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Digital adoption, automation, and labor markets in developing countries☆

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ABSTRACT

We study how digital adoption by firms—a precursor to automation—shapes the labor market structure and worker outcomes in developing countries. Using a large sample of developing countries, we document a strong and negative link between firm digital adoption and self-employment rates. This relationship persists even after controlling for the level of development and other factors associated with the distinct employment structure of developing countries. In contrast, there is no link between digital adoption and unemployment rates. We develop a model with equilibrium unemployment, self-employment, endogenous firm entry, and information-and-communications technology (ICT) adoption, and show that positive linkages between the cost of technology adoption (and therefore technology adoption itself) and salaried-firm entry costs are crucial for rationalizing the empirical relationship between firm digital adoption and self-employment.

1. Introduction

How does digital adoption by firms, which can be a precursor to automation, affect worker outcomes and the labor market structure in developing countries? Is greater firm digital adoption associated with salaried job losses, greater search for self-employment opportunities, and greater unemployment or, instead, with increased salaried-firm entry and job creation? We address these questions empirically and through the lens of a quantitative framework.[1]

Using a large sample of developing countries, we document that firm digital adoption is strongly and negatively related to self-employment rates. Critically, this relationship persists after controlling for differences in the level of economic development, the sectoral composition of employment, and other factors associated with the incidence of self-employment. At the same time, we find no apparent link between firm digital adoption and unemployment rates. Several competing mechanisms can shape the relationship between firm digital adoption and labor market outcomes. For example, greater firm digital adoption can incentivize firms to replace salaried jobs with capital, leading to lower job creation, greater self-employment as individuals strive to find alternatives to salaried jobs, and potentially higher unemployment. Conversely, greater digital adoption can improve access to streamlined (digital) procedures and services that facilitate market access and reduce firms' effective barriers to entry or, alternatively, it can enhance the

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[1] Digital adoption refers to the adoption of information and communication technologies (ICT) and can take several different forms, such as the introduction of electronic devices (computers, smartphones, etc.) into the workplace and the adoption of software and other hardware that may facilitate and/or replace certain tasks previously done manually. In this paper, we use the terms digital adoption and technology adoption interchangeably.

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benefits of information-and-communications-technologies (ICT)-labor complementarities and boost expected profits. Qualitatively, these last two channels foster salaried-firm entry and, as firms create more jobs, can trigger a reallocation of individuals away from self-employment and into salaried employment. However, whether greater digital adoption has non-trivial quantitative implications for self-employment and unemployment depends crucially on the strength of these mechanisms as well as on the household- and firm-side factors that shape the labor reallocation process.

To parse out the quantitative relevance of these mechanisms, we build a framework with equilibrium unemployment and salaried-firm creation where households make salaried and self-employment participation decisions and salaried firms make technology adoption decisions. In this environment, salaried firms with low productivity upon entry produce using salaried labor, whereas firms with high-enough productivity upon entry incur a fixed cost of technology adoption and access a production technology that combines ICT capital and salaried labor. This framework delivers an endogenous share of firm digital adoption that is influenced, among other things, by both firm-entry costs and the cost of ICT adoption.

Our quantitative analysis delivers two main messages. The first message is that greater firm digital adoption must also bring about lower firm-entry costs in order to quantitatively rationalize the strong negative relationship between firm digital adoption and self-employment rates in the data. In particular, lower ICT adoption costs or greater ICT-labor complementarities alone—two factors that also lead to greater firm digital adoption—generate negligible reductions in self-employment absent concomitant reductions in firm-entry costs. We interpret these findings as reflecting the fact that initiatives behind the adoption of ICT by firms and governments have simultaneously led to improvements in the basic conditions that support salaried-firm creation—reliable infrastructure, access to more streamlined regulations and to credit, etc.—and ultimately to lower effective barriers to firm entry (examples of these initiatives include digital-payment, -form-filing, and e-governance systems that reduce red tape, or mobile banking and digital platforms that facilitate access to markets). The second message from our analysis is that the muted response of unemployment to greater firm digital adoption is primarily shaped by the ease with which individuals can enter self-employment—a reflection of underlying barriers to self-employment entry—with barriers to salaried-firm entry playing a much more muted role.

Our focus on self-employment and unemployment as summary measures of worker outcomes in developing countries stems from two reasons. First, self-employment—comprised primarily of individuals running owner-only firms that engage in little innovation—is a defining feature of the labor market structure of these economies. It is also an important outside option to salaried employment amid limited salaried-firm and -job creation and the absence of formal safety nets. Indeed, average self-employment rates in developing countries hover around 45 percent of the labor force (vs. 15 percent in advanced economies), with rates being as high as 85 percent in some economies. Second, recent studies suggest that more than 60 percent of jobs in developing countries are susceptible to automation (World Bank, 2016; Schlogl and Sumner, 2018). As such, understanding the link between digital adoption, job loss, and unemployment is particularly important, all the more so since digital adoption is positively correlated with the level of economic development and the latter is associated with higher average unemployment rates (World Bank, 2016; Feng et al., 2020). In the absence of direct and comparable measures of job loss across developing countries, we adopt the unemployment rate as a simple (albeit imperfect) indicator of job loss.

To understand the strong negative link between digital adoption and self-employment rates, consider a scenario where a reduction in the cost of ICT adoption, which all else equal increases firm digital adoption, lowers the cost of salaried-firm creation as well—that is, greater digital adoption is associated with lower barriers to entry. The increase in new salaried-firm entry alongside lower ICT adoption costs expands the total number of salaried firms and also increases the share of firms that use the ICT production technology. As a result, ICT capital demand increases, which bolsters job creation and triggers a large reallocation of workers from self-employment into salaried employment. This reallocation generates a large reduction in self-employment.

In contrast, an increase in digital adoption that is not accompanied by lower barriers to firm entry—that is, the cost of ICT adoption or any other factor that expands digital adoption is orthogonal to firm-entry costs—fails to generate sizable reductions in self-employment rates. The reason is simple: absent changes in salaried-firm entry costs, the base that ultimately supports salaried employment in the economy—the number of salaried firms—remains largely unchanged, with ICT capital and not employment being the main adjustment factor to reductions in ICT adoption costs. More broadly, this result implies that reducing the cost of ICT adoption alone, which is primarily reflected in greater ICT capital usage, does not generate large-enough quantitative changes in firms' incentives to enter, thereby limiting the quantitative expansion in job creation. Instead, reductions in initial entry barriers—which are influenced by digital adoption—are pivotal for increasing salaried job creation and attracting enough workers from self-employment. However, the link between firm digital adoption and entry barriers appears to play little role in shaping unemployment. Indeed, our analysis shows that regardless of whether greater digital adoption is rooted in lower ICT adoption costs alone—implying negligible reductions in self-employment—or in reductions in the cost of ICT adoption that also bring firm-entry costs down—implying large, empirically-consistent reductions in self-employment—the change in unemployment is muted.

To better understand the disconnect between firm digital adoption and the unemployment rate, note that both job creation by salaried firms (labor demand) and participation decisions by households (labor supply) shape the reallocation process from self-employment into salaried employment amid greater digital adoption. In particular, the ease with which individuals can enter self-employment—a reflection of underlying barriers to self-employment entry—directly influences households' decisions over their members' search for salaried employment. Intuitively, a very high probability of entering self-employment (which reflects very low barriers to entry) makes households more prone to sending individuals to search for salaried employment in response to an increase in salaried labor demand induced by greater firm digital adoption. Given the expansion in salaried-job vacancies, unemployment can increase if the increase in the number of searchers for salaried-employment positions is bigger than the decline in the number searchers for self-employment. In our disciplined quantitative analysis, however, the magnitude of reallocation of household members towards search for salaried work is commensurate with the reduction in search for self-employment, leading to negligible changes in unemployment that are consistent with the data. We contribute to the existing literature by characterizing the link between firm digital adoption (and, by implication, susceptibility to automation) and labor markets, with a focus on unemployment and the distinct labor market structure of developing countries.

