis, and other useful information such as the number of jobs within a firm and the owner's motivation for starting a business (whether it is due to a necessity or an opportunity). We compute for the share of female-owned firms in a country for a given year and use this as our dependent variable for cross-country regressions. We measure size using the number of jobs. In GEM, the number of jobs is grouped into four categories: no jobs, 1–5 jobs, 6–19 jobs, and 20+ jobs. We exclude firms that do not have positive employment. We use annual data on real GDP per capita from the Penn World Tables as our measure of economic development. To examine whether economic development correlates with higher participation of females in entrepreneurship, we run OLS regressions as follows

$$fem\_share_{it} = \beta_0 + \beta_1 \log(GDP_{it}) + \beta_2 \log(GDP_{it})^2 + \delta' \mathbf{\Gamma} + \varepsilon_{it}$$

where fem_share_{it} is the share of female-owned firms in country i at year t and $\mathbf{\Gamma}$ represents the set of controls used, namely the motivations of the owner, size of the business (for the full sample regression) and country fixed effects. Results are shown in Table A1 below.

Table A1: Share of Female-owned Firms

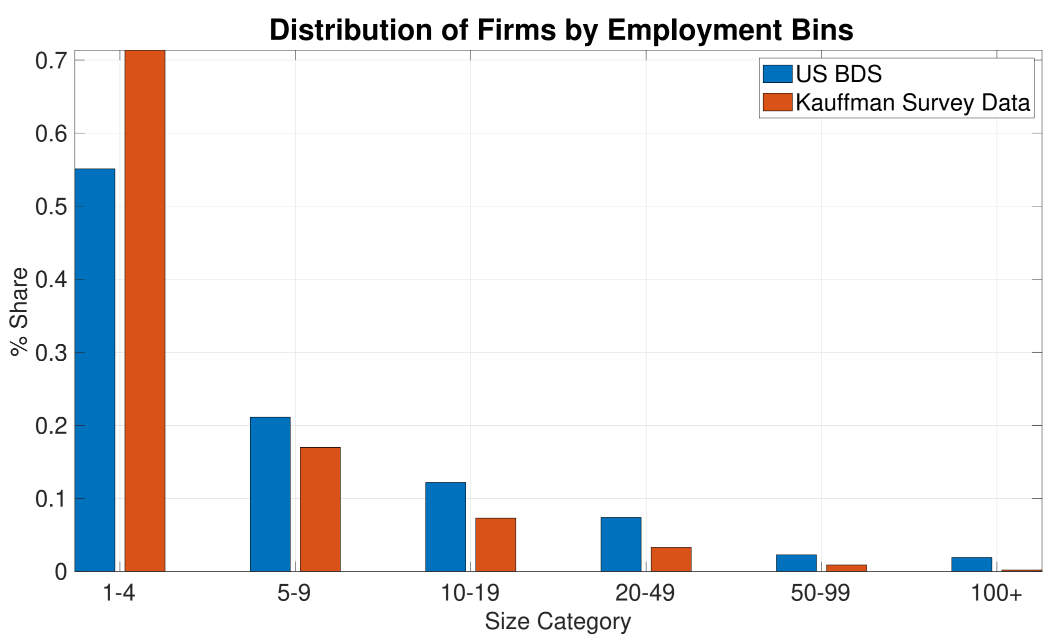
	(1) All firms	(2) Medium-sized firms (20+ jobs)	(3) Small firms (1–5 jobs)
$\log(GDP)$	0.9902**	2.2451*	0.5852*
	(0.4474)	(1.2875)	(0.3454)
$\log(GDP)^2$	-0.0209***	-0.0749	-0.0256*
	(0.0066)	(0.0486)	(0.0132)
Control for size	Y	N	N
Country FE	Y	Y	Y
Observations	2,451	661	942
R-squared	0.288	0.299	0.602

Note: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Size is measured using number of jobs in a firm. We also control for entrepreneurial motives.

A.2 Size Distribution and Ownership Composition of Firms

The Business Dynamics Statistics (BDS) is a U.S. 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.2 we compare the distribution of firms by employment bins in BDS and KFS data.

Figure A.2: 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 U.S. 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 A2, we verify that the shares of female and male entrepreneurs in the KFS sample resemble closely the ones in the ASE.[1]

Table A2: 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

A.3 Variable Definitions

Table A3 summarizes the definitions of some of the 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 A3 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]

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

[2] Moreover, it is important to stress that there is no law in the U.S. 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.6 contain the winsorized level variables.

[4] In general, 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. Running regressions on non-winsorized risk and profitability measures give the same qualitative results.

Table A3: 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, limited liability company, corporation or partnership.
Business Debt	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.
State FE	It refers to the 50 states of the U.S.
Sector FE	It refers to the 4-digit NAICS code, except for loan rejection regressions where 2-digit NAICS is used instead since there is not enough sectoral variation to run probit regressions without encountering optimization failure.

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.3). Additionally, males seem to have more work experience in the same industry, and in general (see Figure A.4). Finally, unsurprisingly, male owners devote more time operating the business compared to females (see Figure A.5), 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. On a side note, it is also possible to check the reason why both female and male entrepreneurs in the KFS sample have decided to open their business (see Figure A.5). Interestingly, 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. While male individuals seem to prefer self-employment as a way to be their own boss and to earn their primary income.

