SKILL BIAS, FINANCIAL FRICTIONS, AND SELECTION INTO ENTREPRENEURSHIP

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and Selection into Entrepreneurship

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Abstract. Financial frictions adversely affect productivity by discouraging entrepreneurship, which is often measured by the self-employed. This paper distinguishes different types of self-employment when studying this question. Using micro data for 77 countries from all income levels, we show that employers' labor shares are increasing with GDP per capita, whereas own-account employment (self-employed without employees) is decreasing. We also find an almost universally negative selection on education into own-account status relative to wage workers and positive selection into employers. To quantitatively match these facts, we introduce skill-biased productivity progress across countries in an occupational choice model with financial frictions. Our model predicts an average of 19% output gains in low-income countries from removing financial frictions. In contrast, an alternative model with skill-neutral technological change cannot match the high own-account employment share in low-income countries, thus overestimating the output gains by 13 percentage points.

1 Introduction

Differences in GDP per capita across countries are primarily accounted for by the total factor productivity (TFP). One hypothesis to explain the low TFP in developing countries is their poorly developed financial markets. To study the aggregate impacts of financial frictions, existing research emphasizes the role of entrepreneurs (see, e.g., Buera et al., 2011; Midrigan and Xu, 2014; Moll, 2014; Buera et al., 2015; Herreño and Ocampo, 2021). These studies model the entrepreneurs who hire employees. However, they do not consider own-account entrepreneurs who do not hire anyone although these entrepreneurs can account for as much as 90% of the labor force in low-income countries as shown in Allub and Erosa (2019). This paper shows that overlooking these own-account entrepreneurs significantly overestimates the effects of removing financial frictions in poor countries.

Specifically, we propose to divide entrepreneurs, often measured by the self-employed, into two categories: 1) own-account workers who are independent workers without employed workers, and 2) employers who are self-employed and hire at least one employee.[1] We then argue that introducing skill-biased technological change can quantitatively account for the relationship between labor shares of different types of self-employment and GDP per capita. As such, our paper helps reconcile diverse findings about development, financial frictions, and entrepreneurship.

We draw on 246 country-year household surveys to empirically distinguish the two types of entrepreneurs. For own-account workers, we find that the labor force share decreases with income per capita, from higher than 80% in low-income countries to lower than 10% in high-income countries. In contrast, the employers' share moves in the opposite direction, increasing from almost zero in low-income countries to a maximum of around 10% in rich countries. We then apply the multinomial probit model to examine how individuals are selected into different types of entrepreneurship based on education. We find that education has an almost universally positive effect on becoming an employer but a negative effect on becoming an own-account worker, true in 94% of our country-year samples. Furthermore, we show that the structural change from the unskilled own-account sector to the skilled modern sector happens within the agriculture, manufacturing, and service sectors as well. Our findings on the contrasting features of the two types of entrepreneurs emphasize the importance of distinguishing the two types from each other.

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[1]Our proposed classification is consistent with the latest International Classification of Status in Employment (ICSE-18-A), published by the International Labour Office in 2018. The ICSE-18-A classifies independent workers, as opposed to dependent workers, into *employers* and *independent workers without employees*. The previous classification ISCE-93 groups employers, own-account workers, contributing family workers, and members of producers' cooperatives as self-employment jobs.

Based on these facts, we build a two-sector general equilibrium model to study the impacts of financial frictions on occupational choices, TFP, and aggregate output. The two sectors are the traditional sector, where the self-employed work on their own accounts without rewards to ability, and the modern sector, where employers hire wage workers to produce with rewards to their abilities.[2] To account for the selection patterns and financial constraints, we assume that agents are heterogeneous in both ability and assets-holding positions, and they sort into the three occupations, as discussed in Roy (1951). Across countries, we focus on two exogenous but correlated differences. One is skill-biased technological change, which means that richer countries have higher ratios of modern- to traditional-sector productivity. This assumption builds on the mounting evidence that cross-country productivity differences are skill-biased, as opposed to skill-neutral (see, e.g., Caselli and Coleman, 2006; Hjort and Poulsen, 2019; Malmberg, 2020). The other difference is the financial development level, which is in the form of employers' borrowing constraints when they rent capital.

Our model has two main predictions, which qualitatively match the empirical findings. The first prediction is that, within a given country, the own-account workers are negatively selected relative to wage workers while employers are positively selected. Two thresholds exist in equilibrium, each consisting of a set of joint values of abilities and wealth. Agents below the lower-ability threshold become own-account workers, whereas agents above the higher-ability threshold become employers, and those between the two thresholds become wage workers. The second prediction is that, across countries, as the modern-sector productivity and the financial development level increase, the labor force share of own-account workers decreases. Skill-biased structural change reduces the marginal threshold of ability levels because of higher returns to ability in the modern sector. Meanwhile, better financial development in richer economies allows high-ability employers to expand their businesses, increasing the equilibrium wage. Both forces draw more able agents from the traditional sector into the modern sector, thus unambiguously reducing the traditional sector's size.

To assess the model's quantitative predictions, we calibrate the model to match the key moments of the U.S. economy and the cross-country slope of own-account employment against log GDP per capita. Our main quantitative experiment lowers the relative productivity in the modern sector and the financial development parameter from the U.S. levels. We find that skill-biased technological change, together with financial development, accounts for the relationship between labor shares and income per capita. We validate the model by showing that it matches the not-targeted moments including the increases in the employers' share and the private debt to GDP ratio with GDP per capita.

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[2]The assumption of differential returns to ability (as proxied by education levels) in the two sectors is consistent with Rosenzweig (1995), who argues that schooling has little influence on productivity if the tasks are simple, whereas there are higher returns to schooling if the tasks are substantially complex.

We use the calibrated model to analyze the aggregate impacts of financial frictions, focusing on the novel channel of labor reallocation across occupations that comes with better financial development. The model predicts that removing financial frictions *decreases* the own-account employment shares in all countries, by an average of 5.6 percentage points in low-income countries (the bottom third of the world's income distribution) and by 2.6 percentage points in middle- and high-income countries (the middle and top third of the world's income distribution). Meanwhile, the employers' shares *decrease* in most economies and *increase* in the poorest ones, but by a much smaller magnitude. Within a country, as the relatively more able rather than the relatively richer agents become employers within the modern sector, misallocation of talents is reduced. Such labor reallocation enables low-income countries to increase modern-sector TFP and GDP per capita by 23% and 19% on average, respectively.

To highlight the importance of considering own-account self-employment when evaluating the aggregate effects of financial frictions, we then compare the benchmark predictions to an alternative model with skill-neutral technological change across countries. Without skill-biased technological change, the model could not match the high shares of own-account employment in poor countries; it only generates an own-account share of 29% in the poorest country, compared to 80% in the data. As a result, when financial frictions are removed, the alternative model predicts the average output gain in poor countries to be 32%, over-predicting by 13 percentage points compared to the benchmark, although it generates similar increases in the modern-sector TFP across all income levels.

We close the paper by evaluating the effects of removing financial frictions in the Indian economy. To do so, we extend the model to require capital inputs in the traditional sector's production. Hence, own-account workers face the same financial constraints as employers. We then re-calibrate the model to key moments of India. We find that removing financial constraints in the modern sector alone and in both the modern and traditional sectors increases GDP per capita by 20.8 and 21.1 percent, respectively, aligning with our benchmark predictions. Furthermore, removing financial frictions in the traditional sector alone only generates 1.5% output gains as labor and capital relocate to the relatively unproductive traditional sector. This quantitatively small effect is consistent with the literature that finds modest effects of microfinance projects.[3]

Literature and Contribution. This paper contributes to the study of entrepreneurship and financial frictions in macroeconomics, which typically models financial frictions as collateral constraints that firms face (see e.g., Buera et al., 2011; Midrigan and Xu, 2014; Allub et al., 2020). Fewer papers acknowledge the large share of unproductive self-employment

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[3]The small effect of financial frictions in the traditional sector also supports our benchmark choice of not having capital inputs in the traditional-sector production.

in poor countries. For example, Herreño and Ocampo (2021) model them as the source of labor demand and focus on the subsistence concerns of poor individuals by incorporating unemployment risks. Two papers explicitly distinguish between own-account workers and employers are the following. Allub and Erosa (2019) use a model with stochastic managerial and working skills to match the relationship between entrepreneurship rates and credit to GDP ratios and explain half of the data. Gu (2021) studies the share of own-account with a focus on the effects of cost of financial intermediation. We complement this literature by introducing skill-biased technological change as an important factor to further account for the relationships between labor shares, debt to GDP ratios, and GDP per capita across countries.

Our empirical findings on the labor share patterns across countries also relate to Gollin (2008) and La Porta and Shleifer (2014), who show the pattern of declining entrepreneurship rates against income levels but do not distinguish different types of entrepreneurship. Relatedly, Poschke (2019) mentions the contrasting share pattern of own-account workers and employers, but the calibrated model does not match the employers' share with development. Our model tends to predict a U-shape between ability and the probability of being an entrepreneur as in (Poschke, 2013a, 2018), who abstract from financial frictions.

By emphasizing the role of structural change in occupational choices, our paper builds on macro-development literature featuring two-sector production. Yet our two sectors do not fit neatly into either the agriculture versus non-agriculture division (e.g. Restuccia et al., 2008; Lagakos and Waugh, 2013; Porzio et al., 2020; Yao and Zhu, 2020), or the home versus market division (e.g. Ngai and Pissarides, 2008; Bridgman et al., 2018). Instead, our traditional sector is defined as the production of outputs counted in the national income and product accounts (NIPAs) that do not hire any paid employees. The sector division closest to our paper is Feng et al. (2020), who emphasize search frictions in the modern sector while we focus on financial frictions. In addition, none of these papers focus on the link between occupational choices and development.

Lastly, this paper adds to the literature of microfinance. Our distinction between own-account self-employed versus employers is widely consistent with the reduced-form evidences. For example, Banerjee et al. (2015a) find that microfinance significantly increases the top tercile profits of businesses that started before the intervention, whereas its benefits to the majority of entrepreneurs are generally indistinguishable from zero. In contrast, the general equilibrium effects of microfinance are mostly unexplored. An exception is Buera et al. (2021), who emphasize the difference between the long-run versus short-run aggregate effects.

2 Empirical Findings

This section presents empirical results on household-level occupational choices across countries. We find that the share of employers rises with GDP per capita while the share of own-account workers decreases. We also show almost universally positive selections on education into employers relative to wage workers as well as the negative selections into own-account workers. In addition, Appendix section B investigates the United States' time series data and finds consistent results with the cross-country patterns.

2.1 Data

The cross-country household-level data are from the *Integrated Public Use Microdata Series, International: Version 7.2* (IPUMS-International). The data include harmonized censuses that cover age, gender, education, employment status, occupation, and some other characteristics. We restrict the sample to prime-age (25-54) male workers, as our paper focuses on occupational choices and abstracts away from labor force participation decisions. The estimate of GDP per capita is taken from the *Penn World Table version 9.1* (PWT 9.1). Specifically, we use output-side real GDP at chained PPPs in 2011 US$ (rgdpo).

Our sample includes 246 country-year surveys across 77 countries, spanning from 1960 to 2015. The data cover economies from all income levels, with the GDP per capita ranging from around $500 (e.g., Ethiopia in 1994) to more than $50,000 (e.g., Ireland in 2006). We divide the entrepreneurs into two types, the own-account workers and the employers. Specifically, the *own-account workers* are those who are self-employed without hired employees and the *employers* are those self-employed who have at least one hired employee. Therefore, the labor force is divided into three classes: two types of entrepreneurs and wage workers. This labor force division is clearly defined and empirically comparable across all the country-year surveys. Empirical details of this division are listed in Appendix Table A1 in the Appendices.[4]

## 2.2 Labor Force Division across Countries

In this section, we present the aggregate and sectoral cross-country patterns of the labor force division.

Panel (a) of Figure 1 plots the country average labor shares of own-account workers among

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[4]For the purpose of this paper, we do not identify the "distinguished" own-account workers such as freelance lawyers or doctors, who only account for negligible shares of the labor force, especially in developing countries.

Figure 1: Labor Force Shares by Self-employment Type Across Countries

(a) Share of Own-Account Workers (Country Average)
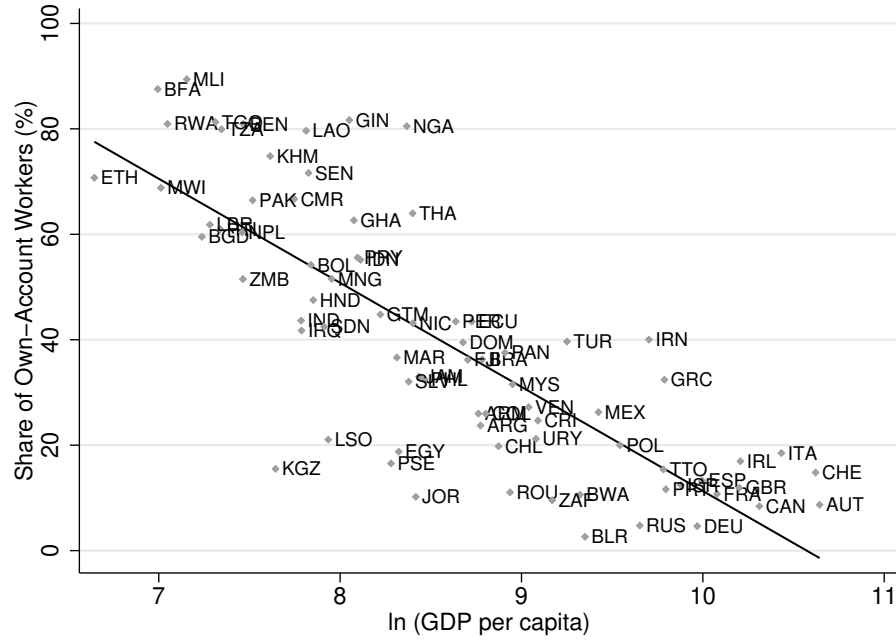
(b) Share of Employers (Country Average)
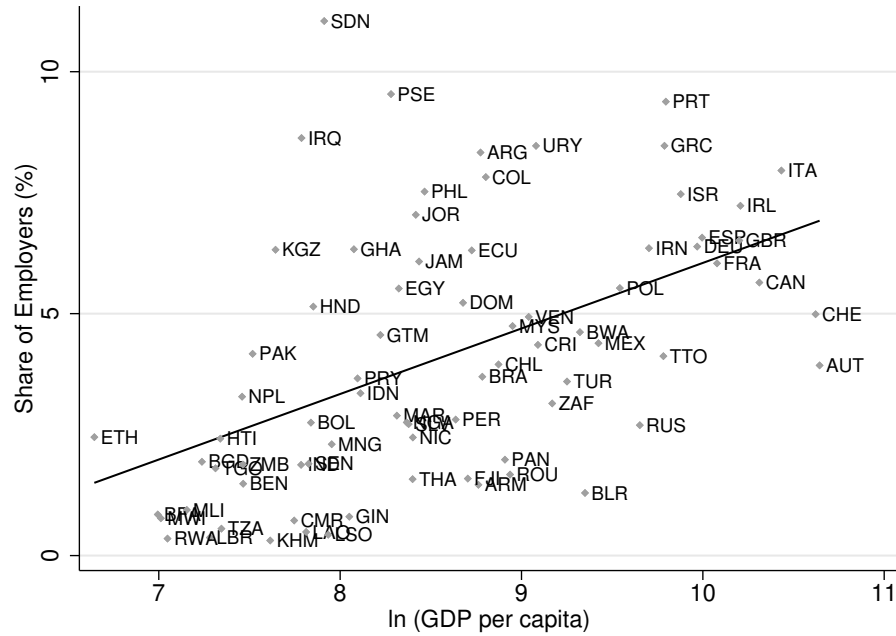
Note: This figure plots the average labor shares of own-account workers and employers, respectively, for prime-aged male workers in one country across all available years.

prime-aged male adults against log GDP per capita. Each diamond represents the average of the own-account employment in one country across all available years. It varies widely across economies, monotonically decreasing from almost 90% in poor countries like Burkina Faso and Mali to less than 1% in rich countries like Germany and Belarus. Panel (b) of Figure 1 then plots the country average of employers' shares. We find that the share of employers increases from almost zero in low-income countries to close to 10% in high-income countries like the U.K. or Italy, and they are less dispersed than the own-account employment.