The nascent empirical literature on digital adoption and routinization, automation, and labor markets centers primarily on the U.S. and other advanced economies, with a focus on the labor share as well as the skill distribution of employment and earnings. Morin (2016), Cortes et al. (2017), Eden and Gaggl (2018), Berg et al. (2018), Schlogl and Sumner (2018), Acemoglu and Restrepo (2018), and Leduc and Liu (2019), among others, provide theoretical underpinnings that complement this literature.[2] Empirical and theoretical work on digital adoption, automation, and labor markets in developing countries is considerably more limited.

Indeed, World Bank (2016) present stylized facts on digital adoption across developing countries but abstract from characterizing labor market outcomes. Das and Hilgenstock (2018) study the link between labor market polarization and exposure to routinization in 85 economies, pointing to the increasing rate at which developing countries are exposed to routinization, while Maloney and Molina (2016) study the potential for labor polarization in developing countries with a focus on automation and outsourcing.[3] However, these studies are silent about the consequences of these changes for unemployment and the employment structure in these economies. As part of our work, we provide a theoretical framework that allows us to identify the most relevant factors shaping the relationships between firm digital adoption, self-employment, and unemployment in developing countries. Our findings highlight the critical link between digital adoption and barriers to firm entry and the relative effective costs of labor reallocation on the household side for a better quantitative understanding of these relationships. More broadly, our work complements Feng et al. (2020), who document that greater economic development is associated with greater unemployment rates, by highlighting the role of households' search behavior across employment categories in shaping unemployment amid greater firm digital adoption.

The rest of the paper is structured as follows. Section 2 presents key stylized facts on digital adoption, and labor market outcomes in developing countries. Section 3 describes the model. Section 4 presents our quantitative findings and dissects the model mechanisms behind our results. Section 5 concludes.

2. Stylized facts

The World Bank's Digital Adoption Index The World Bank's World Development Report 2016 provides indices of digital adoption for business, government, and individuals that are readily comparable across 180 economies for years 2014 and 2016. Given our objective, we focus exclusively on the Business Digital Adoption Index (BDAI), or digital adoption by firms. This index takes values on the 0–1 scale and is constructed for each economy using 4 summary indicators: the number of secure servers, the speed at which files are downloaded, 3G coverage, and the share of firms with websites. While this index is not comprehensive with regards to the types of digital technologies firms can adopt, a clear advantage of the BDAI is that it offers a comparable measure of firm digital adoption for virtually all developing countries.[4]

We note that the BDAI is strongly and positively associated with the Government Digital Adoption Index (correlation of 0.56, significant at the 1 percent level), and that this last index is negatively associated with firm-creation costs (correlation of −0.39, significant at the 1 percent level; as shown below, the BDAI is also negatively associated with firm-creation costs). These two facts suggest that government digital adoption may positively interact with firm digital adoption and hence play a role in lowering barriers to firm entry as well (for example, the introduction of digital-payment and digital-form-filing systems by governments would reduce firms' effective costs of registration and regulatory compliance if firms have access to digital technologies).

Digital Adoption, Firm Creation Costs and Firm Creation, and Labor Market Outcomes in Developing Countries Fig. 1 uses data for 2016 (the latest year the BDAI is available) for a large sample of developing countries and plots the BDAI against the following variables: (1) the cost of creating a business (expressed as a share of income per capita) (upper left quadrant); (2) new firm density (a proxy for new salaried firm creation) (upper right quadrant); (3) the self-employment rate (lower left quadrant); and (4) the unemployment rate (lower right quadrant) (Appendix A.1 lists the developing countries in our sample).

Fig. 1 graphically summarizes the following facts:

1. A strong negative and significant relationship between digital adoption by firms and the cost of creating firms
2. A strong positive and significant relationship between digital adoption by firms and new (salaried) firm density
3. A strong negative and significant relationship between digital adoption by firms and the self-employment rate
4. A mild positive but statistically-weak relationship between digital adoption by firms and the unemployment rate

Previous work shows that firm digital adoption is strongly and positively associated with real GDP per capita (World Bank, 2016). Furthermore, it is well-known that the level of economic development is strongly and negatively associated with self-employment rates (see, for example, Poschke, 2019). To highlight the significance of the link between firm digital adoption and self-employment rates, Table 1 presents results from a simple analysis of the link between firm digital adoption and self-employment rates controlling for other factors that are plausibly associated with differences in self-employment rates across countries.

Table 1 confirms that the negative relationship between firm digital adoption and self-employment rates remains strongly significant even after controlling for real GDP per capita, the industrial employment share of total employment, the services employment share, different measures of labor market regulations (the ratio of the minimum wage to value added per worker and the number of weeks of severance payments), and tertiary school enrollment (a proxy for education) (similar results hold if we also control for the share of total employment in agriculture instead of the shares of industrial or services employment, or if we consider data on firm digital adoption for year 2014; see Table A1 in the Appendix).

For completeness, Table 2 presents an analogous analysis to the one in Table 1 looking at firm digital adoption and unemployment rates and confirms the results that were graphically apparent in Fig. 1. Finally, to further support our focus on developing countries and their

[2] Acemoglu and Restrepo (2017) focus on industrial robot usage and labor markets; Eden and Gaggl (2018) study the evolution of ICT capital goods and the labor share; Fossen and Sorgner (2018) establish a link between digital adoption and employment and entrepreneurship in the U.S.; and Jaimovich and Siu (2019) analyze the role of automation on polarization and U.S. jobless recoveries. Finally, Martinez (2019) presents a model where automation technology at the firm level shapes the substitution between inputs, the labor share, and aggregate productivity. See OECD (2016a, 2016b, 2016c) for recent studies highlighting the potential importance of digital adoption and automation technologies for labor markets in advanced economies.

[3] Bergoeing et al. (2016) use a model of technology adoption where barriers to the creation of new projects and the destruction of stagnant ones play a non-negligible role in explaining differences in the level of development between the U.S. and developing countries. Papers on technology adoption and diffusion across countries include Comin and Hobijn (2004, 2010), Comin et al. (2013), and Comin and Mestieri (2018) (for related work, see Autor and Salomons, 2018, and the references therein). These papers abstract from labor market considerations.

[4] Das and Hilgenstock (2018) construct a measure of routine task intensity (RTI)—a proxy that provides information on exposure to routinization and therefore susceptibility to automation—that covers a non-trivial number of developing countries. Appendix A.3 shows that the RTI measure and the BDAI are strongly related. While the RTI measure may be more precise in capturing susceptibility to automation, it only covers 57 developing countries whereas the BDAI covers more than 100 developing countries. We note that the facts we present below remain unchanged if we use RTI as a measure of susceptibility to automation.