Figure A.3: KFS Owners' Characteristics

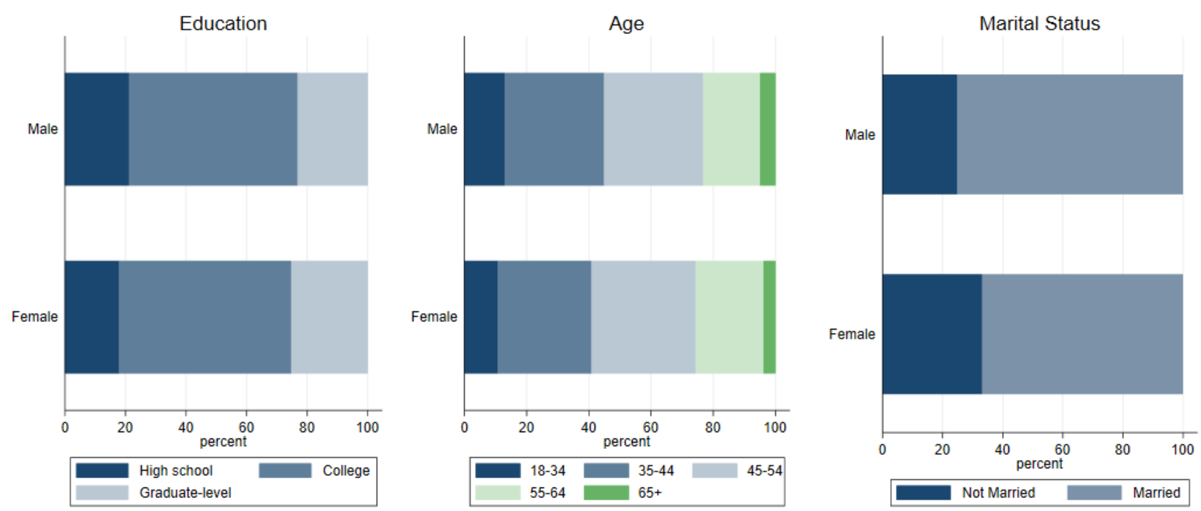
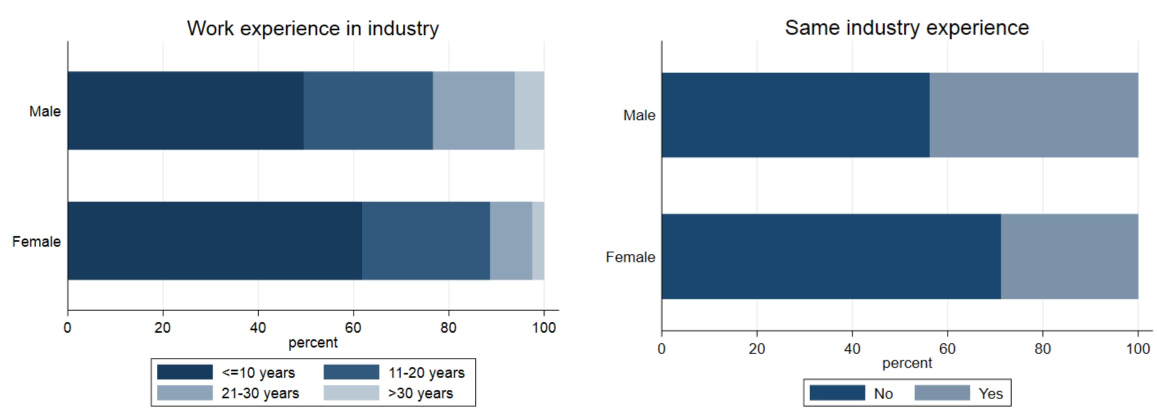
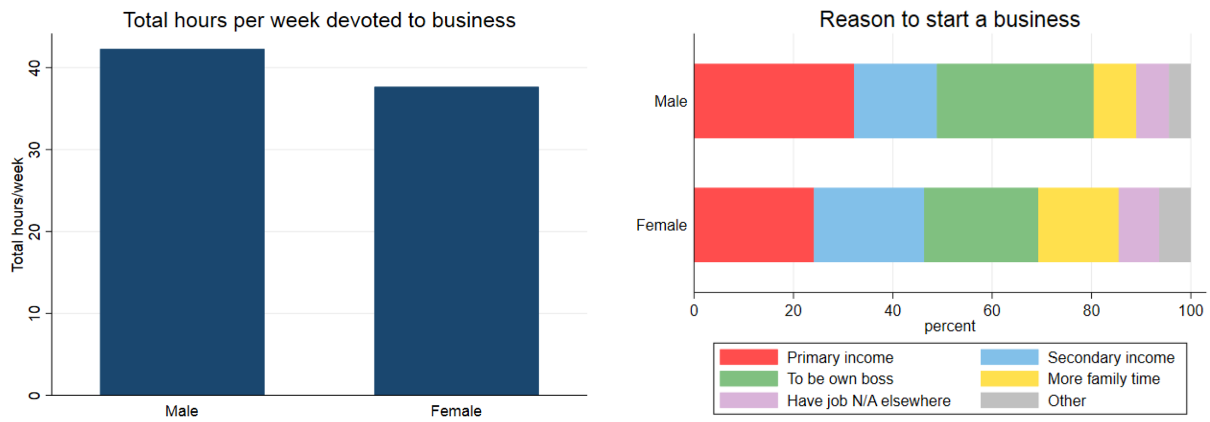