Table 1 reports the coefficient of regressing the shares of own-account workers and employers on log GDP per capita for both the 246 country-year observations and the 77 country average observations. The slope coefficients of the own-account employment regressions are significantly negative at -0.19 for the country-year regression and at -0.20 for the country average regression. This result means a 1 percent increase in GDP per capita on average decreases the own-account rate by 0.19/0.20 percentage points. The slope coefficients of employers' share regressions are 0.016 for the country-year specification and 0.014 for the country average specification, which are significant. Even though some readers may worry that more stringent regulations may make it harder to hire employees in developed countries, this is only a bias against our estimated positive effect of economic growth on the employers' rate.

Table 1: Slope Coefficients of Labor Shares on Income per capita

| | All Surveys | | All Country Averages | |
	Own-account	Employers	Own-account	Employers
ln (GDP per capita)	-0.19***	0.016***	-0.20***	0.014***
	(0.009)	(0.001)	(0.015)	(0.002)
R^2	0.63	0.28	0.64	0.25
Obs.	246	246	77	77

Note: The table reports the slope coefficients from regressions of the prime-age male own-account workers' and employers' shares on log GDP per capita and a constant. The first two columns include all surveys in our data. The third and fourth columns include one observation per country, taking the average labor shares across all years. *** indicates statistical significance at the 1-percent level.

The above analysis covers all industries, as aggregate skill-biased technological change is an emphasis of this paper. However, some readers may be concerned that it is the agriculture sector that drives the cross-country patterns of the two types of self-employment,

Table 2: Slope Coefficients of Labor Shares on Income per capita by Sector

	Agriculture Sector		Manufacturing, etc.		Service Sector	
	Own-account	Employers	Own-account	Employers	Own-account	Employers
ln (GDP per capita)	−0.136***	0.023***	−0.133***	0.011***	−0.119***	0.019***
	(0.026)	(0.006)	(0.018)	(0.002)	(0.011)	(0.003)
R^2	0.257	0.190	0.442	0.211	0.535	0.347

Note: The table reports the slope coefficients from regressions of the prime-age male own-account workers' and employers' shares on log GDP per capita and a constant by sector across 75 countries with available data. The agriculture sector includes agriculture, fishing, and forestry; the "manufacturing, etc." sector includes manufacturing, construction, mining, utility; the service sector includes wholesale and retail trade, hotels and restaurants, transportation, storage, and communications, financial services and insurance, services not specified, business services and real estate, education, health and social work, other services, and private household services. *** indicate statistical significance at the 1-percent level.

especially for the own-account workers. To address this concern, Table 2 reports the slope coefficients of regressing the shares of own-account workers and employers on log GDP per capita in the agriculture, manufacturing, and service sectors, respectively, for the 75 countries with available industry data. The odd columns in Table 2 show that the sectoral shares of own-account workers still decrease sharply with per-capita income, although with less steep coefficients than the benchmark. The even columns show that the slopes of employers' labor force shares on log GDP per capita in the three sectors are similar to the patterns in the full sample, with the slope coefficients ranging from 0.011 to 0.023. Appendix Figure A1 plots the country average labor shares of own-account workers and employers by sector. As a result, we emphasize that the skill-biased structural change from the unskilled traditional sector to the skilled modern sector happens within all three sectors, namely the agriculture, manufacturing, and service sectors.

2.3 Selection into Two Types of Entrepreneurship

In this section, we study how workers are selected into different classes of work based on education. We use the multinomial probit model to estimate the effect of education on the three unordered labor choice responses: own-account worker, wage worker, or employer. Our main measure of education is *the number of years of schooling*, which ranges from 0 to '18 or more' years.

In the multinomial probit model, the unobserved utilities of individual i from choosing $j \in \{o, w, e\}$ are given by

$$v_{ij} = \alpha_j + \beta_j yrs_i + \eta_j X_i + \epsilon_{ij}$$

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where $yrs_i \in \{0, 1, ..., 18\}$ indicates the number of formal schooling years the individual completed; controls in X_i are age, age squared, a dummy for native-born and a dummy for urban-located; ϵ_{ij} is a normally distributed error term; and o, w, e denote own-account worker, wage worker, and employer, respectively. Letting v_i^* be the labor choice of individual i, then

$$v_i^* = arg \max_{j \in \{o,w,e\}} \{v_{io}, v_{iw}, v_{ie}\}.[5]$$

Figure 2: Selection on Years of Schooling into Own-account Workers/Employers
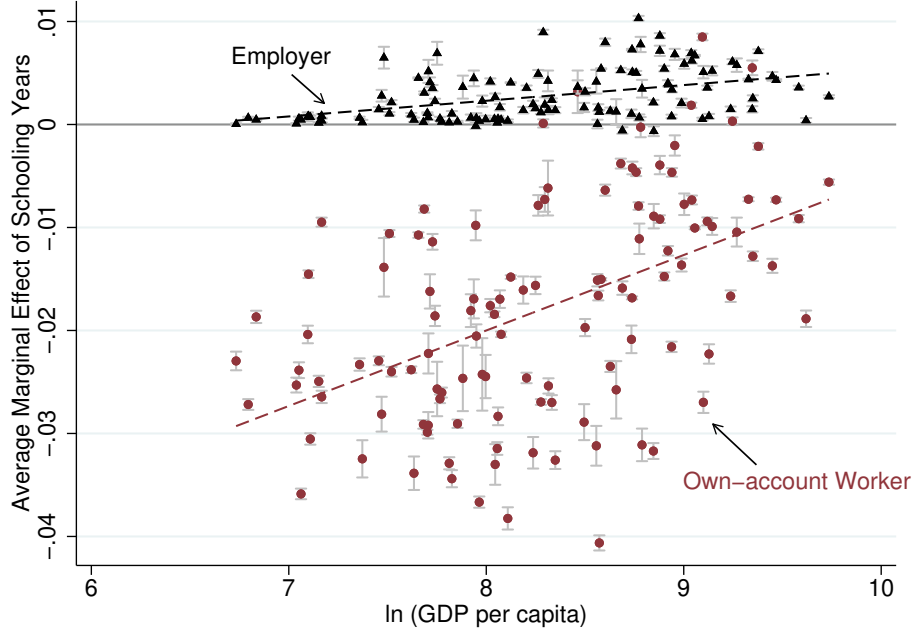
Note: This figure plots the average marginal effects of years of schooling on prime-aged male workers' occupational choices of being own-account workers and employers in each country-year survey.

Figure 2 reports the average marginal effects of education on the working status with the 95% confidence interval against income per capita of 117 country-year observations. For each country-year survey, the black triangle (red dot) indicates the average change in the probability of becoming employers (own-account workers) with one more year of schooling across all individuals. On the one hand, 110 of the 117 country-year observations show significantly positive effects of schooling years on becoming employers (p-value< 0.05). With a small dispersion, one more year of schooling increases the probability of becoming employers by

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[5]Mathematically, the effect of one more year of schooling, from k year(s) to $k+1$ years, on the probability of one being an own-account worker is $p(v_i^* = o|yrs_i = k + 1) - p(v_i^* = o|yrs_i = k) = p(v_{io} > v_{ie}, v_{io} > v_{iw}|yrs_i = k+1) - p(v_{io} > v_{ie}, v_{io} > v_{iw}|yrs_i = k) = p((\epsilon_{io} - \epsilon_{ij}) > (\alpha_j - \alpha_o) + (k+1)(\beta_j - \beta_o) + (\eta_j - \eta_o)X_i, j = w, e) - p((\epsilon_{io} - \epsilon_{ij}) > (\alpha_j - \alpha_o) + k(\beta_j - \beta_o) + (\eta_j - \eta_o)X_i, j = w, e)$, and the effects on being an employer or a wage worker have similar expressions.

0.0029 on average across all country-year surveys. On the other hand, 110 observations exhibit significantly negative average marginal effects of schooling years on being own-account workers, ranging from -0.041 to -0.0020 with a mean of -0.019. Note that the negative selection into the own-account status decreases with development. Although it is beyond this paper's scope, the decreasing negative selection is probably due to the rise of "distinguished" own-account workers with development levels. To summarize, the fact that years of schooling has universally positive effects on becoming an employer but universally negative effects on becoming an own-account worker emphasizes the importance of differentiating the own-account self-employed from the employers, especially in developing economies.

We also use *secondary school completion*, a dummy variable, as an alternative measure of education. This variable is available in 163 country-year data sets. Appendix Figure A2 reports the average marginal effects of secondary school completion on the working statuses, which is the average change in the probability of becoming employers and own-account workers due to secondary school completion across all individuals in a country-year survey. Across all country-year observations, secondary school completion increases the probability of becoming an employer by 0.024 on average with a small dispersion and decreases the probability of becoming an own-account worker by 0.18 on average. We find significantly positive selection into employers in 141 out of 163 country-year surveys and significantly negative selection into own-account-workers in 151 surveys, similar to the universal selection results when using *years of schooling* as the education measure.

3   Model

In this section, we build a general equilibrium model of occupational choices to match the labor force patterns across countries. We allow two sectors in our model, a traditional sector and a modern sector, to capture the substantial decrease in the traditional own-account workers' labor share that coincides with development. Workers are heterogeneous in both ability and endowment wealth, and they sort as in Roy (1951).[6]

3.1   Environment

The economy is populated with a continuum of infinitely lived agents with measure 1. Each individual is endowed with heterogeneous ability in efficiency units $h \in [\underline{h}, \overline{h}]$ distributed according to $\mu(h)$ and wealth $a \in [\underline{a}, \overline{a}]$. With a constant hazard rate of $1 - \lambda$, the ability is destroyed due to exogenous demand shock, and a new ability h' is drawn from $\mu(h)$. Because

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[6]We regard schooling years as a proxy for workers' innate production ability.

of idiosyncratic shocks on individuals' abilities, our model allows for switching occupations in each period. Agents also make saving and borrowing decisions at the same equilibrium interest rate of r. Under financial frictions, they face a borrowing constraint, which depends on their asset holdings a.

Each period, workers can choose to work in one of the two sectors: a traditional sector and a modern sector. In the traditional sector, agents are own-account self-employed without returns to ability and produce based on the traditional sector's productivity A_T according to

$$y_T = A_T.^7$$

This assumption is not meant to dismiss the empirical evidence of dispersion in self-employed workers' income. Rather, the assumption enables us to focus on how the introduction of structural change can affect occupation choices. In the modern sector, employers hire wage workers to produce, and the production rewards abilities according to

$$y_M = A_M h (l^\alpha k^{1-\alpha})^\gamma,$$

where A_M is the productivity, h is the employer's ability, l is the labor input in efficiency units, and k is the capital input.

Individuals consume both traditional and modern-sector goods. Following Buera et al. (2011), the utility function features the form

$$u(c_T, c_M) = \frac{1}{1-\sigma} [\theta c_T^{1-1/\rho} + (1-\theta) c_M^{1-1/\rho}]^{\frac{\rho(1-\sigma)}{\rho-1}},$$

where ρ is the elasticity of substitution between traditional and modern sector goods, θ governs the share of traditional-sector goods in consumption expenditure, and σ measures the degree of relative risk aversion.

In each period, agents choose occupation j, consumption of traditional-sector output c_T and modern-sector output c_M, and an asset-holding position a' for the next period to maximize the value function. The choice of occupation j can be an own-account worker o, a wage worker w, or an employer e. We normalize the modern-sector output price to be one and denote the relative traditional-sector output price to be p_T. Let β be the discount factor.

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[7]In the benchmark model, we assume traditional sector production does not use capital inputs because the traditional-sector capital share is empirically small and has no credible estimates. We will relax this assumption in an extension of the model in Section 5.