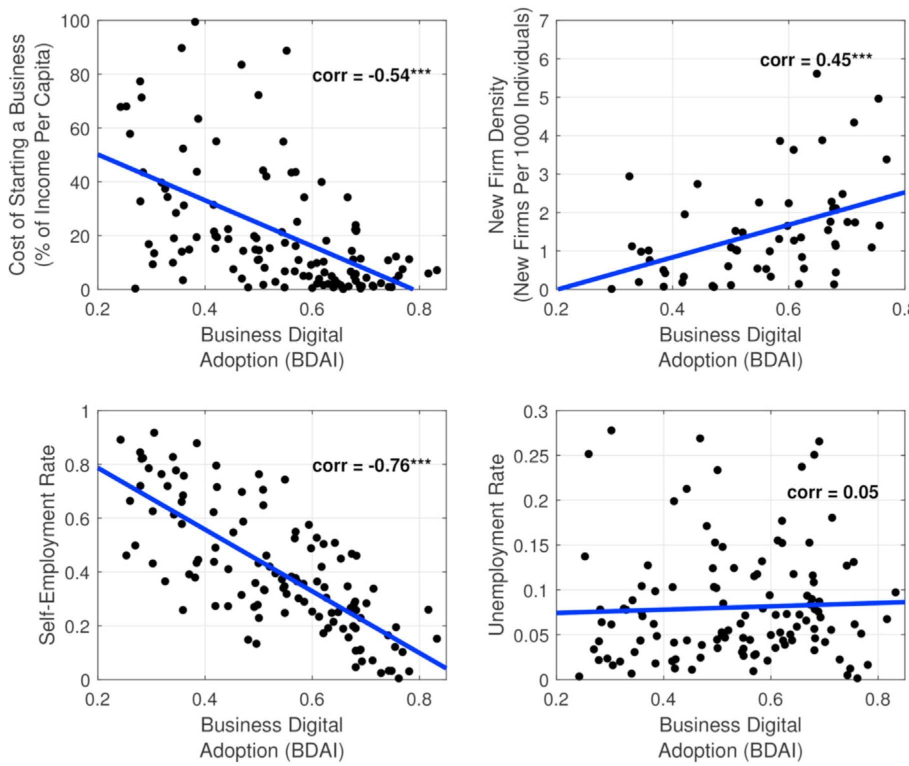

Fig. 1. Business digital adoption index, cost of starting a business, new firm density, and labor market outcomes in developing countries in 2016.
Sources: World Bank World Development Report 2016, World Bank Enterprise Surveys, World Bank Entrepreneurship Report, and World Bank World Development Indicators. Notes: The self-employment rate is expressed as a share of the labor force. New firm density is a proxy of new salaried firm creation that is comparable across economies and is defined as the number of new firm registrations per 1000 individuals (not all developing countries in our sample have data on new firm density; hence the smaller number of observations in the upper right quadrant of the figure relative to the other quadrants). See Appendix A.1 for the complete list of economies used in this figure. *** denotes significance at the 1 percent level.

Table 1
Self-employment rates and business digital adoption index (BDAI) (2016).

Dep. Var.: Self-Empl. Rate	(1)	(2)	(3)	(4)	(5)
BDAI	−1.171***	−0.534***	−0.405***	−0.406***	−0.429**
	(-14.39)	(-4.77)	(-3.75)	(-3.55)	(-2.46)
Log Real GDP PC		−0.125***	−0.0805***	−0.0723***	−0.0532*
		(-8.15)	(-4.08)	(-3.51)	(-1.70)
Industrial Empl. Share			−0.533***	−0.581***	−0.615**
			(-3.76)	(-3.83)	(-2.53)
Services Empl. Share			−0.254**	−0.279***	−0.524***
			(-2.44)	(-2.72)	(-3.18)
Min. Wage/VA per Worker				0.0211	0.0562
				(0.65)	(1.02)
Severance Payment				0.000385	0.00107
				(0.55)	(1.12)
Tertiary Edu. Enrollment					0.000643
					(0.88)
Constant	1.029***	1.827***	1.587***	1.523***	1.454***
	(21.82)	(18.89)	(13.05)	(11.78)	(7.44)
Adjusted R^2	0.577	0.718	0.757	0.765	0.773
Observations	134	128	128	124	71

Sources: World Bank World Development Indicators, Doing Business Report, and World Bank World Development Report 2016 (http://www.worldbank.org/en/publication/wdr2016/Digital-Adoption-Index). Notes: the self-employment rate is computed as the number of self-employed individuals divided by the labor force in 2016. BDAI corresponds to the Business Digital Adoption Index for 2016. Log Real GDP PC corresponds to the log of real GDP per capita in PPP terms in 2016. The severance payment represents pay for redundancy dismissal for a worker with 5 years of tenure (expressed in salary weeks). See Appendix A.1 for the list of countries used in this table. t statistics in parentheses. Standard errors are heteroskedasticity-robust. *** and ** denote significance at the 1 and 5 percent levels, respectively.

unique characteristics, Table A3 in Appendix A.2 shows that there is no significant link between firm digital adoption and self-employment in advanced economies.

3. The model

The economy has a population of unit mass, a representative household with a measure one of members, and two broad firm categories—salaried firms and self-employed firms. The labor market is characterized by search and matching frictions. We assume a closed economy to focus on the labor market (our findings are unchanged in an open economy setting).

The creation of salaried firms is endogenous and subject to barriers in the form of sunk entry costs. Based on their productivity upon entry, these firms choose whether to use a regular technology based solely on salaried workers or, if their productivity is high enough, a technology

Table 2
Unemployment rates and business digital adoption (BDAI) (2016)

Dep. Var.: Unempl. Rate	(1)	(2)	(3)	(4)	(5)
BDAI	0.0371	0.0420	−0.00543	−0.0321	0.0131
	(1.05)	(0.80)	(-0.09)	(-0.53)	(0.13)
Log Real GDP PC		−0.000493	−0.0119	−0.00708	−0.00867
		(-0.07)	(-1.28)	(-0.75)	(-0.71)
Industrial Empl. Share			0.0542	0.0755	−0.0501
			(0.60)	(0.80)	(-0.50)
Services Empl. Share			0.113**	0.108**	0.164**
			(2.60)	(2.43)	(2.10)
Min. Wage/VA per Worker				0.0173	0.0234
				(1.27)	(0.84)
Severance Payment				−0.000568**	−0.000476
				(-2.28)	(-1.34)
Tertiary Edu. Enrollment					−0.000254
					(-0.46)
Constant	0.0581***	0.0589	0.119**	0.0906	0.0829
	(3.06)	(1.25)	(2.03)	(1.55)	(1.17)
Adjusted R^2	0.001	−0.005	0.035	0.052	0.050
Observations	134	128	128	124	71

Sources: World Bank World Development Indicators, Doing Business Report, and World Bank World Development Report 2016. Notes: the self-employment rate is computed as the number of self-employed individuals divided by the labor force in 2016. BDAI corresponds to the Business Digital Adoption Index for 2016. Log Real GDP PC corresponds to the log of real GDP per capita in PPP terms in 2016. The severance payment represents pay for redundancy dismissal for a worker with 5 years of tenure (expressed in salary weeks). See Appendix A.1 for the list of economies used in this table. Standard errors are heteroskedasticity-robust. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

that combines salaried labor and ICT capital. However, this technology is available after incurring a fixed cost associated with technology adoption. We assume that ICT capital is an imperfect substitute to the type of salaried workers used with the regular technology, but also a complement to a second category of salaried workers (who can be interpreted as skilled) so as to allow for a notion of ICT capital-skill complementarity (ss shown in Eden and Gaggl (2020), Cross-country differences in ICT capital could simply be driven by different endowments of skilled and unskilled labor). This environment delivers an endogenous share of firm digital adoption that is influenced, among other things, by the cost of ICT adoption and firm-entry costs. In turn, these costs and the type of production technology adopted by firms shape the extent of salaried job creation.

Households make choices over their members' participation in the labor market: some members search for salaried jobs (in either salaried category) while others search for self-employment opportunities. Those who become self-employed effectively create self-employed (i.e., owner-only) firms and use their own labor to produce. Even if individuals do not face search frictions when looking for self-employment, the presence of such frictions in salaried employment generate equilibrium unemployment. Finally, participation in the labor market is costly for households, and these costs shape the reallocation of labor between salaried and self-employment amid changes in firm digital adoption.