Figure A.4: KFS Owners' Work Experience



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

Figure A.5: KFS Number of Hours Worked & Reasons to Open a Business



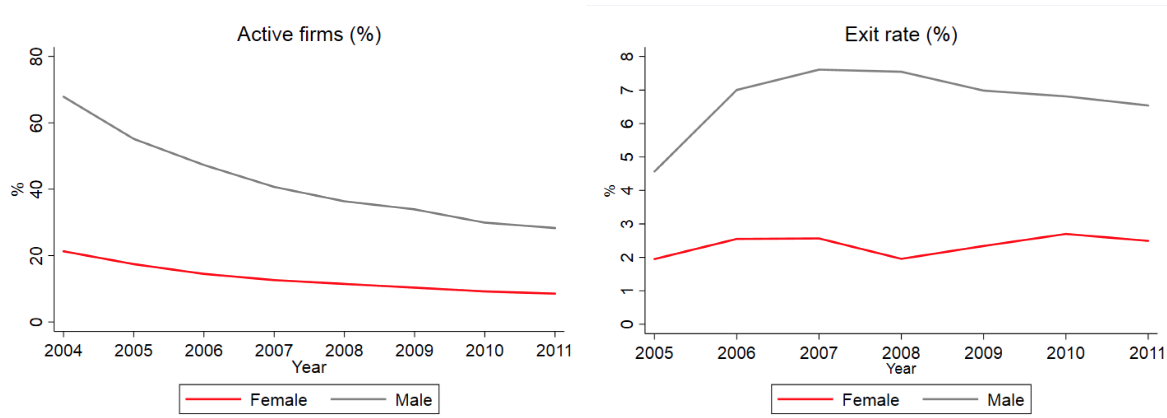
A.6 Firm Performance After Entry

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.6, 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.6: Behavior of Financial Variables Over Time

In Figure A.7, 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.7: Active and Exiting Firms Over Time

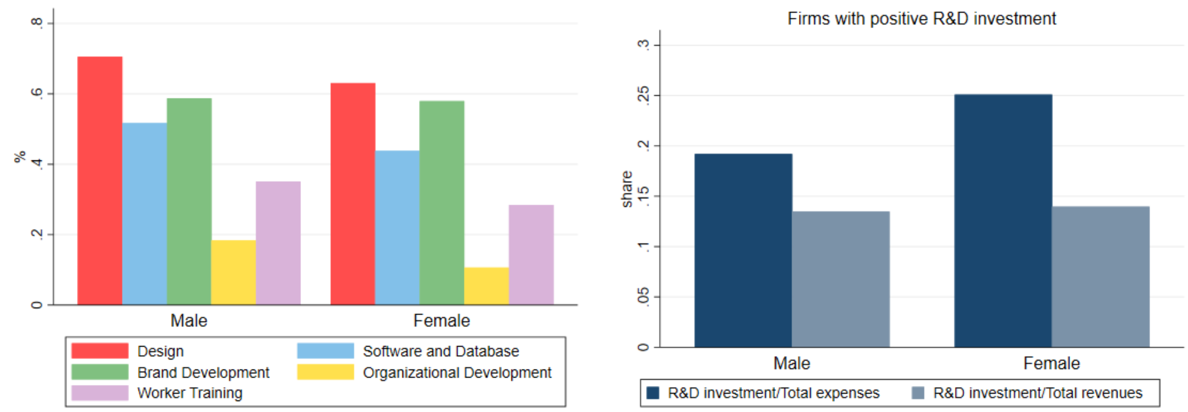


We also examine profitability of businesses using different measures, as shown in Figure A.8. Female-led businesses seem to have slightly higher profitability, when weighted by assets, revenues and equity. That male-led businesses do not have higher profit margins leads us to exclude the possibility 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 no statistically significant difference in the profitability of male- and female-led firms.

Figure A.8: Profitability of Firms

Next, we examine research and development (*R&D*) activities and spending of entrepreneurs. The left panel of Figure A.9 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.9 shows that average *R&D* spending as a share of total expenses and revenues do not differ across genders.

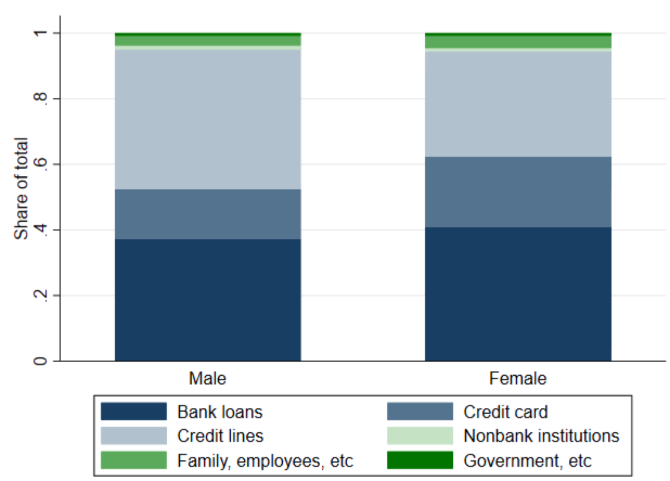
Figure A.9: *R&D* Investment of Firms



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 A4 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 A4 and Figure A.11 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.