Then the value of an agent indexed by ability h and wealth a can be written as

$$v(h, a) = \max_{j \in \{o, w, e\}} \{v^o(h, a), v^w(h, a), v^e(h, a)\} \tag{1}$$

$$v^j(h, a) = \max_{c_T, c_M, a'} u(c_T, c_M) + \beta\{\lambda v(h, a') + (1 - \lambda)\mathbb{E}_{h'}[v(h', a')]\}$$

$$\text{s.t.} \quad p_T c_T + c_M + a' \leq I^j(h, a) + (1 + r)a.$$

With asset holding for the next period chosen at a', the agent has a value of $v(h, a')$ in the next period if he maintains the ability h, and he has an expected value of $\mathbb{E}_{h'}[v(h', a')]$ if his ability is redrawn. $I^j(h, a)$ is the per-period income flow for occupation j. For own-account workers, a homogeneous income is earned,

$$I^o(h, a) = p_T A_T.$$

A wage worker earns an income that is linear in his ability

$$I^w(h, a) = wh,$$

where wage rate w is the equilibrium wage per efficiency unit. Employers hire wage workers and rent capital to produce modern-sector goods. An employer with asset a faces the borrowing limit $k \leq \phi a$ as in Moll (2014). The optimal labor choice $l(h, a)$ and capital choice $k(h, a)$ solve

$$I^e(h, a) = \max_{k, l > 0} \quad A_M h \left(l^\alpha k^{1-\alpha}\right)^\gamma - wl - (r + \delta)k$$

$$\text{s.t.} \quad k \leq \phi a$$

where r is the rental rate of capital and δ is the rate of depreciation. Financial frictions is summarized by $\phi \geq 1$.

Stationary Equilibrium. A stationary competitive equilibrium is composed of an invariant distribution of ability and wealth $G(h, a)$; agents' policy functions $c_T(h, a)$, $c_M(h, a)$, $a'(h, a)$ and $j(h, a)$; employers' policy functions $l(h, a)$ and $k(h, a)$; and prices p_T, w, and r such that:

1. Given prices p_T, w and r, the policy functions $c_T(h, a)$, $c_M(h, a)$, $a'(h, a)$, $j(h, a)$, $k(h, a)$ and $l(h, a)$ solve individuals' problem (1);

2. Asset, labor, traditional and modern sector goods markets clear, respectively,

(Asset) $\qquad K \equiv \int_{\{(h,a)|j(h,a)=e\}} k(h,a)G(dh,da) = \int_{h,a} a(h,a)G(dh,da),$

(Labor) $\qquad \int_{\{(h,a)|j(h,a)=e\}} l(h,a)G(dh,da) = \int_{\{(h,a)|j(h,a)=w\}} hG(dh,da),$

(Traditional-sector goods)

$$\int_{h,a} c_T(h,a)G(dh,da) = \int_{\{(h,a)|j(h,a)=o\}} A_T G(dh,da),$$

(Modern-sector goods)

$$\int_{h,a} c_M(h,a)G(dh,da) + \delta K = \int_{\{(h,a)|j(h,a)=e\}} A_M h \left(l^\alpha k^{1-\alpha}\right)^\gamma G(dh,da);$$

3. The joint distribution of ability and wealth is stationary:

$$G(h,a) = \lambda \int_{\{(\tilde{h},\tilde{a})|\tilde{h}\leq h, a'(\tilde{h},\tilde{a})\leq a\}} G(d\tilde{h},d\tilde{a}) + (1-\lambda)\mu(h) \int_{\{(\tilde{h},\tilde{a})|a'(\tilde{h},\tilde{a})\leq a\}} G(d\tilde{h},d\tilde{a}).$$

3.2   Model Predictions

We consider two mechanisms by which development can affect the shares of two types of entrepreneurs in our model: the financial development level and skill-biased technological change.

Before proceeding to the model comparative statics under financial frictions, we start with the simplest scenario absent of financial frictions. Let $\phi \to \infty$, and then the labor force division is purely determined by ability h. In the traditional sector, own-account workers earn a homogeneous income without rewards to ability. In the modern sector, workers' wage profile is a linear function of ability, while employers' profits feature increasing marginal returns to ability, which attract the highest-ability agents. As a result, there exist two cutoff values of ability, $\underline{h}^*$ and $\bar{h}^*$: agents with ability below the lower cutoff value $\underline{h}^*$ are own-account self-employed, agents with ability above the higher cutoff value $\bar{h}^*$ become employers, and those in-between become wage workers. This is the first-best allocation of talents across occupations. This labor force division is illustrated in Figure 3. Note that own-account workers and employers earn the lowest and the highest income, respectively, among the three occupations. Thus our model tends to predict a higher variance of the earnings of the self-employed together compared to wage workers, which is consistent with the evidence for Brazil in Allub and Erosa (2019).

In the presence of financial frictions ($\phi < \infty$), one's occupational choice depends on the com-

Figure 3: Labor Force Division with NO Financial Frictions
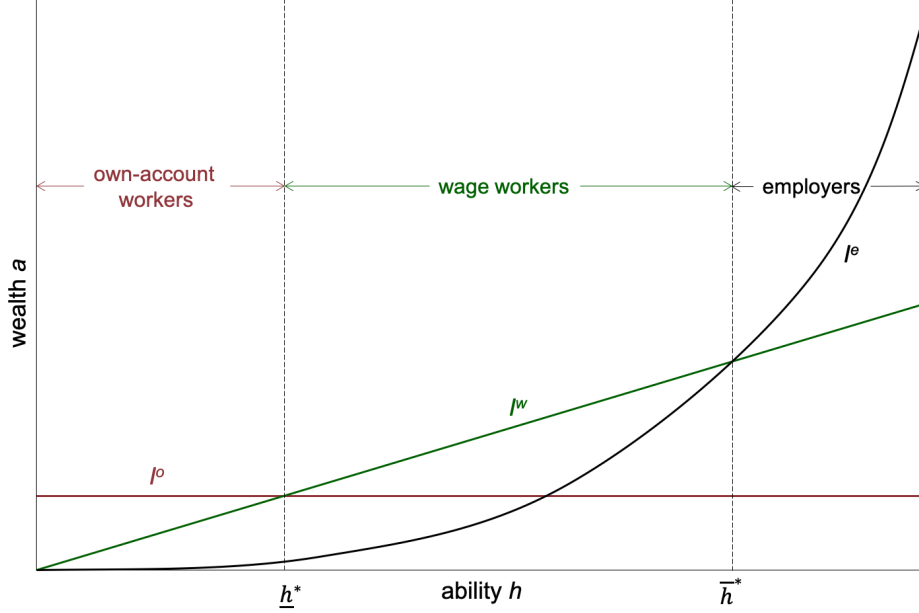
Note: This figure plots the flow income of own-account workers in red, wage workers in green, and employers in black. The dashed lines indicate the two cutoff values of ability in the absence of financial frictions.

bination of asset-holding position and ability. In this case, agents with the lowest abilities are still own-account workers. However, a set of mediocre-ability but high-wealth agents become employers, and a set of high-ability but low-wealth agents are pushed out of entrepreneurship and become wage workers. This labor force allocation creates misallocation of talents in the modern sector.

Panel (a) of Figure 4 illustrates the effect of alleviating financial frictions (an increase in ϕ) on the labor force division. A higher level of financial development allows (potential) employers with binding borrowing constraints to rent more capital and expand (start) their businesses, thus increasing the equilibrium interest rate. Such increase attracts less able but wealthy employers (green area in grids) to drop out from entrepreneurship and switch from renting to lending capitals. Meanwhile, the high-ability but low-wealth agents (green area in ///) start renting capital and operating businesses in the modern sector. This process reduces the misallocation of talents in the modern sector. The new equilibrium set of higher-average ability employers demand more workers, thus increasing the equilibrium wage. As a result, own-account workers enter the modern sector as wage workers (red shaded area). In the aggregate, after an increase in ϕ, the change in employers' labor force share is ambiguous, but the modern sector's output unambiguously increases. Therefore, as the traditional sector shrinks and the more productive modern sector expands, aggregate output grows.

Panel (b) of Figure 4 demonstrates the effect of skill-biased technological change (an in-

Figure 4: Comparative Statics When ϕ or A_M Increases

(a) Relaxing financial constraints

(b) Introducing Skill-biased Technological Change
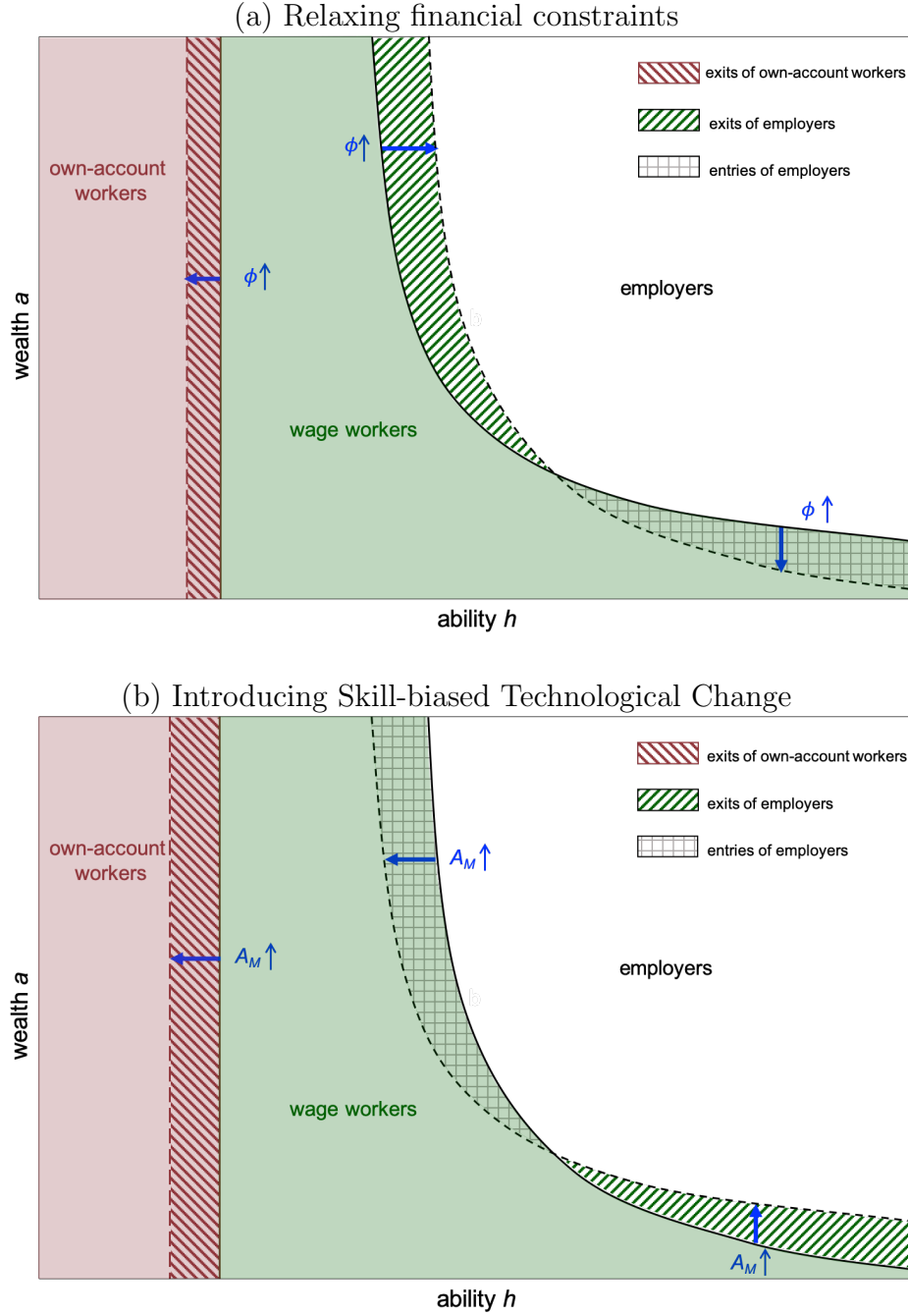
Note: Own-account workers are indicated by the set of the ability and wealth pairing in red, employers are indicated by the top-right area in white, and wage workers constitute the middle area in green.

crease in A_M holding A_T constant) on the labor force division under financial frictions. Higher returns to ability in the modern sector directly increase the equilibrium wage, drawing marginally high-ability own-account workers into the modern sector. Meanwhile, for an

employer, optimal capital input increases, which is analogous to a tighter borrowing constraint. As a result, the poorest former employers (green area in ///) quit despite having high abilities and become wage workers, while the richest former wage workers with relatively high abilities (green area in grids) become employers. In contrast to the previous case of alleviating financial frictions, the process of skill-biased technological change worsens the misallocation of talents in the modern sector. In equilibrium, the labor force share of wage workers increases, while the share of own-account workers declines. Though the change in employers' share is ambiguous, the modern sector's scale expands, and aggregate output increases.

To summarize, in the absence of financial frictions, talents are efficiently allocated across occupations. However, in the presence of financial frictions, higher levels of financial development and modern-sector technological progress have opposite effects on the misallocation of talents in the modern sector. At the same time, they both reduce the traditional sector size and increase aggregate output.

4   Quantitative Analysis

To quantitatively analyze the model, we calibrate the model to match the U.S. economy's key characteristics and the cross-country pattern of own-account employment. We then evaluate the model's predictions of the cross-country labor force and financial development patterns for three scenarios: i) varying both skill-biased technological progress A_M/A_T and financial frictions measured by ϕ, ii) varying only A_M/A_T, and iii) varying only ϕ. Setting the first scenario as a benchmark, we further quantify the aggregate effects of alleviating financial frictions and compare the results with an alternative model with skill-neutral technology progress. In addition, an extension with capital input in the traditional sector shows similar results as the benchmark.

4.1   Parameterization

To estimate the model, we focus on the first scenario that countries differ in both skill-biased technological progress and financial development. For simplicity, the traditional sector productivity A_T is normalized to be 1. The calibration follows two steps. Firstly, we calibrate parameters about technology, ability distribution, and preference to match key U.S. economy moments. The U.S. economy is assumed to be perfect credit with $\phi \to \infty$ (i.e., no financial constraints). Secondly, keeping $\phi \to \infty$, we lower A_M from the U.S. level to solve for poor economies and calibrate the elasticity of substitution between traditional and modern goods.

We begin by directly setting some parameter values following the literature, as in Panel A of Table 3. The period is set to be one year. We choose the coefficient of relative risk aversion $\sigma = 1.5$ and the capital depreciation rate $\delta = 0.06$ as in Buera et al. (2011). The ability h is assumed to follow a log-normal distribution, with a normalized mean of 1.