3.1. Total output

A perfectly-competitive output aggregator chooses total salaried-firm output $Y_{s,t}$ and total self-employment output $Y_{e,t}$ to maximize profits $\Pi_{y,t} = \left[Y_t - p_{s,t}Y_{s,t} - p_{e,t}Y_{e,t}\right]$ subject to $Y_t = \left[Y_{s,t}^{\frac{\phi_y-1}{\phi_y}} + Y_{e,t}^{\frac{\phi_y-1}{\phi_y}}\right]^{\frac{\phi_y}{\phi_y-1}}$, where $\phi_y > 1$, $p_{s,t}$ is the relative price of total salaried-firm output, and $p_{e,t}$ is the relative price of total self-employment output. The first-order conditions yield standard demand conditions for each output category: $Y_{s,t} = \left(p_{s,t}\right)^{-\phi_y} Y_t$ and $Y_{e,t} = \left(p_{e,t}\right)^{-\phi_y} Y_t$. In turn, the normalized aggregate price index can be expressed as $1 = \left[p_{s,t}^{1-\phi_y} + p_{e,t}^{1-\phi_y}\right]^{\frac{1}{1-\phi_y}}$.

3.2. Salaried firms and production

Basic Structure The salaried firm structure builds on the well-known Ghironi and Melitz (henceforth GM) (2005) framework, where instead of having firms sort into export and non-export status based on their productivity and the presence of fixed and sunk costs, firms make production-technology decisions.[5]

There is an endogenous measure of monopolistically-competitive salaried firms. Each firm produces a single differentiated output variety ζ, $y_{s,t}(\zeta)$, and faces a sunk cost f_e to enter the market. Immediately upon entry, each firm draws its idiosyncratic productivity a from a common distribution $G(a)$ with support $[a_{\min}, \infty)$,where the realized a remains unchanged until firm exit takes place with probability $0 < \delta < 1$. Since each firm produces a single variety ζ with idiosyncratic productivity a, we refer to firm ζ as firm a for short.

Firms are characterized by the technology embedded in the intermediate inputs they use in production. Firms with idiosyncratic productivity a below an endogenous threshold $a_{i,t}$ choose intermediate goods produced with a regular technology that only uses salaried workers (a proxy for unskilled workers)—referred to as r technology for short—which makes them r firms. Firms with productivity $a \geq a_{i,t}$ instead use intermediate goods produced with a technology based on information-and-communication-technologies (ICT) capital—referred to as i technology for short—which makes them i firms. This i technology uses three production factors: ICT capital, the same type of salaried workers as r firms (r salaried workers, who can be interpreted as unskilled workers), and i salaried workers (a proxy for skilled workers), where ICT capital is a relative complement to i salaried workers and a relative substitute to r salaried workers. The use of the i technology, however, entails paying a fixed cost f_i, which represents the cost of digital adoption. Of note, the fixed cost f_i and the endogenous productivity threshold $a_{i,t}$ will ultimately determine the number of i firms and, combined with the total number of salaried firms, the

[5] Our salaried production structure is also related to Zlate (2016), who builds on GM to analyze firms' decisions to produce domestically or offshore their production.

share of firm digital adoption.

Finally, total salaried output is given by $Y_{s,t} = \left(\int_{\zeta \in Z} y_{s,t}(\zeta)^{\frac{\epsilon-1}{\epsilon}} d\zeta\right)^{\frac{\epsilon}{\epsilon-1}}$ where Z is the potential number of active salaried firms.

Linking Digital-Adoption Costs and Salaried-Firm-Entry Costs Guided by the negative relationship between firm digital adoption and the cost of salaried-firm creation presented in Fig. 1 as well as the discussion of the factors linking digital adoption and firm-entry costs in the Introduction, we assume that f_i and f_e are positively related. In particular, we posit that $f_e = \lambda_f f_i$, where $\lambda_f > 1$ is a parameter. What ultimately matters for our purposes is that f_e and f_i are positively related and that any changes in f_i are associated with changes in f_e in the same direction and vice versa (therefore, an equally valid assumption that delivers identical results is $f_i = \lambda_e f_e$, where $0 < \lambda_e < 1$ is a parameter). More broadly, this assumption generates facts that are consistent with the correlations between firm digital adoption, firm-creation costs, and new firm creation in Fig. 1.

Evolution of Salaried Firms There is an unbounded number of potential salaried entrants. Denoting by N_t the measure of active salaried firms and by $N_{e,t}$ the measure of new entrants, the evolution of the total number of salaried firms is

$$N_t = (1-\delta)\left[N_{t-1} + N_{e,t-1}\right]. \tag{1}$$

Given how these firms decide which production technology they use and recalling that $a_{i,t}$ is the threshold productivity above which firms use the i technology, the measures of i and r firms are given by $N_{i,t} = \left[1 - G(a_{i,t})\right] N_t$ and $N_{r,t} = G(a_{i,t}) N_t$, respectively.

Firm Profits and Threshold Productivity Individual firm profits from having productivity a and using the r technology are given

$$d_{r,t}(a) = \left[\rho_{r,t}(a) - \frac{mc_{r,t}}{a}\right] y_{r,t}(a),$$

where $\rho_{r,t}(a)$ is the real price, $mc_{r,t}$ is the price of r intermediate goods, and $y_{r,t}(a)$ is firm output. Individual firm profits from having productivity a and using the i technology are given

$$d_{i,t}(a) = \left[\rho_{i,t}(a) - \frac{mc_{i,t}}{a}\right] y_{i,t}(a) - f_i,$$

where $\rho_{i,t}(a)$ is firm the real price, $mc_{i,t}$ is the price of i intermediate goods, $y_{i,t}(a)$ is firm output, and f_i is the fixed cost of digital adoption. Then, we can define total profits for firm a as $d_t(a) = d_{i,t}(a) + d_{r,t}(a)$. Note that for a firm to be indifferent between production technologies, it must be that $d_{i,t}(a_{i,t}) = d_{r,t}(a_{i,t})$. This condition pins down the idiosyncratic threshold productivity level $a_{i,t}$.

Optimal Pricing It is straightforward to show that the demand function for firm a's output is $y_{j,t}(a) = \left(\rho_{j,t}(a)/p_{s,t}\right)^{-\epsilon} Y_{s,t}$ for $j \in \{i, r\}$, where $\epsilon > 1$ is the elasticity of substitution between output varieties and $p_{s,t}$ is the relative price of aggregate salaried-firm output $Y_{s,t}$. Then, given the profit functions for firm a defined above, firm a's optimal real price for each category $j \in \{i, r\}$ is $\rho_{j,t}(a) = \frac{\epsilon}{\epsilon-1}\frac{mc_{j,t}}{a}$.

Salaried Firm Averages There are two average idiosyncratic productivity levels, one for i firms, $\widetilde{a}_{i,t}$, and one for r firms, $\widetilde{a}_{r,t}$, which can be written as $\widetilde{a}_{i,t} = \left[\left(\frac{1}{1-G(a_{i,t})}\right)\int_{a_{i,t}}^{\infty} a^{\epsilon-1} dG(a)\right]^{\frac{1}{\epsilon-1}}$ and $\widetilde{a}_{r,t} = \left[\frac{1}{G(a_{i,t})}\int_{a_{min}}^{a_{i,t}} a^{\epsilon-1} dG(a)\right]^{\frac{1}{\epsilon-1}}$,respectively. Moreover, both $\widetilde{a}_{i,t}$ and $\widetilde{a}_{r,t}$ are increasing in the threshold productivity $a_{i,t}$. It follows that we can write average salaried-firm profits as $\widetilde{d}_t = \left(\frac{N_{r,t}}{N_t}\right)\widetilde{d}_{r,t} + \left(\frac{N_{i,t}}{N_t}\right)\widetilde{d}_{i,t}$, where $\widetilde{d}_{r,t} \equiv d_{r,t}(\widetilde{a}_{r,t})$ and $\widetilde{d}_{i,t} \equiv d_{i,t}(\widetilde{a}_{i,t})$. Along similar lines, the average prices for r and i firms are given by $\widetilde{\rho}_{r,t} \equiv \rho_{r,t}(\widetilde{a}_{r,t})$ and $\widetilde{\rho}_{i,t} \equiv \rho_{i,t}(\widetilde{a}_{i,t})$, and average salaried output in each category is given by $\widetilde{y}_{r,t} \equiv y_{r,t}(\widetilde{a}_{r,t})$ and $\widetilde{y}_{i,t} \equiv y_{i,t}(\widetilde{a}_{i,t})$. Finally, the relative price of aggregate salaried output is $p_{s,t} = \left[N_{r,t}\left(\widetilde{\rho}_{r,t}\right)^{1-\epsilon} + N_{i,t}\left(\widetilde{\rho}_{i,t}\right)^{1-\epsilon}\right]^{\frac{1}{1-\epsilon}}$.