Figure A.10: 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

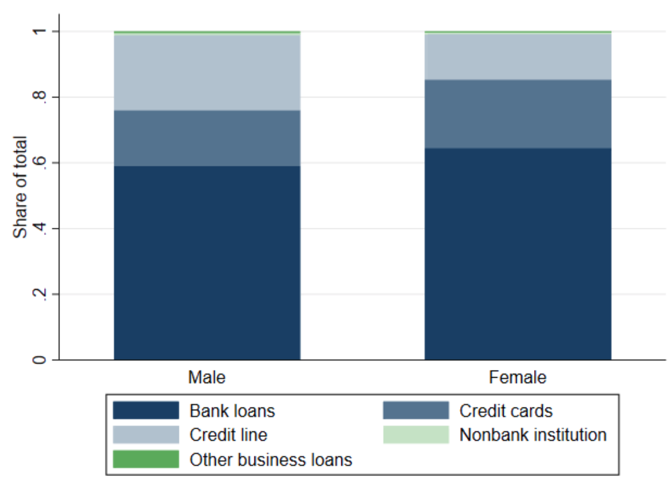
Table A4: Gender Differences in Sources of Funding (in USD)

	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.

from nonbank financial institutions, business credit cards and other business loans sourced elsewhere (e.g. federal agencies). As shown in Figure A.11, 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.

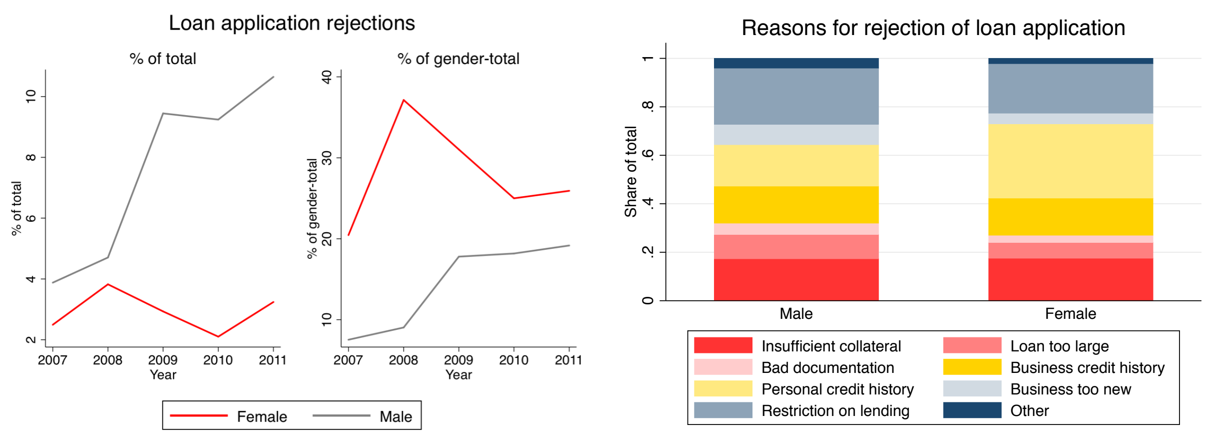
Figure A.11: Composition of Outside Debt of Male and Female Entrepreneurs



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.12, 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.12 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.12: 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 (see Figure A.13), regardless of whether the loan applications get approved or not (see Figure A.14).

Figure A.13: Collateral in Loan Applications

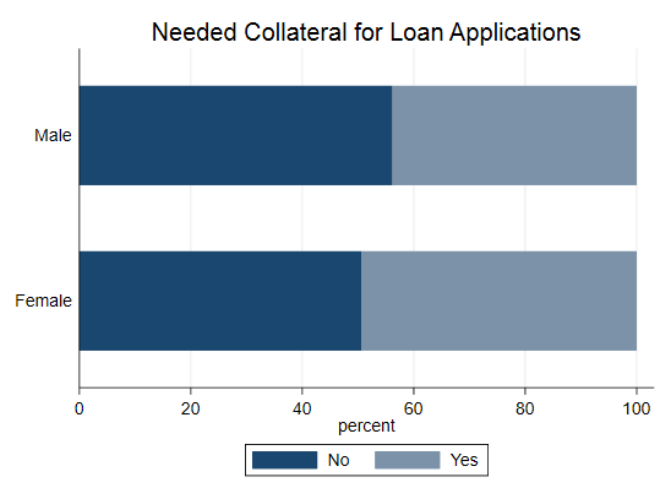
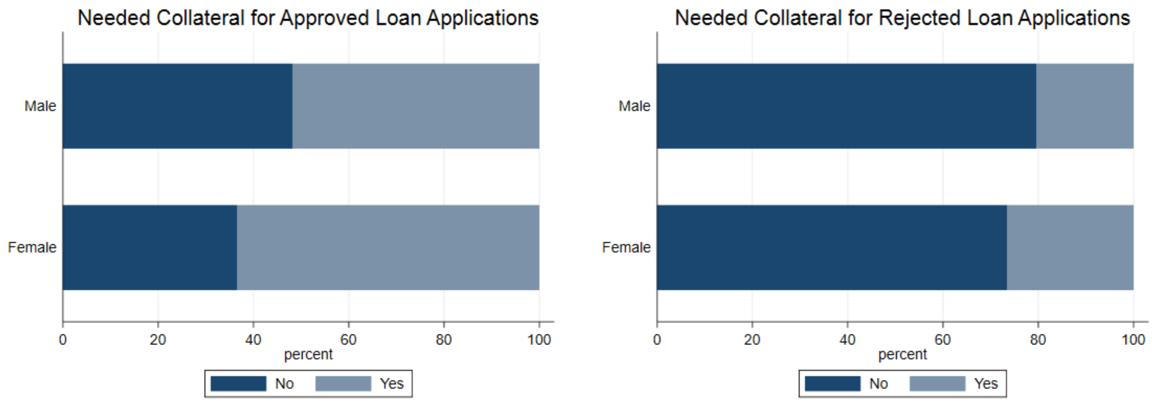


Figure A.14: Collateral in Loan Application Approvals and Rejections



A.8 Risk Aversion

In Table A5, 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.[6] We observe that slightly less female entrepreneurs apply for loans. However, conditional on applying, their loan applications have a lower probability of always getting approved,[7] 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.