Table 3: Parameters

Parameter	Description	Value
Panel A: Assigned Parameters		
δ	Depreciation rate	0.06
σ	Risk aversion	1.5
$\mathbb{E}(h)$	Mean of ability	1
A_T	Productivity of traditional sector	1
Panel B: Calibrated Parameters		
A_M^{US}	Productivity of traditional sector	1.6
γ	1−entrepreneur profit share	0.77
α	Labor share	0.56
$Var(h)$	Variance of ability distribution	0.22
λ	1-hazard rate	0.91
θ	Traditional goods share	0.21
β	Discount factor	0.92
ρ	Elasticity of substitution	2.3

Note: This table reports parameter values and interpretations under the benchmark calibration.

We then calibrate the remaining eight parameters jointly to match eight moments in the data. The parameters are: i-iii) technology of the modern sector, A_M^{US}, γ, and α; iv-v) individuals' ability distribution, $Var(h)$ and λ; vi) the share of traditional goods in consumption expenditure, θ; vii) the discount factor $\beta = 0.92$; and viii) the elasticity of substitution between traditional and modern goods, ρ. The calibrated parameters are listed in Panel B of Table 3.

The first seven parameters jointly target key moments of the U.S. economy: i) the share of own-account workers; ii) the share of employers; iii) capital share; iv) GINI index; v) employers' (firms') exit rate; vi) expenditure share of traditional goods; and vii) capital to output ratio. We use the data moments in 2000 or 2001, as the year 2001 covers the most

data sets across all years in our sample. The last parameter, ρ, targets the slope of own-account employment on per-capita income across countries. We report each moment and its model counterpart in Table 4.

Table 4: Targeted Moments

Moments	Model	Data
U.S. own-account labor force share	10%	10%
U.S. employers' labor force share	7.2 %	7.1%
U.S. capital share	0.33	0.33
U.S. GINI index	40	40
U.S. employers' exit rate	8.2%	8.3%
U.S. expenditure share	2.8%	$< 5\%$
U.S. capital to output ratio	3.1	3.0
Slope of own-account employment	-0.21	-0.20

Note: The table reports the moments targeted in the benchmark calibration and the model's predictions for each corresponding moment.

Technology of the modern sector, A_M^{US}, γ, and α. As the productivity of the traditional sector A_T is normalized to 1, the modern sector's productivity A_M^{US} is most informative about the share of own-account workers. Since the U.S. data do not distinguish between own-account workers and employers among self-employed agents, we use high-income countries' data from IPUMS-International and PWT 9.1 as a reference. The top-10 percentile income countries of 246 country-year observations have GDP per capita from \$21,803 to \$50,640, with the mean \$31,694, which is fairly close to \$45,743 of the U.S. level in 2001. Their own-account employment ranges from 6.7% to 24% with the average at 12%. Among these high-income countries, Canada in 2001 might be the most similar economy to the U.S. in 2001, with GDP per capita at \$36,219 and own-account workers' share at 7.9%. We choose $A_M^{US} = 1.6$ to match a fitted value of own-account self-employment at 10%, which is the midpoint between Canada in 2001 and the average of the top 10% income countries in the sample.

The profit share of employers is indicated by $1 - \gamma$ in the production function, which ties closely to the employers' share. We calibrate $\gamma = 0.77$ such that the employers' share is 7.2%, approximately the midpoint between Canada in 2001 (6.5%) and the mean of the top 10% income countries (7.6%). This result is also close to the widely cited 7.6% in Cagetti and De Nardi (2006). Thus, the labor share in the production of modern-sector goods is

determined simultaneously by $\alpha = 0.56$ as we match the capital income share of 0.33, which is the standard value in the literature (see e.g., Allub and Erosa, 2019; Gollin, 2002).

Distribution of ability, $Var(h)$ and λ. The variance of ability distribution mostly targets the GINI index of 40 from the World Bank. The hazard rate, $1 - \lambda$, is mostly related to the firm (employer) exit rate of 8.3%, citing from *Business Dynamics Statistics* (BDS). Our calibrated results show $Var(h) = 0.22$ and $\lambda = 0.91$.

Traditional sector share, θ. The parameter of traditional goods' consumption share in the utility function mostly governs the expenditure share in the traditional sector of the United States. We conjecture it to be smaller than 5% and calibrate θ to be 0.21 accordingly.

Discount factor, β. The discount factor β is mainly chosen to match the capital to output ratio of 3.0 from the PWT 9.1. The calibrated result $\beta = 0.92$ turns out to the same value as used in Buera et al. (2011) and Midrigan and Xu (2014).

Elasticity of Substitution, ρ. It remains to calibrate the elasticity of substitution between traditional and modern sector goods. In the first scenario, where countries differ exogenously in their modern sector productivity, the parameter ρ largely affects the slope of simulated shares of own-account workers against per-capita income. We target the slope coefficient of -0.20 from the country-average regression results in Table 1.

Specifically, given a specific elasticity of substitution, we start with calibrating the first six parameters of the model to the U.S. data by solving one country. Afterward, to match the slope of the own-account employment to GDP per capita, we solve a set of countries in the model with potential values of A_M and a set of financial development levels ranging from perfect credit ($\phi \to \infty$) to financial autarky ($\phi = 1$).[8] We then employ the equilibrium prices P_T and sectoral outputs from each economy to compute the chain-weighted indexes (or chained-dollar indexes) used by the NIPAs and the Bureau of Economic Analysis as in Appendix Section C.[9] All output values are scaled such that the wealthiest economy matches the 2001 U.S. GDP per capita of \$45,743.

Our calibration results, as shown by the solid black line in Figure 5, suggests that ρ is about 2.3, which is similar to the estimates in the literature. Autor et al. (1998) conclude that the substitution elasticity between high and low-skilled labor in the aggregate produc-

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[8]By assumption, poorer countries have both lower A_M and ϕ than richer countries. Specifically, the set of A_M is $\{1.6, 1.3, 1, 0.8, 0.65, 0.5, 0.4, 0.3, 0.22, 0.15, 0.08\}$ and the set of ϕ is $\{\infty, 5, 3, 2.2, 1.9, 1.7, 1.5, 1.37, 1.25, 1.15, 1\}$. By choosing these A_M and ϕ, our model generates the same range of GDP per capita as in the data, and the private debt to GDP ratio decreases almost evenly to 0.

[9]Note that although the absolute value of A_M is smaller than A_T in poor countries, the modern sector can still be more productive than the traditional sector in value terms. This is because the traditional and modern sectors produce different goods, and the relative price of the traditional good, P_T, is around 0.03 in the poorest country in our calibrated model.

Figure 5: Labor Force Shares of Own-Account Workers in Model and Data
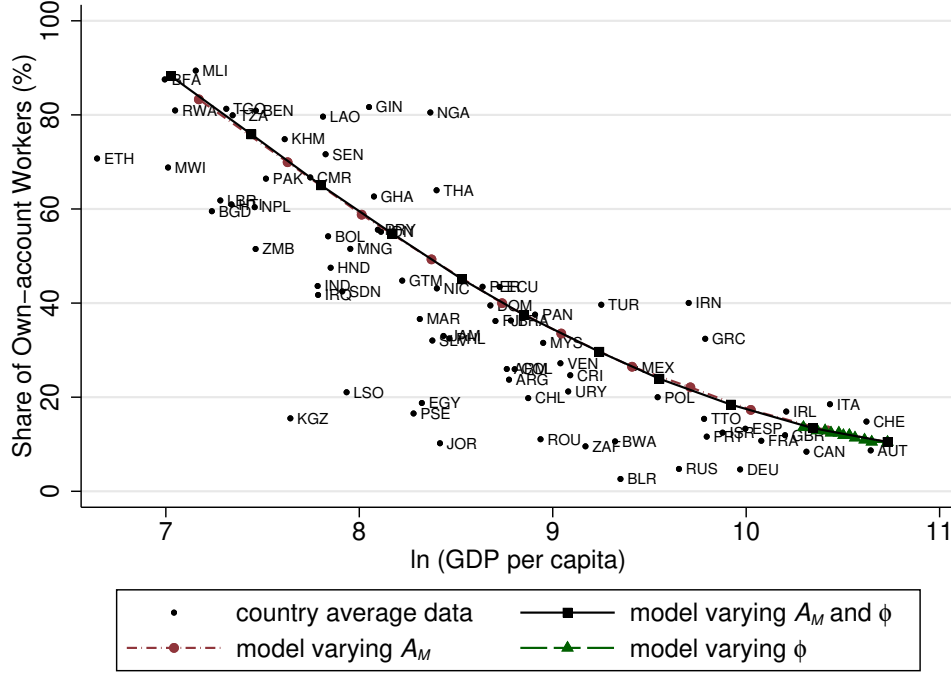
tion function is very unlikely to fall outside 1 and 2. Since unskilled labor correlates with traditional-sector output and skilled labor correlates with modern-sector output, their estimated elasticity is connected to ours. Broda and Weinstein (2006) estimate elasticities of substitution across diverse varieties of goods, finding a median estimate of around 2.2 to 3.7.

Now given the elasticity of substitution at 2.3, we also test the model's predictions in the second and third scenarios: lowering only A_M and lowering only ϕ. The dash-dot red line in Figure 5 illustrates the second scenario's result, where the effect is close to that of the first scenario with a slope coefficient at -0.21. The dashed green line plots the model predictions of the second scenario, which has a slope coefficient of -0.079. Differences in financial development contribute to the decrease of own-account employment against per-capita income, but in a much smaller magnitude than that of skill-biased technological change.

The model predictions of the second and third scenarios validate our calibration strategy of ρ. For the third scenario, the calibrated ρ to match the slope of own-account employment is substantially higher than in the literature. In addition, the calibrated model of the second scenario cannot match the spread in GDP per capita across economies. For the second scenario, the prediction of the own-account employment pattern is fairly close to that of the first scenario, suggesting that the joint effects are dominated by the cross-country skill-biased

20

technological difference A_M.

4.2   Predictions on Not Targeted Moments

We now evaluate our calibrated model's predictions of not-targeted moments. We compare the model's predictions with data for three cross-country patterns: employers' labor force shares, selection on ability into two types of entrepreneurship, and the financial development level measured by the private debt to GDP ratio.

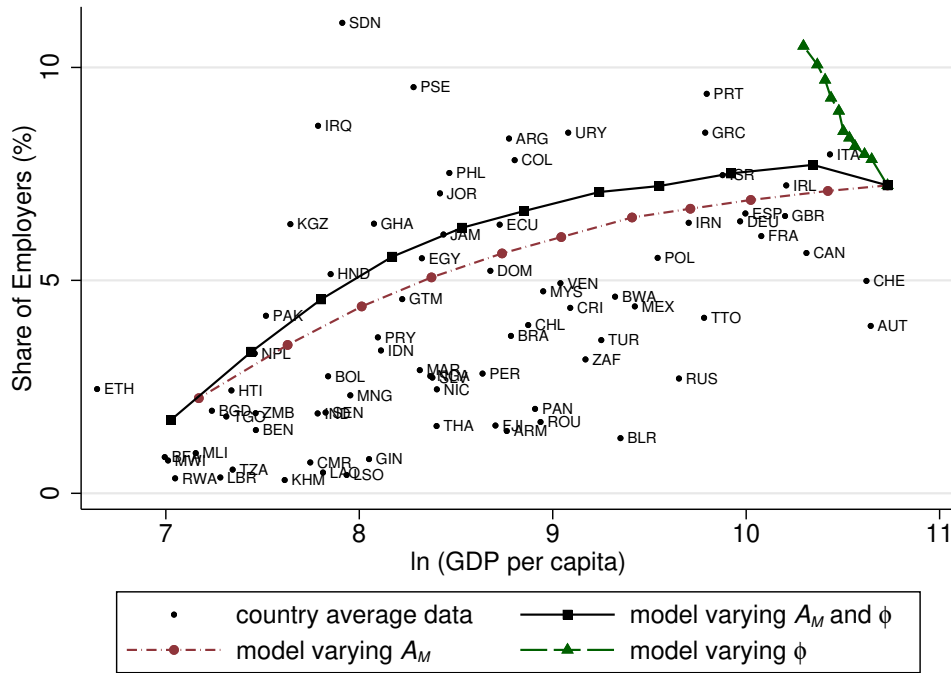Figure 6: Labor Force Shares of Employers in Model and Data

Figure 6 plots employers' labor force shares against per-capita income in the model and data. The dash-dot red line, dashed green line, and solid black line present the model predictions of i) varying both A_M and ϕ, ii) varying only A_M, and iii) varying only ϕ, respectively. As shown by the solid black line of case i), combining two exogenous differences predicts a slope coefficient at 0.015, which is close to the data slope of 0.016 for country-year regressions and 0.014 for country-average regression in Table 1. In case ii), the model predicts a slope of employers' share at 0.013, which is also in the ball park of the slope coefficients in the data. However, the third case of varying only borrowing constraint ϕ leads to a contradicting result: the share of employers decreases against income per capita with a slope coefficient of -0.078. This result closely relates to a model without the traditional sector, where better financial development leads to smaller shares of employers in richer countries, equivalent

21

to larger firm sizes. Nevertheless, this is not the case after considering the cross-country differences in A_M/A_T, or equivalently significant shares of own-account employment in poor countries.

Figure 7: Average Ability of Own-account Workers and Employers in Model
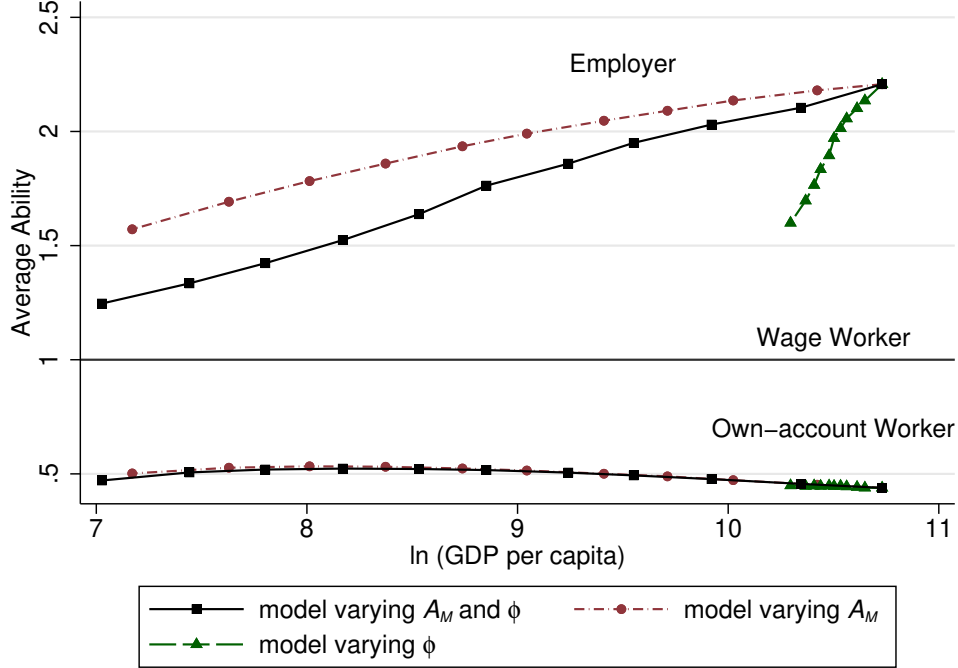
Note: This figure plots the average ability of own-account workers and employers against log GDP per capita in the model. The average ability of wage workers is normalized to 1.