Intermediate-Goods Producers There is a measure one of perfectly-competitive producers in charge of supplying intermediate goods to i and r firms. The production of intermediate goods for r firms uses only regular (or r) salaried workers $n^r_{r,t}$. In contrast, the production of intermediate goods for i firms uses i salaried workers $n^i_{i,t}$, ICT capital $k_{i,t}$, and r salaried workers $n^i_{r,t}$, where ICT capital and i salaried workers are complements and r salaried workers are imperfectly substitutable with the ICT capital-i worker composite. Given this structure, total r salaried employment is $n_{r,t} \equiv n^r_{r,t} + n^i_{r,t}$.

Intermediate-goods producers post vacancies $v_{i,t}$ and $v_{r,t}$ to hire new i and r salaried workers, respectively. Once matches materialize, they choose how to assign r workers to one of the two production technologies by choosing the share ω_t of total r salaried employment $n_{r,t}$ used in the production of intermediate goods for i firms (that is, alongside $n^i_{i,t}$ and $k_{i,t}$). Then, it follows that $n^i_{r,t} = \omega_t n_{r,t}$ and $n^r_{r,t} = (1-\omega_t) n_{r,t}$. In contrast, i workers are only used in the production of intermediate goods for i firms.

Formally, intermediate-goods producers choose vacancies $v_{r,t}$ and $v_{i,t}$, the desired measure of r and i workers $n_{r,t+1}$ and $n^i_{i,t+1}$, the fraction ω_t of total r salaried workers that is allocated to the production of intermediate goods for i firms, and ICT capital $k_{i,t+1}$ to maximize $\mathbb{E}_0 \sum_{t=0}^{\infty} \Xi_{t|0} \Pi_{s,t}$ subject to

$$\begin{aligned}\Pi_{s,t} = &\left[mc_{r,t} z_{r,t} H(n^r_{r,t}) - w^r_{r,t} n^r_{r,t} - \psi_r v_{r,t}\right] \\ &+ \left[mc_{i,t} z_{i,t} F(n^i_{r,t}, n^i_{i,t}, k_{i,t}) - w^i_{i,t} n^i_{i,t} - w^i_{r,t} n^i_{r,t}\right], \\ &- (k_{i,t+1} - (1-\delta_i) k_{i,t}) - \psi_i v_{i,t}\big]\end{aligned}$$

the perceived evolution of salaried employment

$$n_{r,t+1} = (1-\rho_s)\left[n_{r,t} + v_{r,t} q(\theta_{r,t})\right], \tag{2}$$

$$n^i_{i,t+1} = (1-\rho_s)\left[n^i_{i,t} + v_{i,t} q(\theta_{i,t})\right], \tag{3}$$

as well as

$$n^r_{r,t} = (1-\omega_t) n_{r,t}, \tag{4}$$

and

$$n^i_{r,t} = \omega_t n_{r,t}, \tag{5}$$

where $\Xi_{t|0}$ is the household's stochastic discount factor, the production functions $H(n^r_{r,t})$ and $F(n^i_{i,t}, n^i_{r,t}, k_{i,t})$ are constant-returns-to-scale, and $z_{r,t}$ and $z_{i,t}$ are exogenous sectoral productivities. ψ_r and ψ_i are the flow costs of posting a vacancy to attract r and i workers, respectively; $w^r_{r,t}$ and $w^i_{r,t}$ are the real wages of r workers producing intermediate goods for r and i firms, respectively; $w^i_{i,t}$ is the real wage of i workers; and $q(\theta_{r,t})$ and $q(\theta_{i,t})$ are the corresponding job-filling probabilities (a function of their respective market tightness $\theta_{r,t}$ and $\theta_{i,t}$, defined further below), all of which are taken as given by producers. Above, $0 < \delta_i < 1$ is the exogenous depreciation rate of ICT capital and $0 < \rho_s < 1$ is the exogenous separation probability of salaried workers.

The first-order conditions yield a standard ICT-capital Euler equation

$$1 = \mathbb{E}_t \Xi_{t+1|t}\left[mc_{i,t+1} z_{i,t+1} F_{k_i,t+1} + (1-\delta_i)\right], \tag{6}$$

an optimal decision over the allocation of r workers across the production of intermediate goods for r and i firms

$$mc_{i,t} z_{i,t} F_{n^i_r,t} - w^i_{r,t} = mc_{r,t} z_{r,t} H_{n^r_r,t} - w^r_{r,t}, \tag{7}$$

as well as standard job creation conditions for salaried employment in each of the two categories

$$\frac{\psi_r}{q(\theta_{r,t})} = (1-\rho_s)\mathbb{E}_t \Xi_{t+1|t}\left[\begin{array}{c}(1-\omega_{t+1})\left[mc_{r,t+1} z_{r,t+1} H_{n^r_r,t+1} - w^r_{r,t+1}\right] \\ +\omega_{t+1}\left[mc_{i,t+1} z_{i,t+1} F_{n^i_r,t+1} - w^i_{r,t+1}\right] + \dfrac{\psi_r}{q(\theta_{r,t+1})}\end{array}\right], \tag{8}$$

and

$$\frac{\psi_i}{q(\theta_{i,t})} = (1-\rho_s)\mathbb{E}_t\Xi_{t+1|t}\left[mc_{i,t+1}z_{i,t+1}F_{n_i^i,t+1} - w_{i,t+1}^i + \frac{\psi_i}{q(\theta_{i,t+1})}\right]. \quad (9)$$

The optimal decision over ω_t is intuitive: firms equate the net real marginal revenue product of labor from allocating an *r* worker to the production of intermediate goods for *r* firms to the corresponding net real marginal revenue product of labor from allocating the worker to the production of intermediate goods for *i* firms (introducing *r* worker-moving costs does not change our conclusions). The ICT-capital Euler and job creation conditions are standard, with each job creation condition equating the expected marginal cost of posting a vacancy to the expected marginal benefit, where the latter is given by the marginal revenue product of labor net of the real wage and the continuation value of the employment relationship. In the case of the job creation condition for *r* workers, the expected marginal benefit of posting a vacancy is given by the weighted average of the marginal revenue product of labor net of the wage for the two sub-categories of *r* workers, where the weights are optimally chosen when, once matched, producers allocate *r* workers across the two production technologies.

3.3. Households and self-employment

Households own all firms, spend resources to create salaried firms, and make labor force participation decisions by choosing the measure of household members who search for employment in each category, including self-employment. By choosing the share of household members who search for self-employment, households effectively create self-employed firms whose only input is self-employment labor n_e.