Table A5: 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 Always 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

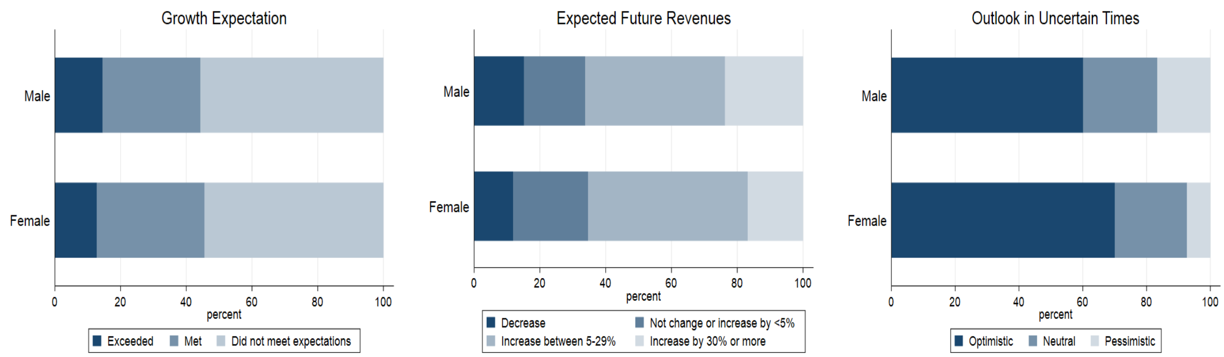
Notes: Credit risk scores are given on a scale of 1 to 5, where 1 represents the lowest risk class and 5 is the highest risk class. Applied for a loan is a binary variable = 1 if firm applied for a loan, and =0 otherwise. Loan always approved is a binary variable = 1 if loan application is always approved, 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.

[6] 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.

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

Moreover, we look at expectations and outlook of entrepreneurs surveyed by the KFS, shown in Figure A.15. Owners were asked whether their expectations for growth since the start of their business up until 2008 have been met or not (left panel of Figure A.15), and it seems that for both male and female owners, the extent to which expectations have been met do not differ. When asked about owners' expected future revenues in 2011 (middle panel of Figure A.15), male owners seem to have higher expectations in this regard. Lastly, when asked about owners' outlook during uncertain times (right panel of Figure A.15), female owners seem to be more optimistic.

Figure A.15: KFS Owners' Expectations and Outlook



Next, in Table A6, we show that there is no robust evidence that female entrepreneurs are less likely to apply for a loan. Under the baseline definition, female-owned firms are 2-3% less likely to apply for a loan, even after controlling for a firm's credit risk profile and past profitability. This is consistent with what we observe in Table A5. However, when we use the alternative definition based on primary ownership, we instead find that female entrepreneurs are not less likely to apply for loans as male entrepreneurs.

Table A6: Applied for a Loan

	Baseline: 100% male/female			Primary Owner		
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.0196*	-0.0198*	-0.0305*	-0.0066	-0.0128	-0.0201
	(0.0105)	(0.0116)	(0.0156)	(0.0095)	(0.0105)	(0.0142)
Controls	Y	Y	Y	Y	Y	Y
Credit risk score	N	Y	Y	N	Y	Y
Profitability	N	N	Y	N	N	Y
Sector/Region/Year FE	Y	Y	Y	Y	Y	Y
Observations	7,709	6,586	3,861	9,206	7,852	4,545
Pseudo-R^2	0.0693	0.0828	0.113	0.0697	0.0791	0.115

Notes: Estimates are marginal effects at the average. 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. Controls for the number of owners, and for individual characteristics such as education, experience, race, and age are included. Profitability in the previous period is measured using the profit margin of the previous year.

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.

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 A2, 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 A7, we also present results using the linear probability model, and confirm the same findings.

Table A7: Loan Application Rejections – Linear Probability Model

	(1)	(2)	(3)	(4)
	Full Sample	Full Sample	Full Sample	Excluding Personal Credit History
Female	0.1186***	0.0985***	0.1263***	0.1037**
	(0.0591)	(0.0541)	(0.0602)	(0.0562)
Controls	Y	Y	Y	Y
Leverage	Y	N	Y	Y
Personal debt	N	Y	Y	Y
Sector FE	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	578	697	561	518
R^2	0.337	0.302	0.355	0.329

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 always rejected, and = 0 if loan applications are always approved. Controls for the number of owners, and for individual characteristics such as education, experience, race, and age are included.

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

	(1)	(2)	(3)	(4)
	Probit FE	LPM	Probit FE	LPM
$\text{Female}_{primary\ owner}$	0.0752**	0.0821*		
	(0.0422)	(0.0491)		
Share of female owners			0.1248**	0.1167**
			(0.0525)	(0.0560)
Controls	Y	Y	Y	Y
Leverage	N	Y	Y	Y
Personal debt	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	774	720	628	734
R^2	0.217	0.277	0.271	0.306

Notes: For Probit FE models, estimates are marginal effects at the average. 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 always rejected, and = 0 if loan applications are always approved. Controls for the number of owners, and for individual characteristics such as education, experience, race, and age are included. In column (1), leverage is not included due to optimization failure.