For the model prediction of the selection into two types of entrepreneurship, Figure 7 plots the average ability of own-account workers and employers, normalizing the wage workers' average ability to 1. The employers' average ability is higher than that of the wage workers and increases in income per capita. In contrast, own-account workers' average ability is approximately half of the wage workers'. This prediction is consistent with our empirical findings on positive (negative) selection on ability into employers (own-account workers) in Figure 2.[10]

Regarding the indicator of a country's financial development level, we look at the *private debt to GDP ratio* both in the data and model. Using the Financial Structural Database (Version September 2019), we follow Buera et al. (2011) to calculate the private debt as the summation of private credit by deposit money banks and other financial institutions, private

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[10]Note that our model cannot replicate the decreasing degree of negative selection into own-account workers as income level increases. See the model extension in (Porzio, 2017, pp. 75-79) for a framework that qualitatively matches this feature in the data.

bond market capitalization, and one-third of the stock market capitalization. We then get the private debt to GDP ratio of the U.S. in 2001 at 310%. In the International Monetary Fund (IMF) data, for the U.S. in 2001, the private debt in percent of GDP is 194%.[11] In the model, we define the private debt to GDP ratio as the employers' aggregate debts in percent of the GDP in equilibrium. Our model prediction for the U.S. is 215%, which locates in between the above two ratios.

Figure 8: Private Debt to GDP Ratios in Model and Data
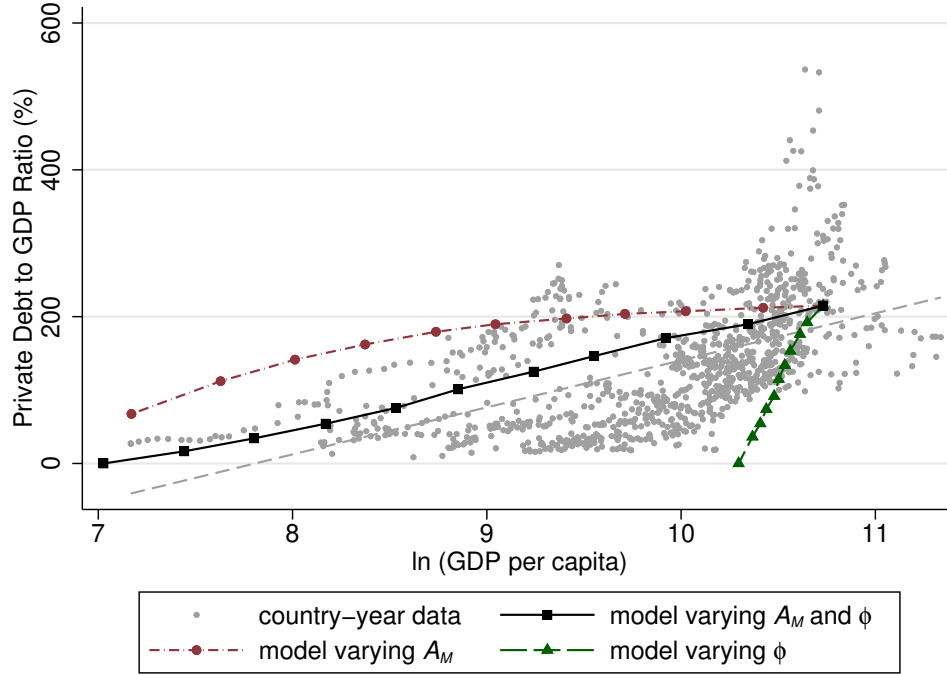
Note: This figure plots the private debt to GDP ratios against log GDP per capita in the data and model. Each grey dot represents one country-year data from *Financial Structural Database: Version June 2017*.

Figure 8 plots the private debt to GDP ratio against income per capita in the model and data. The Financial Structural Database consists of 1,032 country-year observations, and the data slope coefficient of regressing the ratio on GDP per capita is 0.64. Varying ϕ alone with A_M fixed at the U.S. level over-predicts the change of financial development against the income level, with the slope coefficient at 5.3. In particular, the predictions match data from high-income countries better than data from low-income countries. In contrast, the model with varying A_M alone, which presents a slope coefficient of 0.38, over-predicts the private debt to GDP ratio in low- and middle-income countries. Combining the two forces of technological progress and financial development predicts a slope coefficient of 0.60, which

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[11]IMF defines private debt in percent of GDP as the total stock of debt liabilities issued by households and non-financial corporations, including all debt instruments, as a share of GDP.

is the closest to the data.

We conclude that our model featuring cross-country differences in both modern sector technological progress A_M and financial frictions ϕ can account for the relationship between financial development (private debt to GDP ratio) and per-capita income level. Among the two forces, the cross-country pattern of labor force division is mainly driven by the former: skill-biased technological change. Though financial development imposes a contradicting force on the pattern of employers' share against income level, the joint effect is dominated by the effect of skill-biased technological change.[12]

4.3   Effects of Alleviating Financial Frictions Globally

We set the benchmark model as the third scenario above, where countries differ exogenously in both financial development and skill-biased technological progress, as it best matches the key cross-country characteristics. To assess the aggregate impacts of financial frictions, we gradually alleviate the borrowing constraints from the benchmark values to the perfect credit case ($\phi \to \infty$) and compute the changes in employers' share, own-account workers' share, modern-sector TFP, and GDP per capita. Figure 9 plots these changes against GDP per capita for the corresponding benchmark economies. Each line compares the changes in moments between a world with a set of finite ϕ values in poor economies and a world where every economy is free of financial frictions. Vertical lines divide the world into three income groups: low-income, middle-income, and high-income.[13]
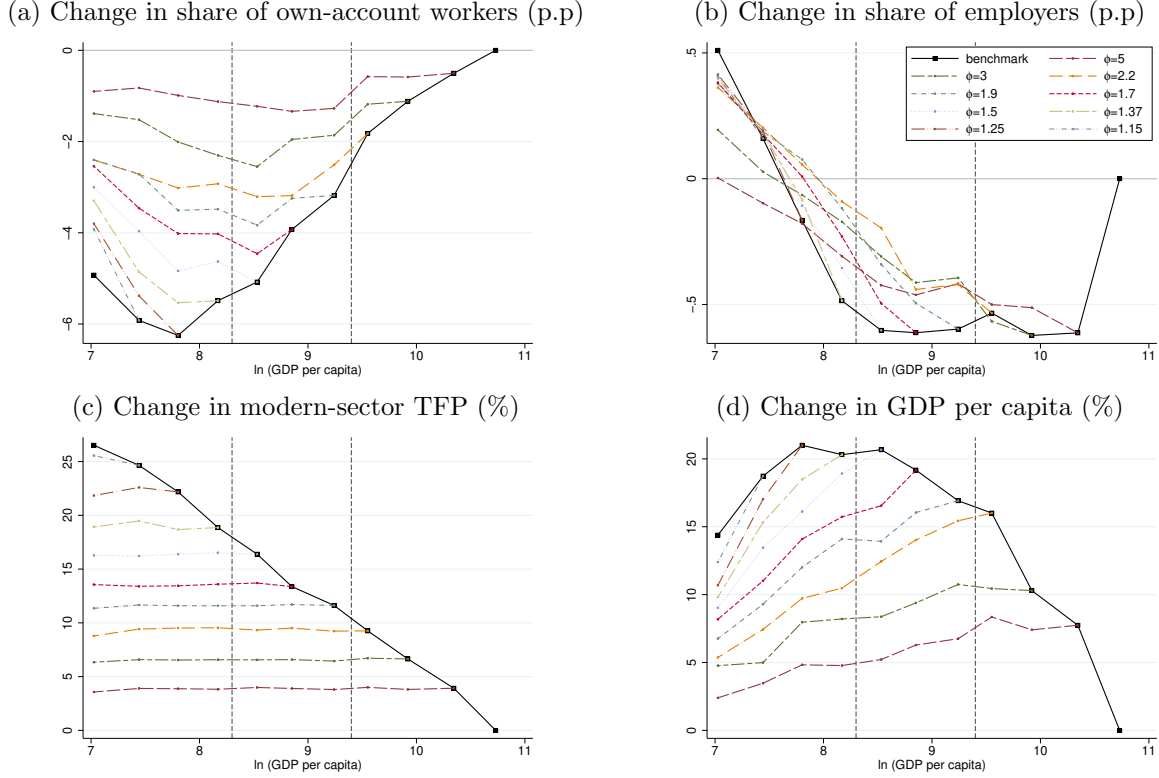
Panel (a) of Figure 9 plots the effect of increasing ϕ on own-account employment. As we discussed for Panel (a) of Figure 4, alleviating borrowing constraints always decreases the traditional sector size at different levels of financial development and modern sector technology. In low-income countries, removing the financial constraints decreases own-account shares by 5.6 percentage points on average; in richer countries, the effect decreases from 5.1 to 0.5 percentage points (solid black line).

Panel (b) of Figure 9 reports the effect of relaxing borrowing constraint ϕ on employers' labor force share, which is ambiguous as discussed for Panel (a) of Figure 4. Removing financial frictions in low-income economies has heterogeneous effects on the shares of employers, which

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[12]Our model also matches the cross-country pattern of the capital to output ratios decently. Using country-year observations after 1960 in PWT 9.1, the regression of capital to output ratios against log GDP per capita yields a slope coefficient of 0.51, while our model predictions are 0.60, 0.56, and 0.61 in the three scenarios, respectively.

[13]The intervals for low- (bottom third of the world's income distribution), middle- (middle third), and high-income (top third) countries are $\leq \$3,980$, between $\$3,980$ and $\$12,450$, and $\geq \$12,450$ based on country-average GDP per capita from 1960 to 2017 for all countries in the PWT 9.1. These thresholds are close to the thresholds for lower middle-, upper-middle- and high-income countries from the World Bank.

Figure 9: Effects of Removing Financial Frictions

(a) Change in share of own-account workers (p.p)

(b) Change in share of employers (p.p)

(c) Change in modern-sector TFP (%)

(d) Change in GDP per capita (%)

Note: This figure plots the aggregate impacts of financial frictions on labor shares, modern-sector TFP and GDP per capita. The solid black lines indicate the effects of removing financial friction from benchmark economies, and other lines are the changes from fixed ϕ to frictionless. The x-axis is the per-capita income level of the benchmark economies. The y-axes in the top panels are percentage point changes and those in the bottom panels are percentage changes. Vertical lines separate the three terciles of the world income distribution.

ranges from 0.5 to -0.5 percentage points. In contrast, the changes in employers' shares are negative in middle- and high-income countries, with an average of -0.60 percentage points. Upon alleviating financial frictions, some high-ability but low-wealth former wage workers can start operating businesses, whereas some low-ability but high-wealth former employers are forced out due to increasing equilibrium prices. The latter effect of exits dominates in middle- and high-income countries, while the former effect of new entries dominates in the poorest economies.

The impact on modern-sector TFP is plotted in Panel (c) of Figure 9.[14] Removing financial constraints always increases modern-sector TFP. The impact's magnitude is monotonically decreasing with income levels. For the poorest country, modern-sector TFP increases by more than 25%. This equilibrium effect combines two forces. At the intensive margin, the incum-

[14]Appendix Section D presents the definition of the modern-sector TFP.

bent employers who were financially constrained can now rent more capital and produce more efficiently. At the extensive margin, some low-ability high-wealth former employers exit, and some high-ability low-wealth former wage workers enter to become employers, increasing employers' average ability. Both forces contribute to the increase in modern-sector TFP. In addition, when we control for the change in ϕ of each step, the changes in modern-sector TFP are similar across income per capita.

Finally, Panel (d) of Figure 9 shows the effect of reducing financial frictions on GDP per capita. In low-income countries, the average aggregate gain of removing financial frictions is approximately 18%; in middle- to high-income countries, the gains decrease with income per capita. There are two contributing factors: the decline in the employment share of the traditional sector (Panel a) and the efficiency improvement in the modern sector (Panel c). In low-income countries, the first force dominates as the modern sector only accounts for a very small or moderate part of the aggregate economy. Therefore, the pattern of GDP per capita gains resembles that of changes in own-account employment in those countries. In middle- and high-income countries, two effects contribute more equally. In addition, rather than completely removing the borrowing constraint (solid black line), we relax it by a small step, and the gains are substantial as well (dashed lines). In particular, for the poorest economy in financial autarky, GDP per capita increases by 2.0% when the borrowing constraint ϕ is relaxed to 1.15.

In our model, removing financial constraints significantly increases modern-sector TFP and aggregate GDP per capita, especially in poor countries, resulting from the reallocation of talents across two sectors and within the modern sector.