Formally, households choose consumption c_t, the measure of household members who search for self-employment $s_{e,t}$, *r* salaried employment $s_{r,t}$, and *i* salaried employment $s_{i,t}$; the desired measure of individuals in self-employment $n_{e,t+1}$, total *r* salaried employment $n_{r,t+1}$, *i* salaried employment $n_{i,t+1}^i$; the number of new salaried firms $N_{e,t}$; and the desired number of salaried firms N_{t+1} to maximize $\mathbb{E}_0\sum_{t=0}^{\infty}\beta^t\left[\mathbf{u}(c_t) - \mathbf{h}(lfp_{e,t}, lfp_{i,t}, lfp_{r,t})\right]$ subject to the budget constraint

$$c_t + f_e N_{e,t} = w_{i,t}^i n_{i,t}^i + w_{r,t}^r n_{r,t}^r + w_{r,t}^i n_{r,t}^i + \widetilde{d}_t N_t + p_{e,t}z_{e,t}n_{e,t} + \Pi_{s,t} + \Pi_{y,t},$$

the evolution of total salaried employment in each category $j \in \{i, r\}$

$$n_{j,t+1} = (1-\rho_s)\left[n_{j,t} + s_{j,t}f(\theta_{j,t})\right], \quad (10)$$

the evolution of self-employment

$$n_{e,t+1} = (1-\rho_e)(n_{e,t} + s_{e,t}\phi_e), \quad (11)$$

and the evolution of salaried firms

$$N_{t+1} = (1-\delta)\left[N_t + N_{e,t}\right], \quad (12)$$

taking explicit account of the fact that $n_{r,t}^r = (1-\omega_t)n_{r,t}$ and $n_{r,t}^i = \omega_t n_{r,t}$ where ω_t is taken as given. That is, households choose desired total *r* salaried employment $n_{r,t+1}$ but recognize that, once matched, intermediate-goods producers decide how to assign *r* workers to one of the two production technologies and take that decision as given. We define labor force participation for each employment category as $lfp_{e,t} = n_{e,t} + s_{e,t}$, $lfp_{i,t} = n_{i,t}^i + s_{i,t}$, and $lfp_{r,t} = n_{r,t} + s_{r,t}$. $\mathbf{u}(c_t)$ is increasing and concave, and $\mathbf{h}(lfp_{e,t}, lfp_{i,t}, lfp_{r,t})$ is increasing and convex in each participation category $lfp_{j,t}$ for $j \in \{e, i, r\}$.

In the budget constraint, $\widetilde{d}_t N_t$ denotes total average profits from owning salaried firms; $p_{e,t}z_{e,t}n_{e,t}$ are total real profits from self-employed firms, where total self-employment production is $Y_{e,t} = z_{e,t}n_{e,t}$ and $z_{e,t}$ is exogenous sectoral productivity; $\Pi_{s,t}$ are lump-sum real profits from intermediate-goods producers; and $\Pi_{y,t}$ are lump-sum real profits from the output aggregator. Turning to the perceived evolution of employment, $f(\theta_{r,t})$ and $f(\theta_{i,t})$ are the salaried job-finding probabilities and ρ_e is the exogenous separation probability of self-employed individuals, all of which are taken as given by households. Finally, $0 < \phi_e \leq 1$ is the exogenous probability with which individuals find self-employment opportunities. This probability can be interpreted as embodying in a reduced-form way any frictions associated with self-employment entry.

As we describe in Section 4.1, the functional form we adopt for $\mathbf{h}(lfp_{e,t}, lfp_{i,t}, lfp_{r,t})$ allows for differential weights for each participation category, implying that the marginal cost of participation across employment categories need not be the same (that is, $\mathbf{h}_{lfp_e} \neq \mathbf{h}_{lfp_r} \neq \mathbf{h}_{lfp_i}$). In particular, the functional form we use can accommodate the fact that it may be more costly for household members to participate as *i* workers (that is, $\mathbf{h}_{lfp_i} > \mathbf{h}_{lfp_e}, \mathbf{h}_{lfp_r}$; this could reflect in a reduced-form way the need for skill acquisition or additional education in that employment category relative to other categories). Analogously, the same functional form can accommodate the fact that participation in self-employment may plausibly be less costly compared to salaried employment (that is, $\mathbf{h}_{lfp_e} < \mathbf{h}_{lfp_i}, \mathbf{h}_{lfp_r}$; this would capture in a reduced-form way the presence of lower barriers to entry into self-employment compared to salaried employment). We let a disciplined calibration of the model determine the extent to which the relative marginal costs of participation across employment categories differ.

The first-order conditions yield a salaried-firm creation condition

$$f_e = (1-\delta)\mathbb{E}_t\Xi_{t+1|t}\left[\widetilde{d}_{t+1} + f_e\right], \quad (13)$$

labor force participation decisions for *r* and *i* salaried workers

$$\frac{\mathbf{h}_{lfp_{r,t}}}{\mathbf{u}'(c_t)}\frac{1}{f(\theta_{r,t})} = (1-\rho_s)\mathbb{E}_t\Xi_{t+1|t}\left[w_{r,t+1}^r(1-\omega_{t+1}) + w_{r,t+1}^i\omega_{t+1} + \left(\frac{1}{f(\theta_{r,t+1})} - 1\right)\frac{\mathbf{h}_{lfp_{r,t+1}}}{\mathbf{u}'(c_{t+1})}\right], \quad (14)$$

and

$$\frac{\mathbf{h}_{lfp_{i,t}}}{\mathbf{u}'(c_t)}\frac{1}{f(\theta_{i,t})} = (1-\rho_s)\mathbb{E}_t\Xi_{t+1|t}\left[w_{i,t+1}^i + \left(\frac{1}{f(\theta_{i,t+1})} - 1\right)\frac{\mathbf{h}_{lfp_{i,t+1}}}{\mathbf{u}'(c_{t+1})}\right], \quad (15)$$

and a participation decision for self-employment

$$\frac{\mathbf{h}_{lfp_{e,t}}}{\mathbf{u}'(c_t)}\frac{1}{\phi_e} = (1-\rho_e)\mathbb{E}_t\Xi_{t+1|t}\left[p_{e,t+1}z_{e,t+1} + \left(\frac{1}{\phi_e} - 1\right)\frac{\mathbf{h}_{lfp_{e,t+1}}}{\mathbf{u}'(c_{t+1})}\right], \quad (16)$$

where $\Xi_{t+1|t} = \beta\mathbf{u}'(c_{t+1})/\mathbf{u}'(c_t)$ is the household's stochastic discount factor. Intuitively, households equate the marginal cost of creating a new salaried firm to the expected marginal benefit of doing so. The latter is given by expected average firm profits and the continuation value if the firm remains in the market next period. Turning to the labor force participation decisions, households equate the expected marginal cost of sending one more household member to search for *r* or *i* salaried employment to the expected marginal benefit, where the choice to send household members to search for *r* salaried employment is influenced by the allocation of *r* salaried employment to the production of intermediate goods for *r* or *i* firms (that is, the choice over ω_t). From a general standpoint, the marginal benefit of salaried participation is given by the expected discounted real wage and the continuation value of having a household member remain employed net of the utility cost from participating as a salaried worker in each salaried employment category. Analogously, households equate the marginal cost of becoming self-employed to the expected marginal benefit. The latter is given by the marginal product of a self-employed individual and the continuation value of remaining in self-employment next period net of the utility cost of self-employment participation.

Since the total population in the economy is normalized to one, the total labor force participation rate is $lfp_t = lfp_{e,t} + lfp_{i,t} + lfp_{r,t}$ and we can define the economy-wide unemployment rate as $ur_t \equiv (s_{e,t} + s_{i,t} + s_{r,t})/lfp_t$. Thus, household search behavior across employment categories is an important component that shapes the unemployment rate.