Table A9: Loan Application Rejections Including Credit Risk Score

	(1)	(2)	(3)
	Baseline	Primary Owner	Share of female owners
Female	0.1306**	0.1138**	0.1359**
	(0.0534)	(0.0386)	(0.0531)
Controls	Y	Y	Y
Sector FE	Y	Y	Y
Region FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	542	705	722
R^2	0.275	0.253	0.260

Notes: Estimates are marginal effects at the average. 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 always rejected, and = 0 if loan applications are always approved. Controls for the number of owners, and for individual characteristics such as education, experience, race, age, and credit risk scores are included.

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). In Table A9, we also control for the credit risk score of entrepreneurs and confirm further our main result.

A.9.2 Risk and Profitability

In Table A10 and Table A11, 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 – Primary Owner

	(1)	(2)	(3)	(4)
	leverage	sd(ROA)	$\frac{Profit}{Assets}$	$\frac{Profit}{Revenues}$
$\text{Female}_{primary\ owner}$	0.0130	0.2258	0.1448	0.0026
	(0.0174)	(0.1710)	(0.0907)	(0.0091)
Controls	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	13,117	7,636	9,224	9,041
R^2	0.070	0.141	0.084	0.291

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 number of owners, legal status of the firm, and size. Size is measured by $\log(revenues)$.

Table A11: Measures of Risk-Taking and Profitability – Share of female owners

	(1)	(2)	(3)	(4)
	leverage	sd(ROA)	$\frac{Profit}{Assets}$	$\frac{Profit}{Revenues}$
Share of female owners	0.0126	0.1205	0.3244***	0.0126
	(0.0187)	(0.1710)	(0.1012)	(0.0102)
Controls	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y
Region FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	13,307	7,727	9,309	9135
R^2	0.069	0.137	0.085	0.298

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 number of owners, legal status of the firm, and size. Size is measured by $\log(revenues)$.

A.9.3 Misallocation

In Table A12, 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 A12: $arpk$ and $arpl$ across genders

	(1)	(2)	(3)	(4)
	$arpk$	$arpl$	$arpk$	$arpl$
$\text{Female}_{primary\ owner}$	0.0954**	0.0516		
	(0.0441)	(0.0442)		
Share of female owners			0.0931**	0.0526
			(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. Controls for individual characteristics include education, experience, race and age. Other controls include the number of owners, legal status of the firm and number of hours worked per week.

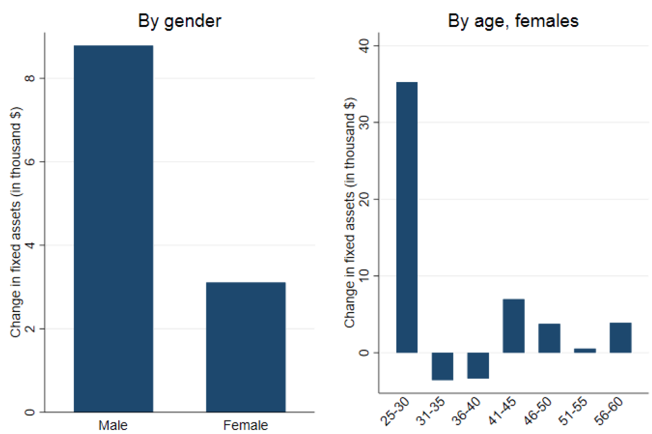
B Additional Quantitative Analysis

B.1 Interpreting differences in λ in the Model

Using the KFS data, we have shown that there is strong evidence of gender differences in credit access, a phenomenon that has also been documented in several other papers. In our work, we capture such empirical incidence by modelling differently the borrowing limit that affect female and male entrepreneurs respectively, by positing that $\lambda_m > \lambda_f$. We emphasize that it is not within the scope of our analysis to microfound the reasons behind gender-driven imbalance in the credit market, which in particular could be related to taste-based or statistical motives. We therefore limit our investigation to assessing the empirical relevance and quantifying the effect of gender-driven imbalance in credit access on aggregate outcomes such as the allocation of talent and resources across productive units, and total U.S. production.

However, an interesting avenue of future research would be to explore plausible reasons to microfound the borrowing constraints λ_m and λ_f even further. One possible explanation we were able to directly verify in our KFS data regards the possibility that female entrepreneurs may be discriminated against by lending institutions due to reasons of maternity risk. Specifically, in an institutional environment where the legislation on maternity leave for autonomous workers is scarce, maternity could be seen as an element of risk from the point of view of lenders. Since controlling for age in our empirical analysis on loan rejection rates does not fully capture the maternity risk channel, and this raises the possibility of further investigating this mechanism in future research. In this case, gender differences in borrowing constraints would be possible to microfound on the basis of statistical discrimination.

Figure B.1: Change in Fixed Assets



We are not the first to advance this kind of hypothesis. Recent works by Core (2020), Zandberg (2020), and Gottlieb et al. (2019) have empirically documented that policy changes which make it easier for female entrepreneurs to run their business while having children positively impact their entrepreneurial rates and activities. This is certainly not the only explanation behind gender differences in financial constraints, but could effectively be part of the story. Figure B.1 shows that, on average, female entrepreneurs experience periods of disinvestment around the time in which most of the female population decide to have children.