4.4   Alternative Model with Skill-neutral Technological Progress

Our benchmark analysis presented in the previous section emphasizes skill-biased technological change (i.e., varying the relative technology A_M/A_T across countries). We now compare how the impacts of financial frictions differ in an alternative model without skill-biased technological change. To solve the world with skill-neutral technological progress across countries, we fix A_M/A_T at the U.S. level and use the same values for the other parameters as in the benchmark model. By construction, this alternative model matches the targeted aggregate moments in the U.S. In addition, by lowering both A_M and A_T proportionally, the model generates a similar range of income levels as in the benchmark. Nevertheless, it fails to match the cross-country pattern of labor force division. The predicted own-account employment in the poorest country is only 29%, which is much lower than around 80% in the data. Meanwhile, the model predicts that employers' share weakly decreases from 9% to

7% with development, which is incorrect qualitatively and quantitatively.[15]

Figure 10: Removing Financial Frictions in Model with Skill-neutral Technological Progress

(a) Change in modern-sector TFP (%)

(b) Change in GDP per capita (%)
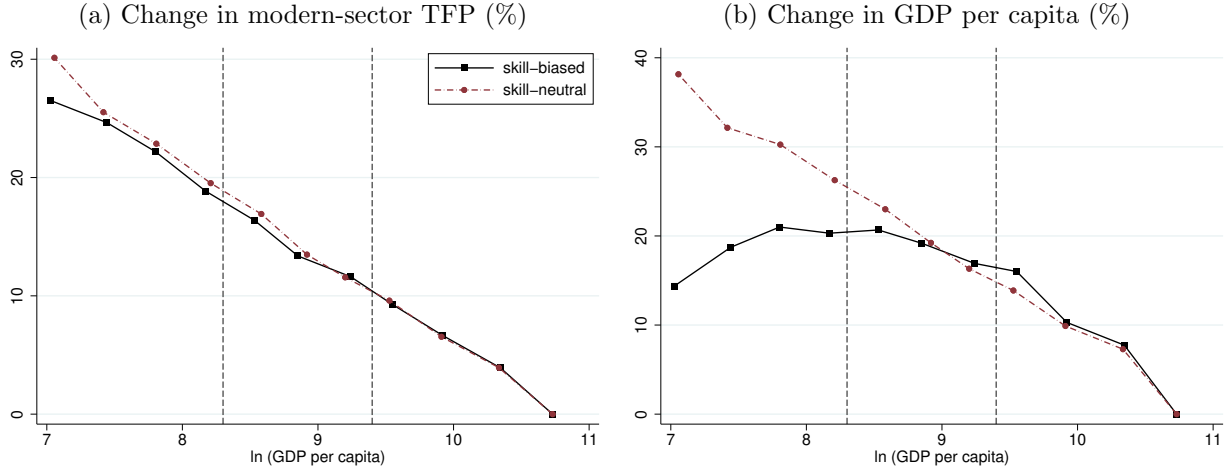
Note: This figure plots the comparison of the aggregate impacts of financial frictions in the benchmark model and in a model with skill-neutral technological progress. The x-axes are the per capita income levels of the benchmark economies and the y-axes represent the percentage change. Vertical lines separate the three terciles of the world income distribution.

To hypothetically remove the financial frictions, we change the borrowing constraints from benchmark values to infinity. We then compare the resulting effects on modern-sector TFP and GDP per capita between models with skill-biased and skill-neutral technological progress in Figure 10. Panel (a) shows almost identical effects of removing financial frictions on modern-sector TFP in the two models: modern-sector TFP increases by 20-30% in the poorest countries, and the gains decrease gradually. This result is consistent with our previous finding that modern-sector TFP is mainly affected by borrowing constraints. For the change in GDP per capita (Panel b), middle- and high-income countries have similar patterns in two models. However, in low-income countries, the alternative model with skill-neutral technological progress predicts that gains in GDP per capita decrease from 38% to 26% as income per capita increases. In contrast, our benchmark model with skill-biased technological progress predicts a weakly increasing gain, averaged at 19%. For the poorest economy with a GDP per capita of around $1,000, the model with skill-neutral technological progress generates over two times the increase in GDP per capita than that of the model with skill-biased technological progress.

Why does the alternative model over-predict gains of GDP per capita in low-income coun-

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[15]In the benchmark model, the calibrated set of parameter values correctly predicts both the slopes of own-account and employers' shares. However, with skill-neutral technological progress, the model predicts that own-account workers' and employers' labor shares move in the same direction with development due to relaxed financial constraints, which contradicts the data.

tries? When financial frictions are removed, the changes of modern-sector TFP are generally close in the two models. However, the model with skill-neutral technological progress predicts an unrealistically large scale of the modern sector. Consequently, the aggregate gains from the modern sector are overestimated compared to the model with skill-biased technological progress. We conclude that the underestimation of own-account employment in poor countries exaggerates the impacts of financial frictions in a world with skill-neutral technological progress to a great extent.

5   Policy Implications

In this section, we discuss the effects of removing financial frictions in a developing country, which relate to the microfinance projects. For this purpose, we add capital inputs, as well as financial frictions, to the production function of traditional sector goods. We further assume an own-account worker with asset a is subject to the same financial constraints as in the modern sector. Hence, the own-account worker's income is given by

$$I^o(h, a) = \max_{k>0} \quad p_T A_T k^\eta - (r + \delta)k$$

$$s.t. \qquad k \leq \phi a$$

We choose the capital share in the traditional sector η to be 0.1 as suggested in Gollin et al. (2007). Although our traditional-sector technology that exists in all industries is not the same as the agricultural technology that uses capital inputs in Gollin et al. (2007), they relate to each other. Due to the absence of more direct evidence, we set $\eta = 0.1$. Hence, we implicitly assume non-agricultural traditional-sector production activities, e.g., making handmade straw hats at home and providing shoe-shining on the streets, have the same capital share as growing agricultural crops on backyard farms.[16]

To validate the extended model, we repeat the steps in Section 4.1 and re-calibrate the model to match the U.S. moments and the slope of own-account share against log GDP per capita. The new calibration chooses modern-sector productivity $A_M^{US} = 1.3$ and the elasticity $\rho = 2.5$, while all other parameters have the same values as in the benchmark model. Overall, this extended model properly matches the cross-country labor shares of employers and private debt to GDP pattern. [17]

We now proceed to evaluate the effects of removing financial frictions in India, a developing

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[16]We conduct a robustness check with $\eta = 1/3$ in Appendix Section E and find similar results.

[17]Regressing model predicted own-account workers' shares, employers' shares, and private debt to GDP ratios on log GDP per capita yield slope coefficients of -0.22, 0.014, and 0.59, respectively.

Table 5: India Moments and Parameters

Moments	Data	Model	Parameters
Own-account labor force share	43%	43%	$A_M^{IND} = 0.3$
Employers' labor force share	2.1%	2.3%	$\gamma = 0.87$
GINI index	32	34	$Var(h) = 0.1$
Employers' exit rate	4.7%	4.7%	$\lambda = 0.93$
Capital to output ratio	1.9	1.8	$\beta = 0.89$
Private debt to GDP ratio	0.31	0.31	$\phi = 1.21$

Note: The table reports the moments targeted in the calibration of India and the model's prediction and parameter value for each corresponding moment.

country that has been well-known in microfinance programs. For more country-specific evaluations, we deviate from the previous assumptions that countries only differ in A_M and ϕ and allow cross-country heterogeneity in other aspects. Specifically, we keep the same preference across countries such that $\rho = 2.5$ and $\theta = 0.21$. We then calibrate all other parameters to the Indian moments averaged across 1990s, a period before the springing up of large-scale microfinance programs.

Table 5 reports the six targeted moments, model predictions, and the corresponding parameters. We first choose the productivity $A_M^{IND} = 0.3$ and the span-of-control parameter $\gamma = 0.87$ to match the labor force shares of own-account workers and employers at 43% and 2.1%, respectively, which are averages of the 1993 and 1999 moments using IPUMS-International data. Then $\alpha = 0.62$ is simultaneously determined by $(1 - \alpha)\gamma = \frac{1}{3}$ such that the capital income share with perfect credit markets is about 0.28, which is close to the target of 0.3 in ?. Secondly, for the distribution of ability, the variance $Var(h) = 0.1$ mainly targets the GINI index of 32 in 1994 from the World Bank. We conjecture the employers' exit rate to be close to the establishment exit rate at 4.7% as in ?, which leads to $\lambda = 0.93$. Thirdly, the discount factor $\beta = 0.89$ is mostly informative about the capital to output ratio, which is 1.9 in PWT 9.1. Finally, $\phi = 1.21$ is primarily calibrated to match the private debt to GDP ratio of 0.31 as in the Financial Structure Database (Version September 2019).

To evaluate the effects of removing financial frictions, we then conduct similar exercises to Section 4.3. Table 6 reports the impacts of removing financial frictions in the traditional sector ($\phi_T \rightarrow \infty$), the modern sector ($\phi_M \rightarrow \infty$), and both sectors ($\phi_T, \phi_M \rightarrow \infty$). In

Table 6: Effects of Removing Financial Frictions in India

Experiment	$\phi_T \to \infty$	$\phi_M \to \infty$	$\phi_T, \phi_M \to \infty$
Own-account workers' share (p.p.)	2.6	-6.2	-6.0
Employers' share (p.p.)	-0.28	0.35	0.35
Traditional-sector capital usage (%)	172	-7	19
Modern-sector capital usage (%)	-17	31	29
Traditional-sector TFP (%)	1.1	0.91	1.1
Modern-sector TFP (%)	4.4	20	20
GDP per capita (%)	1.5	21	21

Note: The table reports the aggregate impacts of removing financial frictions in India for the traditional sector, the modern sector, and both sectors. GDP per capita in India is about $1,565, which is the average across 1990s in PWT 9.1.

the first counterfactual experiment that removes financial frictions in the traditional sector, own-account workers' shares increase whereas employers' shares decrease, leading to a *bigger* share of self-employed workers in the aggregate. Moreover, while the relaxed financial constraints results in almost tripled capital input, the traditional-sector TFP, defined as in Appendix Section D, increases by only 1.1%. Meanwhile, the modern-sector TFP increases while capital usage decreases. This is because the poorest and least-able wage workers and employers now move to the traditional sector and rent capital for production. As a result, the aggregate output increases by only 1.5 percent due to a bigger unproductive traditional sector. The second counterfactual experiment only removes financial frictions in the modern sector. In contrast, labor share of employers increases whereas own-account workers decrease, leading to a *smaller* share of self-employed workers in the aggregate, which means firms are on average becoming more efficient and larger. Driven by a bigger and significantly more efficient modern-sector, GDP per capita increases by 20.8 percent. In the third counterfactual experiment that removes financial frictions in both sectors simultaneously, magnitudes of the aggregate impacts closely assemble the second experiment, with a slightly larger GDP per capita gain of 21.1 percent. Note this magnitude is also similar to the effect of removing financial frictions in a developing country in the benchmark model.

In summary, if one only removes the financial frictions in the traditional sector, the gains are very moderate due to relatively low demands for capital in the traditional sector. Thus,

it is not surprising that studies of microcredit programs find a pattern of modestly positive but neither transformative nor persistent effects of expanded access to microcredit on the profits of small businesses (Angelucci et al., 2015; Attanasio et al., 2015; Augsburg et al., 2015; Banerjee et al., 2015b; Crépon et al., 2015; Tarozzi et al., 2015).

6   Conclusions

It is well-known that the entrepreneurship rate declines with GDP per capita. However, not all entrepreneurs are created equal. When dividing entrepreneurs into employers and own-account workers, we draw on household surveys in countries from all income levels to show that employers' labor share increases with income levels, whereas the share of own-account workers decreases. We also show nearly universal negative selection on ability into own-account status and positive selection into employer and wage-earning statuses. We conclude that the impacts of selection and economic growth work differently on own-account workers and employers. This finding highlights the importance of distinguishing between these two types of entrepreneurship rather than grouping them as "self-employed", especially when implementing microfinance projects and evaluating their aggregate impacts.

The empirical finding that own-account workers are negatively selected on education relate them to the "entrepreneurs out of necessity" as in the Global Entrepreneurship Monitor. By definition, necessity entrepreneurs become self-employed because they "have no better choices for work". Although they expect their businesses to grow less, they are likely to stay in the market (Poschke, 2013b). Hence, it is doubtful that substantial employers can be fostered by encouraging necessity micro-businesses operated by negatively selected agents. This view is also consistent with findings in Herreño and Ocampo (2021) that self-employment grants lower TFP in a model features the subsistence concerns of poor individuals by incorporating unemployment risks.

Based on these facts, we build a model featuring a traditional own-account employment sector and a modern sector with financial frictions. In the modern sector, employers hire wage workers to produce under financial constraints, and the output depends on ability. Countries differ exogenously in their modern-sector productivity and financial development levels. All countries have access to a traditional sector in which the own-account self-employed workers produce on their own, and ability plays no role in the output. As such, our model features skill-biased technological differences across countries, as emphasized by, for example, Caselli and Coleman (2006) and Feng et al. (2020). Workers are heterogeneous in both ability and wealth endowment, and they sort into the three occupations. As the productivity of the modern sector rises, progressively more own-account workers sort into the modern sector.

31

Thus, the own-account employment share falls, whereas employers' labor share rises. Our quantitative analysis shows that, in poor countries, the output gain from removing financial frictions is overestimated by about twice in an alternative model that fails to account for the large share of own-account workers.

References

ALLUB, L. AND A. EROSA (2019): "Financial frictions, occupational choice and economic inequality," *Journal of Monetary Economics*, 107, 63–76.

ALLUB, L., P. GOMES, AND Z. KUEHN (2020): "Human capital and financial development: Firm-level interactions and macroeconomic implications," *Working Paper*.

ANGELUCCI, M., D. KARLAN, AND J. ZINMAN (2015): "Microcredit Impacts: Evidence from a Randomized Microcredit Program Placement Experiment by Compartamos Banco," *American Economic Journal: Applied Economics*, 7, 151–182.

ATTANASIO, O., B. AUGSBURG, R. D. HAAS, E. FITZSIMONS, AND H. HARMGART (2015): "The Impacts of Microfinance: Evidence from Joint-Liability Lending in Mongolia," *American Economic Journal: Applied Economics*, 7, 90–122.

AUGSBURG, B., R. D. HAAS, H. HARMGART, AND C. MEGHIR (2015): "The Impacts of Microcredit: Evidence from Bosnia and Herzegovina," *American Economic Journal: Applied Economics*, 7, 183–203.

AUTOR, D., L. KATZ, AND A. KRUEGER (1998): "Computing Inequality: Have Computers Changed the Labor Market?" *The Quartely Journal of Economics*, 113, 1169–1214.

BANERJEE, A., E. BREZA, E. DUFLO, AND C. KINNAN (2015a): "Do credit constraints limit entrepreneurship? Heterogeneity in the returns to microfinance," Working Paper, Northwestern.