3.4. Matching processes and wages

The matching function for salaried category $j \in \{r, i\}$, $m(s_{j,t}, v_{j,t})$, is constant-returns-to-scale and takes as arguments salaried searchers and vacancies in its respective employment category. Then, the job-finding and job-filling probabilities are given by $f(\theta_{j,t}) = m(s_{j,t}, v_{j,t})/s_{j,t}$ and $q(\theta_{j,t}) = m(s_{j,t}, v_{j,t})/v_{j,t}$, respectively, where market tightness is $\theta_{j,t} = v_{j,t}/s_{j,t}$.

Wages are determined via bilateral Nash bargaining between firms and salaried workers. Appendix A.4 shows that the Nash real wages can be written as

$$w^r_{r,t} = \nu \left(mc_{r,t} z_{r,t} H_{n^r_{r,t}} \right) + (1-\nu) \left(\frac{\mathbf{h}'(lfp_{r,t})}{\mathbf{u}'(c_t)} \right), \tag{17}$$

$$w^i_{r,t} = \nu \left(mc_{i,t} z_{i,t} F_{n^i_{r,t}} \right) + (1-\nu) \left(\frac{\mathbf{h}'(lfp_{r,t})}{\mathbf{u}'(c_t)} \right), \tag{18}$$

and

$$w^i_{i,t} = \nu \left(mc_{i,t} z_{i,t} F_{n^i_{i,t}} \right) + (1-\nu) \left(\frac{\mathbf{h}'(lfp_{i,t})}{\mathbf{u}'(c_t)} \right), \tag{19}$$

where $0 < \nu < 1$ is the bargaining power of workers. Thus, the real wage in each category of salaried employment depends not only on the worker's marginal productivity but also on the (utility) costs from labor market participation in that category. Intuitively, all else equal, an increase in the cost of participation puts upward pressure on wages as households demand additional compensation for incurring these costs.

3.5. Symmetric equilibrium and market clearing

Market clearing in the two salaried-firm categories implies that

$$z_{r,t} H(n^r_{r,t}) = N_{r,t} \left(\frac{\widetilde{y}_{r,t}}{\widetilde{a}_{r,t}} \right). \tag{20}$$

and

$$z_{i,t} F(n^i_{r,t}, n^i_{i,t}, k_{i,t}) = N_{i,t} \left(\frac{\widetilde{y}_{i,t}}{\widetilde{a}_{i,t}} \right). \tag{21}$$

In turn, the resource constraint of the economy is given by

$$Y_t = c_t + (k_{i,t+1} - (1-\delta_i) k_{i,t}) + \psi_r v_{r,t} + \psi_i v_{i,t} + f_e N_{e,t} + f_i N_{i,t}, \tag{22}$$

where the costs of vacancy creation, firm creation, and digital adoption are resource costs. Appendix A.5 presents the list of equilibrium conditions.

4. Quantitative analysis

4.1. Calibration

Functional Forms Utility over consumption exhibits CRRA and disutility from labor force participation is convex: $\mathbf{u}(c_t) - \mathbf{h}(lfp_{e,t}, lfp_{i,t}, lfp_{r,t}) = \frac{c_t^{1-\sigma_c}}{1-\sigma_c} - \left[\frac{(\kappa_e(lfp_{e,t}) + \kappa_i(lfp_{i,t}) + \kappa_r(lfp_{r,t}))^{1+\frac{1}{\chi}}}{1+\frac{1}{\chi}} \right]$, where $\sigma_c, \kappa_e, \kappa_i, \kappa_r, \chi > 0$. The production of intermediate goods for r firms is linear in labor, $H(n^r_{r,t}) = n^r_{r,t}$, and the production of intermediate goods for i firms is a CES aggregator of $n^i_{r,t}$, k_i, and $n^i_{i,t}$,

$$F(n^i_{i,t}, n^i_{r,t}, k_{i,t}) = \left[(1-\phi_i) \left(n^i_{r,t} \right)^{\lambda_i} + \phi_i \left(\alpha_k k_{i,t}^{\lambda_k} + (1-\alpha_k)(n^i_{i,t})^{\lambda_k} \right)^{\frac{\lambda_i}{\lambda_k}} \right]^{\frac{1}{\lambda_i}}$$

where $0 < \phi_i, \alpha_k < 1$ and $\lambda_i, \lambda_k < 1$. The salaried matching function for employment category $j \in \{i, r\}$ is $m(s_{j,t}, v_{j,t}) = s_{j,t} v_{j,t} / \left[s^{\xi}_{j,t} + v^{\xi}_{j,t} \right]^{1/\xi}$, where $\xi > 0$ (this functional form guarantees that the matching probabilities are bounded between 0 and 1; see den Haan et al., 2000). Finally, following the macro literature on endogenous firm entry (GM, 2005), we adopt a Pareto distribution for $G(a) = \left[1 - (a_{\min}/a)^{k_p} \right]$ with shape parameter $k_p > \epsilon - 1$.

Parameters from Literature A period is a quarter. We set the risk aversion parameter $\sigma_c = 2$, the subjective discount factor $\beta = 0.985$, and the capital depreciation rate $\delta_i = 0.025$, all of which are standard values in the literature (alternative values for δ_i do not change our main findings). The elasticity of substitution between salaried output varieties is set to $\epsilon = 6$, which delivers markups consistent with in developing countries. We then set $k_p = 6.5$ (which satisfies $\epsilon - 1 < k_p$) and the salaried firm exit rate $\delta = 0.025$ (consistent with available data on average firm exit rates). As is standard in labor search models, the worker bargaining power is $\nu = 0.5$. Without loss of generality and following standard assumptions in related literature, we set the minimum level of idiosyncratic productivity among salaried firms to $a_{min} = 1$, and also set the sectoral productivities $z_e = z_r = 1$. Using existing evidence on salaried employment and self-employment separation rates in developing countries, we set $\rho_e = 0.03$ and $\rho_s = 0.05$ (Bosch and Maloney, 2008). Based on World Bank Enterprise Survey data suggesting that a majority of firms compete against unregistered firms—where the latter are primarily self-employed and micro firms—we set $\phi_y = 5$ as a baseline, which implies a relatively high degree of substitutability between salaried-firm and self-employed-firm output.

We adopt existing estimates for the elasticity of substitution between the two types of salaried labor and ICT capital from Eden and Gaggl (2018) and set $\lambda_k = 0.3$, $\lambda_i = 0.9$, and $\phi_i = 0.47$ due to limited data availability for developing countries. Finally, estimated values for the elasticity of labor supply on the extensive margin—that is, the elasticity of labor force participation—are based solely on salaried workers and vary widely in the literature. Thus, we set extensive-margin elasticity of labor supply to $\chi = 0.26$ as a baseline based on micro-level evidence in Chetty et al. (2011, 2013).[6] The Appendix shows results from several robustness checks using alternative parameterizations of the model, which confirm that our main conclusions remain unchanged.

Mapping of Firm Digital Adoption Between the Data and the Model Recall that our empirical measure of firm digital adoption is the World Bank's Business Digital Adoption Index (BDAI) and that this index takes values between 0 and 1, with 1 capturing full digital adoption based on the four indicators that comprise the BDAI. In our framework, N_i/N represents the share of firms that use the ICT-based production technology, and therefore the share of firms that use digital technologies. Thus, for the purposes of our quantitative analysis, we consider N_i/N as the model counterpart of the BDAI.

Calibrated Parameters Our objective is to shed light on quantitative mechanisms behind the empirical relationships between firm digital adoption, self-employment, and unemployment in Fig. 1. More specifically, our focus is on the slopes of self-employment and unemployment amid greater firm digital adoption, and our calibration strategy is in this spirit. In particular, we choose the lowest BDAI in our country sample as the baseline. We can then lower the cost of digital adoption to trace out the entire BDAI range in the data.