Another type of discrimination that the literature often provides example of is taste-based discrimination. In this case, one could imagine that female entrepreneurs in the KFS sample receive less credit from loan institutions due to a gender bias in loan officers' preferences (see Montoya et al. (2020) for experimental evidence on this). Unfortunately, our dataset does not report information on the side of loan institutions or loan officers and therefore makes it difficult for a researcher to infer a clear instance of taste-based discrimination. What we can control for however, is the specific reason entrepreneurs are given by loan institution when their loan application is rejected. As shown on the right panel of Figure A.12, 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 personal credit situation of the respondent, we always 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 however 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.

B.2 Computing TFPR in the Model

Computing TFPR is usually a way used by researchers in the macroeconomic fields to conceptualize misallocation: If there is misallocation of inputs across productive units, this will result in differences in their marginal value. How to think about it in the case of DRS technology $Y = e^z (K^\alpha L^{1-\alpha})^{1-\nu}$?

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

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 $\frac{e^z(K^\alpha L^{1-\alpha})^{1-\nu}}{K^\alpha L^{1-\alpha}}$ will be different and this is precisely what we compute!

We validate the prediction of our model regarding tpf differences across genders in the KFS data, as shown in Table B1. Recall from Table 9 of the main text, our model predicts tpf to be higher for females. To check this empirically, we run the same regressions as in the main text for $tfpr$, defined 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 input, measured as wage bill, and $\alpha = 0.33$ as in the model calibration exercise.

Table B1: $tfpr$ across genders

	(1) Baseline	(2) Primary Owner	(3) Share of female owners
Female	0.0850*	0.1117***	0.1093***
	(0.0438)	(0.0384)	(0.0386)
R^2	0.235	0.208	0.224

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Survey weights are used. All regressions include the following controls: education, experience, race, age, number of owners, legal status of the firm and number of hours worked per week, as well as sector, region and year fixed effects.

B.3 Calibration

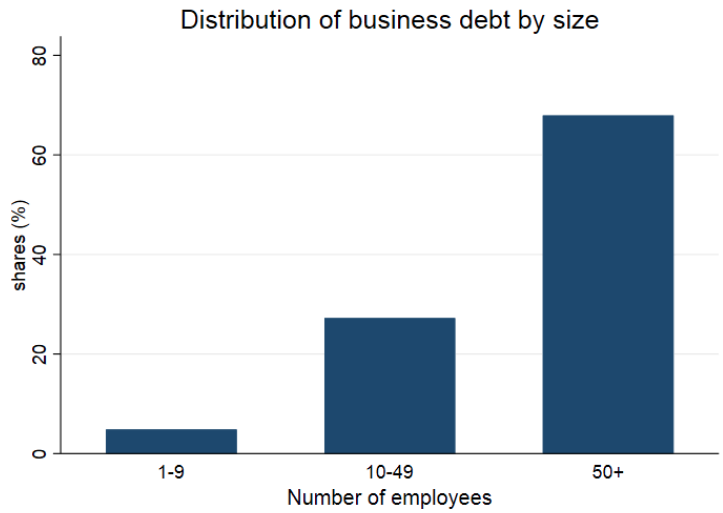
B.3.1 Moments from the KFS Data

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 ratio k/l is computed as logarithm of fixed assets over wages. Leverage b/k is computed as business debt over fixed assets. 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. 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
$(k/l)_{female}$	0.86
$(k/l)_{male}$	0.89
Leverage$_{female}$	0.36
Leverage$_{male}$	0.39
Debt share of Top 10% Firms	0.87
Exit rate$_{female}$	2.41%
Exit rate$_{male}$	6.86%
$\rho_{wages,female}$	0.75
$\rho_{wages,male}$	0.71
$debt/revenues$	0.49
Ratios	
relative $arpk$	0.12
Female/male k/l	0.91
Female/male Businesses Exit rate	0.35

Figure B.2: Distribution of Business Debt



B.3.2 Introducing an Operational Cost for Female Entrepreneurs

In Table B3, we present the alternative 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 reduces nonetheless the net entrepreneurial profits of women. 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 B5.

Table B3: Alternative 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	0.08	Capital Depreciation (Annual)	Clementi & Palazzo (2016)
Fitted			
β	0.9525	Discount factor	
$1-\nu$	0.75	Span of control	
σ_ϵ	0.37	Std. deviation idiosyncratic shock	
ρ_z	0.95	Persistence idiosyncratic productivity	
λ_m	5	Borrowing constraint male	
λ_f	2.35	Borrowing constraint female	
κ_f	2	Operational cost female	

Table B4: Targeted Moments

	US Data	Model
Internally Targeted		
Interest Rate	0.045	0.045
Earnings Share of Top 10% Individuals	0.47	0.46
Employment Share of Top 10% Firms	0.67	0.64
Average Persistence in Firms' Employment	0.73	0.8
Credit(Non-Financial Private Sector)/GDP	0.38	0.36
$\frac{Debt_f}{Debt_m}$	0.5	0.5
$\frac{ExitRate_f}{ExitRate_m}$	0.35	0.38