BANERJEE, A., E. DUFLO, R. GLENNERSTER, AND C. KINNAN (2015b): "The Miracle of Microfinance? Evidence from a Randomized Evaluation," *American Economic Journal: Applied Economics*, 7, 22–53.

BECK, T., A. DEMIRGUC-KUNT, AND R. LEVINE (2000): "A New Database on Financial Development and Structure," *World Bank Economic Review*, 14, 597–605.

——— (2009): "Financial Institutions and Markets Across Countries and over Time: Data and Analysis," *World Bank Policy Research Working Paper 4943*.

BRIDGMAN, B., G. DUERNECKER, AND B. HERRENDORF (2018): "Structural Transformation, Marketization, and Household Production around the World," *Journal of Development Economics*, 133, 102–126.

BRODA, C. AND D. E. WEINSTEIN (2006): "Globalization and the Gains from Variety," *The Quarterly Journal of Economics*, 121, 541–585.

BUERA, F. J., J. P. KABOSKI, AND Y. SHIN (2011): "Finance and Development: A Tale of Two Sectors," *The American Economic Review*, 101, 1964–2002.

——— (2015): "Entrepreneurship and Financial Frictions: A Macrodevelopment Perspective," *Annual Review of Economics*, 7, 409–436.

——— (2021): "The macroeconomics of microfinance," *The Review of Economic Studies*, 88, 126–161.

CAGETTI, M. AND M. DE NARDI (2006): "Entrepreneurship, Frictions, and Wealth," *Journal of Political Economy*, 114, 835–870.

CASELLI, F. AND W. J. COLEMAN (2006): "The World Technology Frontier," *The American Economic Review*, 96, 499–522.

CIHAK, M., A. DEMIRGUC-KUNT, E. FEYEN, AND R. LEVINE (2012): "Benchmarking Financial Development Around the World," *World Bank Policy Research Working Paper*, 6175.

CRÉPON, B., F. DEVOTO, E. DUFLO, AND W. PARIENTÉ (2015): "Estimating the Impact of Microcredit on Those Who Take It Up: Evidence from a Randomized Experiment in Morocco," *American Economic Journal: Applied Economics*, 7, 123–150.

FEENSTRA, R. C., R. INKLAAR, AND M. P. TIMMER (2015): "The Next Generation of the Penn World Table," *American Economic Review*, 105, 3150–3182.

FENG, Y., D. LAGAKOS, AND J. E. RAUCH (2020): "Unemployment and development," Unpublished Working Paper, University of California San Diego.

GOLLIN, D. (2002): "Getting Income Shares Right," *Journal of Political Economy*, 110, 458–474.

——— (2008): "Nobody's business but my own: Self-employment and small enterprise in economic development," *Journal of Monetary Economics*, 55, 219–233.

GOLLIN, D., S. L. PARENTE, AND R. ROGERSON (2007): "The food problem and the evolution of international income levels," *Journal of Monetary Economics*, 54, 1230–1255.
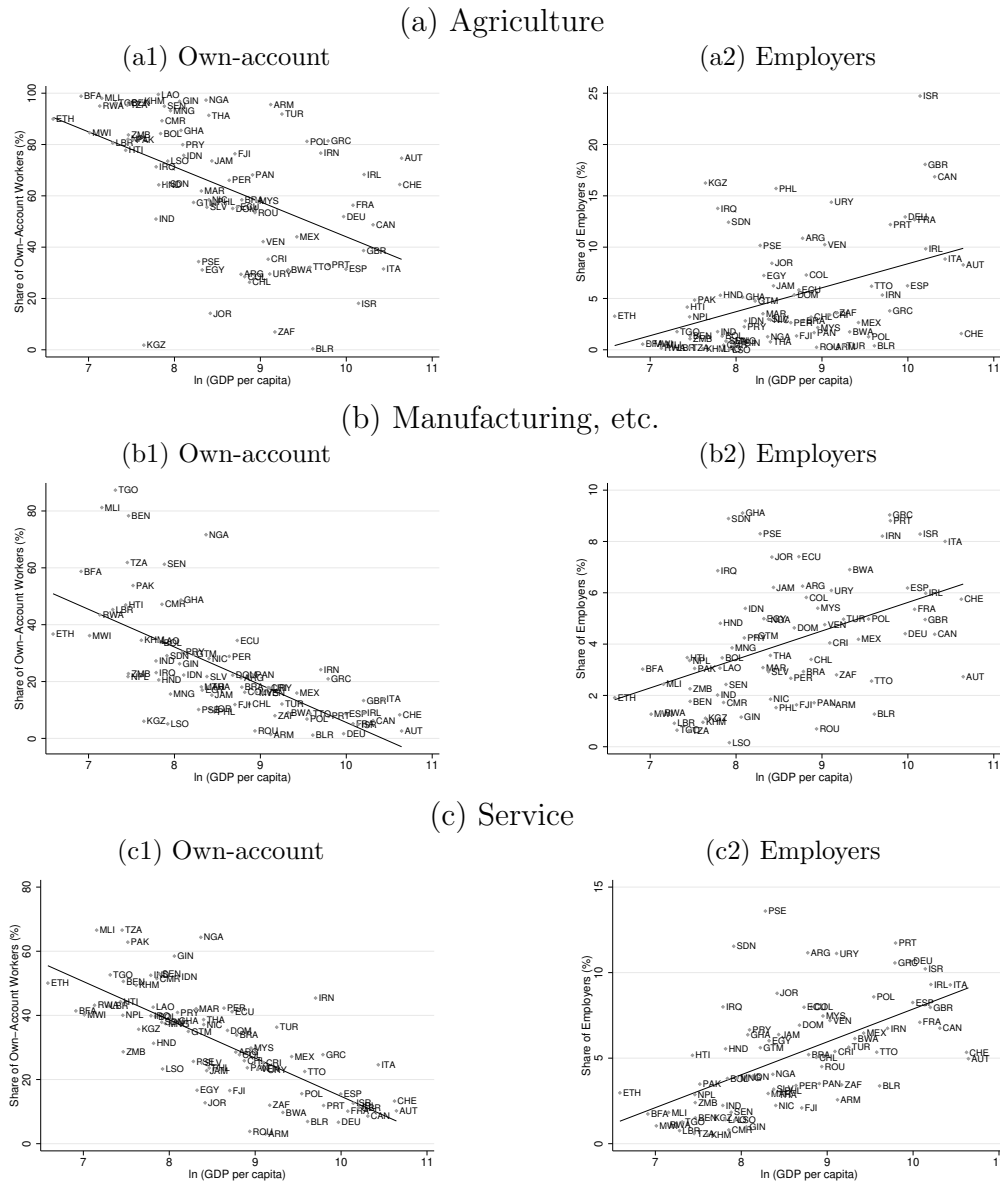
Gu, J. (2021): "Financial Intermediation and Occupational Choice," *Journal of Economic Dynamics and Control*, 133, 104238.

Herreño, J. and S. Ocampo (2021): "Self-Employment and Development," Unpublished working Paper.

Hjort, J. and J. Poulsen (2019): "The Arrival of Fast Internet and Employment in Africa," *American Economic Review*, 109, 1032–1079.

International Labour Office (1993): "Resolution Concerning the International Classification of Status in Employment," 15th International Conference of Labour Statisticians.

——— (2018): "Resolution Concerning Statistics on Work Relationships," Geneva: 20th International Conference of Labour Statisticians.

La Porta, R. and A. Shleifer (2014): "Informality and Development," *Journal of Economic Perspectives*, 28, 109–26.

Lagakos, D. and M. E. Waugh (2013): "Selection, Agriculture, and Cross-Country Productivity Differences," *The American Economic Review*, 103, 948–980.

Landefeld, S., B. R. Moulton, and C. M. Vojtech (2003): "Chained-Dollar Indexes: Issues, Tips on Their Use, and Upcoming Changes," *Survey of Current Business*, 8–16.

Levine, R. and Y. Rubinstein (2013): "Smart and Illicit: Who Becomes an Entrepreneur and Do They Earn More?" Working Paper 19276, National Bureau of Economic Research.

Malmberg, H. (2020): "Skill Bias and Development – Evidence from Trade and Industry Data," Unpublished working Paper.

Midrigan, V. and D. Y. Xu (2014): "Finance and Misallocation: Evidence from Plant-Level Data," *American Economic Review*, 104, 422–458.

Minnesota Population Center (2019): *Integrated Public Use Microdata Series, International: Version 7.2 [dataset]*, Minneapolis, MN: IPUMS, 2019.

Moll, B. (2014): "Productivity Losses from Financial Frictions: Can Self-Financing Undo Capital Misallocation?" *American Economic Review*, 104, 3186–3221.

Ngai, R. L. and C. A. Pissarides (2008): "Trends in Hours and Economic Growth," *Review of Economic Dynamics*, 11, 239–56.

Porzio, T. (2017): "Cross-country differences in the optimal allocation of talent and technology," .

PORZIO, T., F. ROSSI, AND G. SANTANGELO (2020): "The Human Side of Structural Transformation," Unpublished Working Paper.

POSCHKE, M. (2013a): "Who becomes an entrepreneur? Labor market prospects and occupational choice," *Journal of Economic Dynamics and Control*, 37, 693–710.

——— (2013b): "'Entrepreneurs out of necessity': a snapshot," *Applied Economics Letters*, 20, 658–663.

——— (2018): "The Firm Size Distribution across Countries and Skill-Biased Change in Entrepreneurial Technology," *American Economic Journal: Macroeconomics*, 10, 1–41.

——— (2019): "Wage employment, unemployment and self-employment across countries," Working Paper.

RESTUCCIA, D., D. T. YANG, AND X. ZHU (2008): "Agriculture and aggregate productivity: A quantitative cross-country analysis," *Journal of monetary economics*, 55, 234–250.

ROSENZWEIG, M. R. (1995): "Why Are There Returns to Schooling?" *American Economic Review*, 85, 153–158.

ROY, A. D. (1951): "Some Thoughts on the Distribution of Earnings," *Oxford Economic Papers*, 3, 135–46.

RUGGLES, S., S. FLOOD, R. GOEKEN, J. GROVER, E. MEYER, J. PACAS, AND M. SOBEK (2019): *IPUMS USA: Version 10.0 [dataset]*, Minneapolis, MN: IPUMS, 2020.

TAROZZI, A., J. DESAI, AND K. JOHNSON (2015): "The Impacts of Microcredit: Evidence from Ethiopia," *American Economic Journal: Applied Economics*, 7, 54–89.

YAO, W. AND X. ZHU (2020): "Structural Change and Aggregate Employment Fluctuations in China," *International Economic Review, forthcoming*.

Appendices

A Additional Figures and Tables

Figure A1: Labor Shares of Own-account Workers and Employers, by Sector

(a) Agriculture

(a1) Own-account   (a2) Employers

(b) Manufacturing, etc.

(b1) Own-account   (b2) Employers

(c) Service

(c1) Own-account   (c2) Employers

Note: This figure plots the sectoral average labor shares of own-account workers and employers for prime-aged male workers in one country across all available years.

36

Figure A2: Selection on Secondary School Completion into Own-account
Workers/Employers
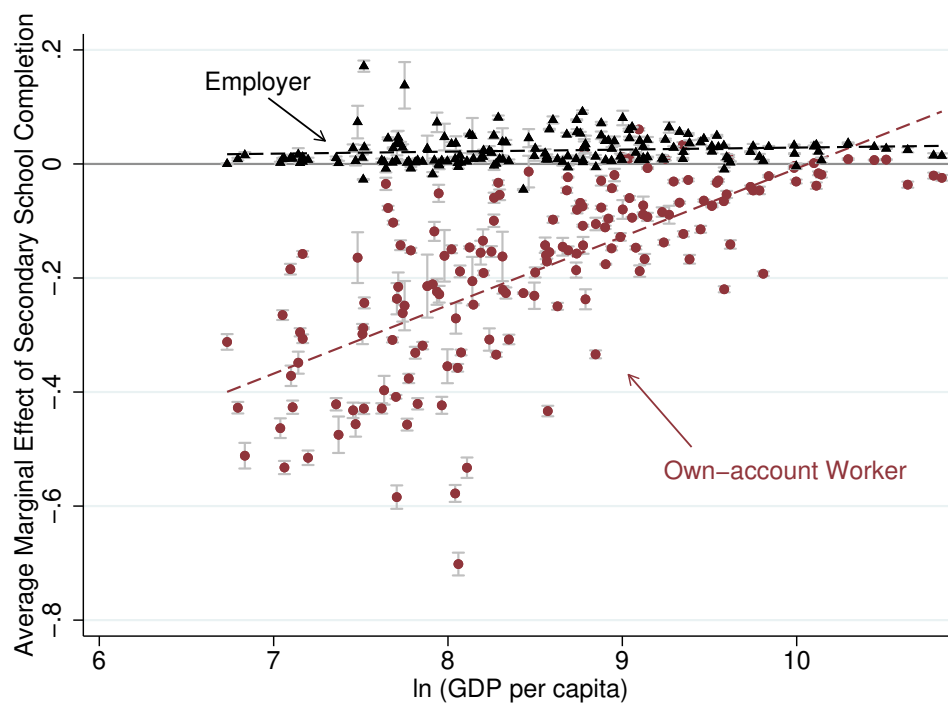
Note: This figure plots the average marginal effects of secondary school completion on prime-aged male
workers' occupational choices of being own-account workers and employers in each country-year survey.

Table A1: Occupation Categorization

Own-account worker	Wage worker	Employer	Unpaid family worker
Working on own account			
Own account, agriculture			
Domestic worker, self-employed			
Subsistence worker, own consumption			
Own account, other			
Own account, without temporary/unpaid help	Wage/salary worker	Employer	Unpaid family worker
Own account, with temporary/unpaid help			
Member of cooperative			
Sharecropper			
Sharecropper, self-employed			
Sharecropper, employed			
Kibbutz member			
Self-employed, not specified			

Note: Our benchmark empirical analysis excludes the unpaid family workers as in Poschke (2019). All our results still hold when we include them.

B Evidence from U.S. Data over Time

Do the cross-country patterns of occupational choices still hold if we look at one country that achieves substantial development over decades? In this section, we draw U.S. data from 1970 to 2017 to answer this question. The data sets are from the *Integrated Public Use Microdata Series, USA: Version 10.0* (IPUMS-USA). Specifically, data sets before 2000 are drawn from the federal state censuses, while yearly data sets from 2001 to 2017 are from the American Community Survey (ACS). In the U.S. surveys, which do not include a variable to distinguish between own-account workers and employers, we have to divide the labor force into *incorporated self-employed, unincorporated self-employed*, and *wage workers*. We regard the incorporated self-employed workers as the counterpart of employers in our analysis in Section 2.2 and 2.3 and the unincorporated self-employed as similar to own-account workers. This categorization is the same as in Levine and Rubinstein (2013), where they propose to use the "self-employed incorporated" as the empirical proxy for the "good entrepreneur" and study the selection into incorporated and unincorporated self-employed agents using the U.S. data.

Table A2: Labor Force Division and Selection of the U.S. Time Series

Panel A: Labor Shares (%)				
	Unincorporated	Difference to 1970	Incorporated	Difference to 1970
1970	9.6		2.1	
1980	9.1	-0.55***	3.3	1.2***
1990	8.3	-1.4***	3.7	1.6***
2000	7.5	-2.2***	4.2	2.1***
2001-2017	7.1	-2.5***	4.3	2.2***
Panel B: Average Marginal Effects of *Years of Schooling*				
	Unincorporated		Incorporated	
1970	0.0015***		0.0028***	
1980	0.0011***		0.0044***	
1990	0.00010***		0.0037***	
2000	-0.0014***		0.0036***	
2001-2017	-0.0037***		0.0037***	

Note: Panel A reports labor shares of unincorporated (incorporated) business owners in the first (third) column and the t-test results of its difference to the 1970 level in the second (fourth) column. Panel B reports the average effect of one more schooling year on becoming unincorporated and incorporated business owners, respectively. We pool data from 2001 to 2017 to estimate the last rows in both Panel A and Panel B. *** indicates statistical significance at the 1-percent level.

The first column in Panel A of Table A2 shows the labor shares of unincorporated business

Figure A3: Share of Self-employment in the U.S.

(a) Unincorporated
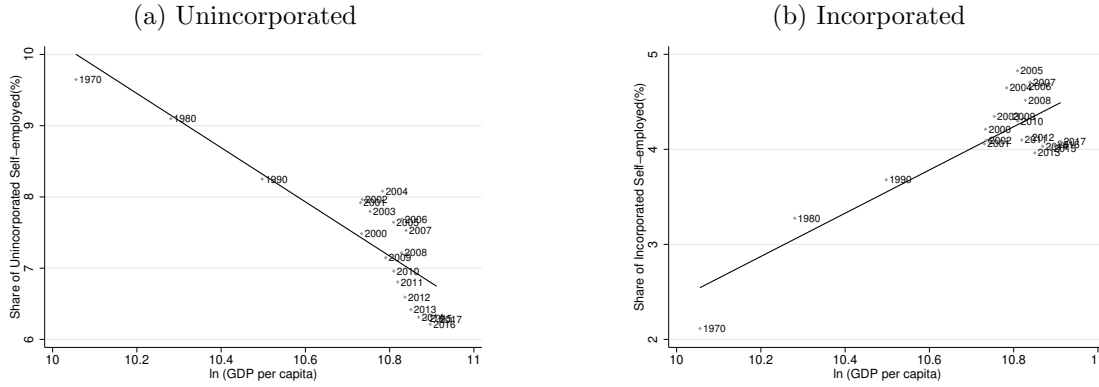
(b) Incorporated

Note: This figure plots the labor shares of unincorporated and incorporated self-employment, respectively, for prime-aged male workers across years in the U.S.

owners in the United States from 1970 to 2017. In the past half-century, the unincorporated self-employment share in the United States monotonically decreases from 9.6% to 7.1%. The second column reports the difference in the unincorporated self-employment share between the level of a recent year and 1970, which is always significantly negative and accumulates to a decrease of 2.5 percentage points on average since the 21st century. The third column in Panel A of Table A2 reports the shares of incorporated self-employed over time in the United States, which increases from 2.1% to 4.3%. The fourth column reports the difference in the unincorporated self-employment share between a recent year and the level in 1970, which increases monotonically over time. Figure A3 plots the detailed labor shares in each year, which echo the contrasting patterns of own-account workers' share and employers' share in our cross-country analysis.

Figure A4: Selection on Education into Unincorporated/Incorporated

(a) Years of Schooling

(b) Secondary School Completion
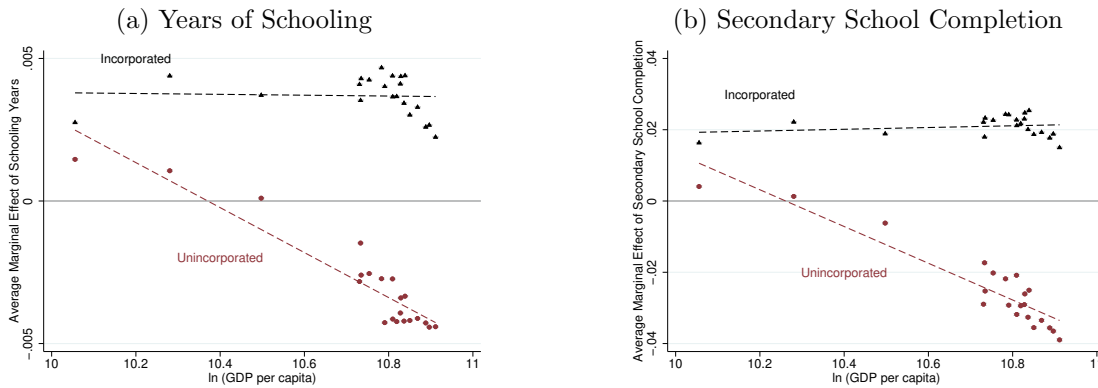
Note: Panel (a) and (b) of this figure plots the average marginal effects of years of schooling and secondary school completion, respectively, on prime-aged male workers' occupational choices of being unincorporated and incorporated business owners across years in the U.S.

40

To study the selection on education into unincorporated and incorporated self-employed, we again use the multinomial probit model to estimate the average marginal effects of schooling years, controlling for age, age squared, and native-born. Panel B of Table A2 shows that one more year of schooling increases the probability of becoming incorporated self-employed by 0.0036 on average. Meanwhile, the effect of education on becoming unincorporated self-employed is significantly negative since 2000, though it was significantly positive with a small magnitude before 2000. Panel (a) of Figure A4 presents the same results in a graphic format. Alternatively, Panel (b) of Figure A4 uses "secondary school completion" as the measure of education and shows similar results.

C Model-generated GDP per capita Across Countries

In the quantitative analysis, we calculate the model-generated cross-country GDP per capita using chained-dollar indexes following Landefeld et al. (2003) as the price of the traditional-sector goods varies greatly.

Model-generated countries are sorted by technology in the modern sector A_M, financial frictions ϕ, or A_M and ϕ together under the assumption that countries with higher A_M also feature higher ϕ. The GDP per capita ratio between two neighboring countries $i+1$ and i is defined as a Fisher quantity index

$$\frac{GDPPC^{i+1}}{GDPPC^i} = \sqrt{L^{i+1,i} \times P^{i+1,i}},$$

$$\text{where} \quad L^{i+1,i} = \frac{P_T^i \times Y_T^{i+1} + Y_M^{i+1}}{P_T^i \times Y_T^i + Y_M^i},$$

$$P^{i+1,i} = \frac{P_T^{i+1} \times Y_T^{i+1} + Y_M^{i+1}}{P_T^{i+1} \times Y_T^i + Y_M^i}.$$

$L^{i+1,i}$ is the Laspeyres quantity index that uses low-income country i's price P_T^i to value high- and low-income country's output, $P^{i+1,i}$ is the Passche quantity index that uses high-income country $i+1$'s price P_T^{i+1}, and Y_T^i (Y_T^{i+1}) and Y_M^i (Y_M^{i+1}) are the aggregate output of traditional- and modern-sector goods in country i ($i+1$), respectively.

D Total Factor Productivity Definition

We follow **?** to calculation of the Total Factor Productivity (TFP).

In the modern sector, for an employer indexed by ability h and wealth a, the optimal labor

input in terms the capital input $k(h, a)$ is

$$l(h, a) = \left[\alpha \gamma A_M h w^{-1} k(h, a)^{(1-\alpha)\gamma} \right]^{\frac{1}{1-\alpha\gamma}}.$$

We define the aggregate total labor input N as the summation of the aggregate labor input L plus the aggregate unweighted entrepreneurial input E that

$$N = L + E$$

$$\text{where} \quad L = \left(\alpha \gamma A_M h w^{-1} \right)^{\frac{1}{1-\alpha\gamma}} \int_{\{(h,a)|j(h,a)=e\}} [hk(h,a)]^{\frac{1}{1-\alpha\gamma}} G(dh, da),$$

$$E = \int_{\{(h,a)|j(h,a)=e\}} G(dh, da).$$

The share of capital employed by one entrepreneur of given ability and wealth is defined as $\kappa(h, a) = k(h, a)/K$. Then the aggregate modern-sector output can be written as:

$$Y_M = \int_{\{(h,a)|j(h,a)=e\}} A_M h^{\alpha\gamma} k^{(1-\alpha)\gamma} G(dh, da)$$

$$= \frac{L^{\alpha\gamma} A_M}{N^{1-(1-\alpha)\gamma}} \left[\int_{\{(h,a)|j(h,a)=e\}} h^{\frac{1}{1-\alpha\gamma}} \kappa(h,a)^{\frac{(1-\alpha)\gamma}{1-\alpha\gamma}} G(dh, da) \right]^{1-\alpha\gamma} K^{(1-\alpha)\gamma} N^{1-(1-\alpha)\gamma}.$$

Therefore, the aggregate modern-sector TFP is

$$TFP_M \equiv \frac{Y}{K^{(1-\alpha)\gamma} N^{1-(1-\alpha)\gamma}} = \frac{L^{\alpha\gamma} A_M}{N^{1-(1-\alpha)\gamma}} \left[\int_{\{(h,a)|j(h,a)=e\}} h^{\frac{1}{1-\alpha\gamma}} \kappa(h,a)^{\frac{(1-\alpha)\gamma}{1-\alpha\gamma}} G(dh, da) \right]^{1-\alpha\gamma}.$$

In the extended model, own-account workers in the traditional sector also rent capital to produce.

The aggregate labor input N_T is solely from own-account workers themselves that

$$N_T = \int_{\{(h,a)|j(h,a)=o\}} G(dh, da).$$

We define the share of capital employed by one own-account worker of given ability and wealth as $\kappa_T(h, a) = k_T(h, a)/K_T$. Then, the aggregate output can be rewritten as

$$Y_T = \int_{\{(h,a)|j(h,a)=o\}} A_T k_T(h, a)^\eta G(dh, da)$$

$$= A_T K_T^\eta \int_{\{(h,a)|j(h,a)=o\}} \kappa_T(h, a)^\eta G(dh, da)$$

The aggregate traditional-sector TFP is defined as the output net of capital and broad labor inputs raised to their respective income elasticities η and $1 - \eta$ that

$$TFP_T = \frac{Y_T}{K_T^{\eta} N_T^{1-\eta}} = \frac{A_T \int_{\{(h,a)|j(h,a)=o\}} \kappa_T(h,a)^{\eta} G(dh, da)}{N_T^{1-\eta}}.$$

In the economy without traditional-sector financial frictions $\phi_T \to \infty$, $\kappa_T(h,a) \equiv \frac{1}{N_T}$ such that $TFP_T = 1$.

E Robustness Check on Traditional-sector Capital Share

In Section 5, we set the traditional-sector capital share η to be 0.1. We now conduct a robustness check with $\eta = 1/3$, the theoretical upper-bound that equals to the modern-sector capital income share with perfect credit markets.

<div align="center">

Table A3: India Moments and Parameters with $\eta = 1/3$

Moments	Data	Model	Parameters
Own-account labor force share	43%	43%	$A_M^{IND} = 0.17$
Employers' labor force share	2.1%	2.0%	$\gamma = 0.875$
GINI index	32	31	$Var(h) = 0.1$
Employers' exit rate	4.7%	4.6%	$\lambda = 0.945$
Capital to output ratio	1.9	1.9	$\beta = 0.88$
Private debt to GDP ratio	0.31	0.31	$\phi = 1.21$

</div>

Note: The table reports the moments targeted in the calibration of India and the model's prediction and parameter value for each corresponding moment.

The calibration following Section 4.1 results in the modern-sector productivity $A_M^{US} = 1$ and the elasticity $\rho = 2.9$, which predicts slope coefficients of own-account employment, employers' shares, and private debt to GDP ratios against log GDP per capita to be -0.20, 0.0077, and 0.58, respectively. We then keep the same preference across countries and calibrate all other parameters to the India as in Section 5. The model decently matches India moments in 1990s as showed in Table A3.

With the new set of parameters in the forth column of Table A3, we further evaluate the

Table A4: Effects of Removing Financial Frictions in India with $\eta = 1/3$

Experiment	$\phi_T \to \infty$	$\phi_M \to \infty$	$\phi_T, \phi_M \to \infty$
Own-account workers' share (p.p.)	4.4	-3.4	-2.5
Employers' share (p.p.)	-0.27	0.23	0.23
Traditional-sector capital usage (%)	43	-11	13
Modern-sector capital usage (%)	-20	38	25
Traditional-sector TFP (%)	2.8	2.4	2.8
Modern-sector TFP (%)	2.9	11	11
GDP per capita (%)	3.1	16	16

Note: The table reports the aggregate impacts of removing financial frictions in India for the traditional sector, the modern sector, and both sectors. GDP per capita in India is about $1,565, which is the average across 1990s in PWT 9.1.

effects of removing financial frictions and report the results in Table A4. Due to the higher capital share, the effects of only removing traditional-sector financial frictions are larger than that in Table 6: the traditional-sector TFP increases by 2.8% and leads to 3.1% increase in GDP per capita, which is more than doubled compared to the result with $\eta = 0.1$. However, only removing financial frictions in the modern sector yields more significant gain in GDP per capita at 16%. This difference in output gain is mainly driven by the assumption that only the modern sector rewards ability such that the reduced misallocation of talent results in 11% increase in the modern-sector TFP. Overall, our conclusion in Section 5 still holds that alleviating financial constraints for own-account workers only generate modest aggregate gain.