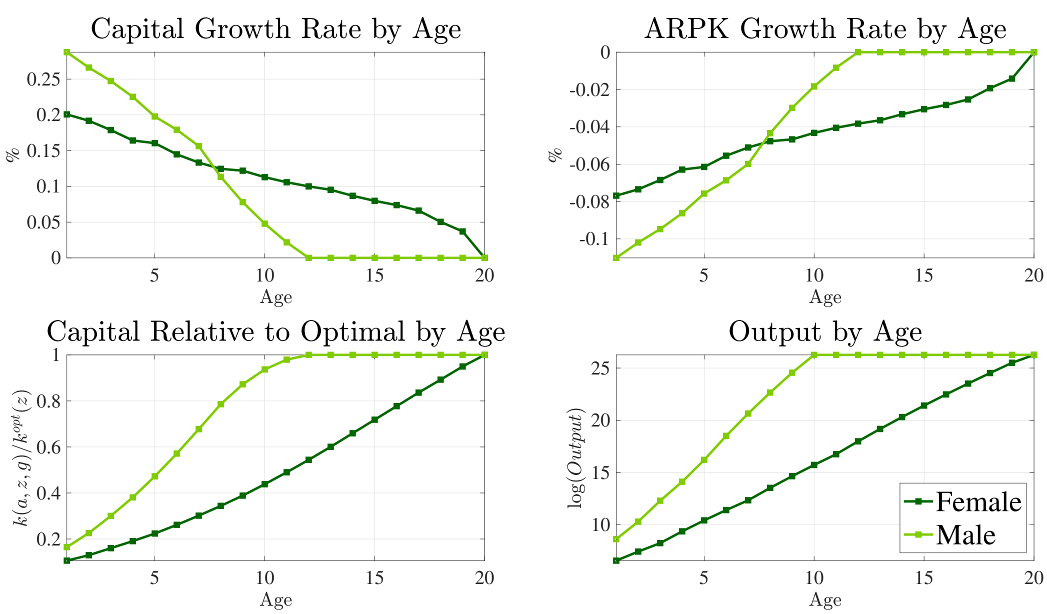
Table B5: Entrepreneurial Rates

	Data	Baseline Model	Model with Fixed Cost κ_f
$\frac{Female}{Male}$ Entrepreneurial Rate	0.35	0.5	0.4

B.4 Quantitative exercise

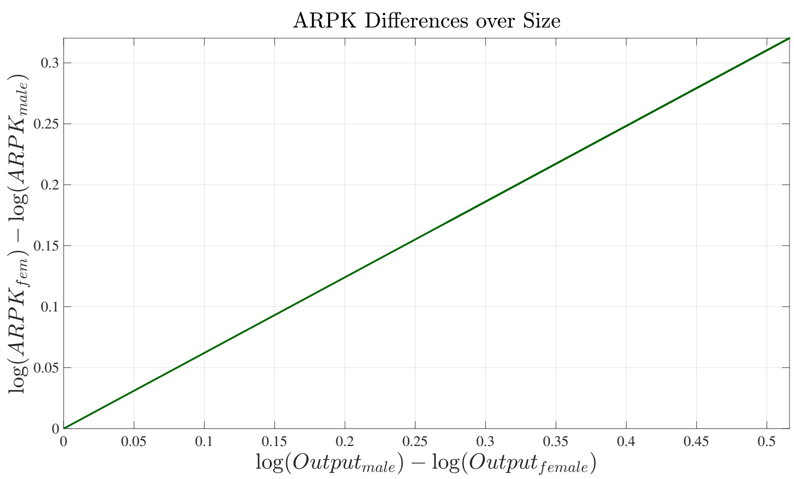
In Figure B.3, we plot illustrative evidence of firms' performance evolution over time. For the sake of the exposition, we consider one female and one male entrepreneurs that start their respective business at time t and are followed for 20 periods after. We further assume that their initial wealth a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

Figure B.3: Firms' Performance over Age



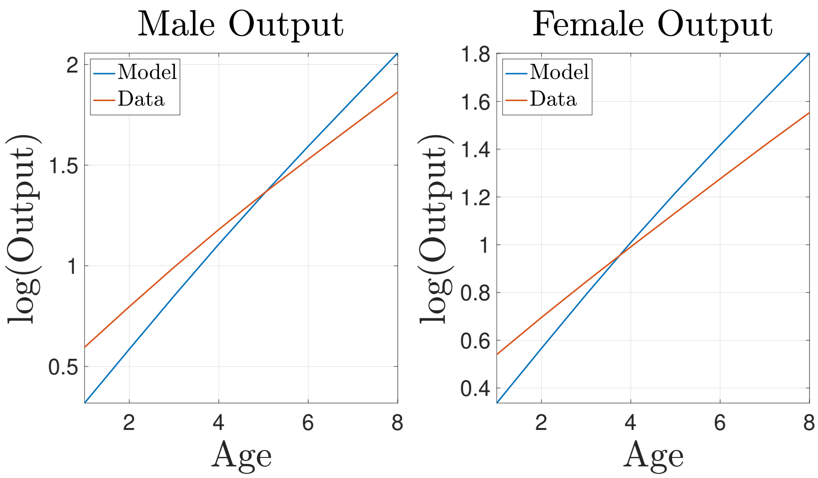
We first compute capital and *arpk* growth rates: capital grows faster when firms are younger (and presumably smaller) and its growth slows down over time. Moreover, it takes time for firms to reach the optimal level of capital for their given productivity z due to the presence of financial frictions. At the same time and with a comparable speed, *arpk* decreases as the firms are able to accumulate capital. Interestingly, 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



Another direct consequence of the progressive accumulation of wealth is the growth in firms' revenues. As entrepreneurs accumulate more wealth, they are able to rent more capital and produce more. Importantly, this process is slower for female entrepreneurs, as they face tighter borrowing constraints (see the right panel in Figure B.3). We can then further compare the life-cycle behavior of female and male-owned firms in the model and in the data by comparing the growth rates of output. As Figure B.5 shows, not only gender differences disappear over time, but our model is able to replicate fairly well growth rates of firms' output for both female and male entrepreneurs.

Figure B.5: Firms' Output over Age



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