[6] Fiorito and Zanella (2012) argue that macro elasticities lie in the 0.8–1.4 range; Cairo et al. (2019) suggest that 2.3 is a common value in the macro literature; and Chang et al. (2018) adopt a value closer to 1 based on Rogerson and Wallenius (2014, 2016). Adopting an elasticity of participation that is higher compared to our baseline value would make our quantitative results stronger and closer to the data.

As a baseline, we assume that the flow cost of posting salaried vacancies is the same in the two salaried employment categories, so that $\psi_i = \psi_r = \psi$ (vacancy cost asymmetries do not change our findings). In turn, we calibrate the remaining parameters $\lambda_f, \alpha_k, \xi, \kappa_e, \kappa_i, \kappa_r, \psi, f_i, z_i$, and ϕ_e such that our model replicates: (1) a baseline BDAI of 0.20 (the lowest in our country sample); (2) the intercept of the trend lines (and not the slopes, which are the endogenous objects we are interested in) that arise from plotting (a) the cost of starting a salaried firm, (b) the self-employment rate, and (c) the unemployment rate against BDAI per Fig. 1; (3) an average ratio of ICT capital compensation to GDP of 0.04 over the BDAI range (Conference Board Total Economy Database); (4) an average labor force participation rate of 0.63 over the BDAI range (World Bank World Development Indicators); (5) a share of i salaried employment in total employment of 1 percent (this corresponds to the estimated share of employment with tertiary education—a proxy for employment that complements ICT capital in production—in an economy with a BDAI of 0.20; World Development Indicators); (6) a wage differential between i and r employment of roughly 50 percent (consistent with average wage differentials between skilled and unskilled employment); and (7) total vacancy posting costs of roughly 1 percent of output (consistent with related literature for developing countries; see, for example, Boz et al., 2015). Finally, the value of ϕ_e is chosen to deliver an effective cost of becoming self-employed of roughly 4 months of r wages (this cost is in line with available estimates on the average barriers to microenterprise development in low-entry-cost industries such as retail trade, wholesale trade, and professional and other services; see, for example, McKenzie and Woodruff, 2006). The resulting parameter values are $\alpha_k = 0.1353, \xi = 0.3611, \kappa_e = 1.2862, \kappa_i = 2.7537, \kappa_r = 1.8358, \phi_e = 0.50, \psi = 0.0569, f_i = 0.002, z_i = 2.0362$, and $\lambda_f = 255.0983$. Since per Section 3 the fixed cost of digital adoption f_i and the sunk entry cost of creating salaried firms are directly related via $f_e = \lambda_f f_i$ with $\lambda_f > 1$, we obtain $f_e = 0.4443$.

Operationalization To compare the model to the data, we reduce the fixed cost of technology adoption f_i from its baseline value so as to generate an empirical range of firm digital adoption (N_i/N) from 0.20 to 0.85. Since changes in f_i are directly reflected in changes in f_e, we are effectively changing a single parameter. Then, this exercise generates unique pairings between firm digital adoption and other model variables and delivers simple model predictions. These model predictions provide a straightforward way to visualize the model's ability to generate the general patterns in the data.

4.2. Firm digital adoption and labor markets: data vs. model

Fig. 2 plots the model prediction—shown as a red dash-dotted line—for the cost of creating a salaried firm (as a share of income per capita), the self-employment rate, and the unemployment rate as we vary firm digital adoption against the data-based trend lines for each relevant variable. For completeness, we also include the model-based trend line (dotted green line), which is based on fitting a linear trend on the model prediction for each variable of interest (for the rest of our analysis and for comparability, we focus on the model predictions instead of the model-based trend lines). Under our disciplined calibration strategy, the model generates a strong negative relationship between firm digital adoption and self-employment rates and a weak link between firm digital adoption and unemployment rates. Both model outcomes are consistent with the patterns in developing countries (moreover, the slopes of the model-based and data-based trend lines are exceedingly similar).

Three related model outcomes provide additional validity to our framework. First, as noted earlier, World Bank (2016) documents a strong and positive relationship between firm digital adoption and real GDP. The increase in digital adoption in our model is associated with a non-trivial increase in total output (see bottom left panel of Fig. A12 in the Appendix). Second, the level of economic development itself is positively associated with greater salaried-employment shares (Poschke, 2019). Since the large decline in self-employment in our framework is almost fully offset by an expansion in salaried employment (in absolute levels and also as a share of total employment), our model is consistent with this fact as well. Third, as shown in Fig. A2 of the Appendix, our model generates a positive relationship between firm digital adoption and new firm creation that is consistent with available data on new firm density (a proxy of new firm entry).

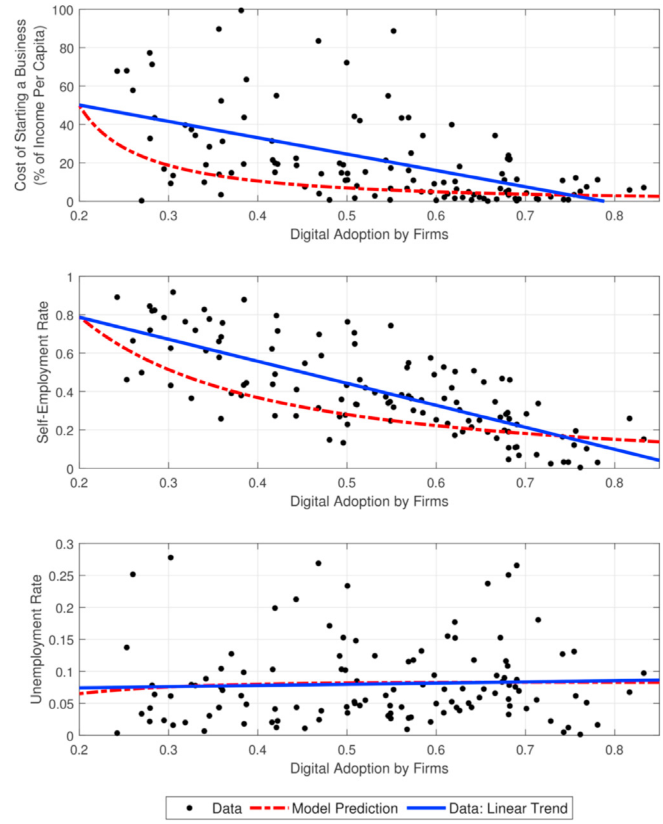

Fig. 2. Firm digital adoption and labor market outcomes: data vs. model.

Of note, given our calibration strategy and by construction, the model-based trend line in Fig. 2 will not match the intercept of the data-based trend line. This last outcome does not represent a limitation of our model since we are primarily interested in how self-employment and unemployment rates change as firm digital adoption increases. Indeed, as we show in Fig. A16 in the Appendix, an alternative calibration strategy whereby the intercept of our model-based trend line matches the intercept of linear trend in the data delivers very similar conclusions (see the Appendix for more details). Along similar lines, note that Fig. 2 shows that as digital adoption increases, our model predictions exhibit a steeper decline in self-employment and in the cost of firm creation (as a share of income per capita) at low levels of firm digital adoption compared to the linear trend in the data. Fig. A3 in the Appendix plots the same model predictions in 2 against the log trend in the data (which introduces curvature in the trend) and confirms that the model-generated change in self-employment amid greater firm digital adoption matches the change captured by the log trend in the data very well. These two additional experiments highlight the model's success in capturing the patterns in the data.

4.3. Economic mechanisms

To delve deeper into the economic mechanisms behind Figs. 2 and 3 plots the steady state of select model variables as we vary N_i/N over its empirical range. As f_i (and therefore the sunk entry cost f_e) falls, the

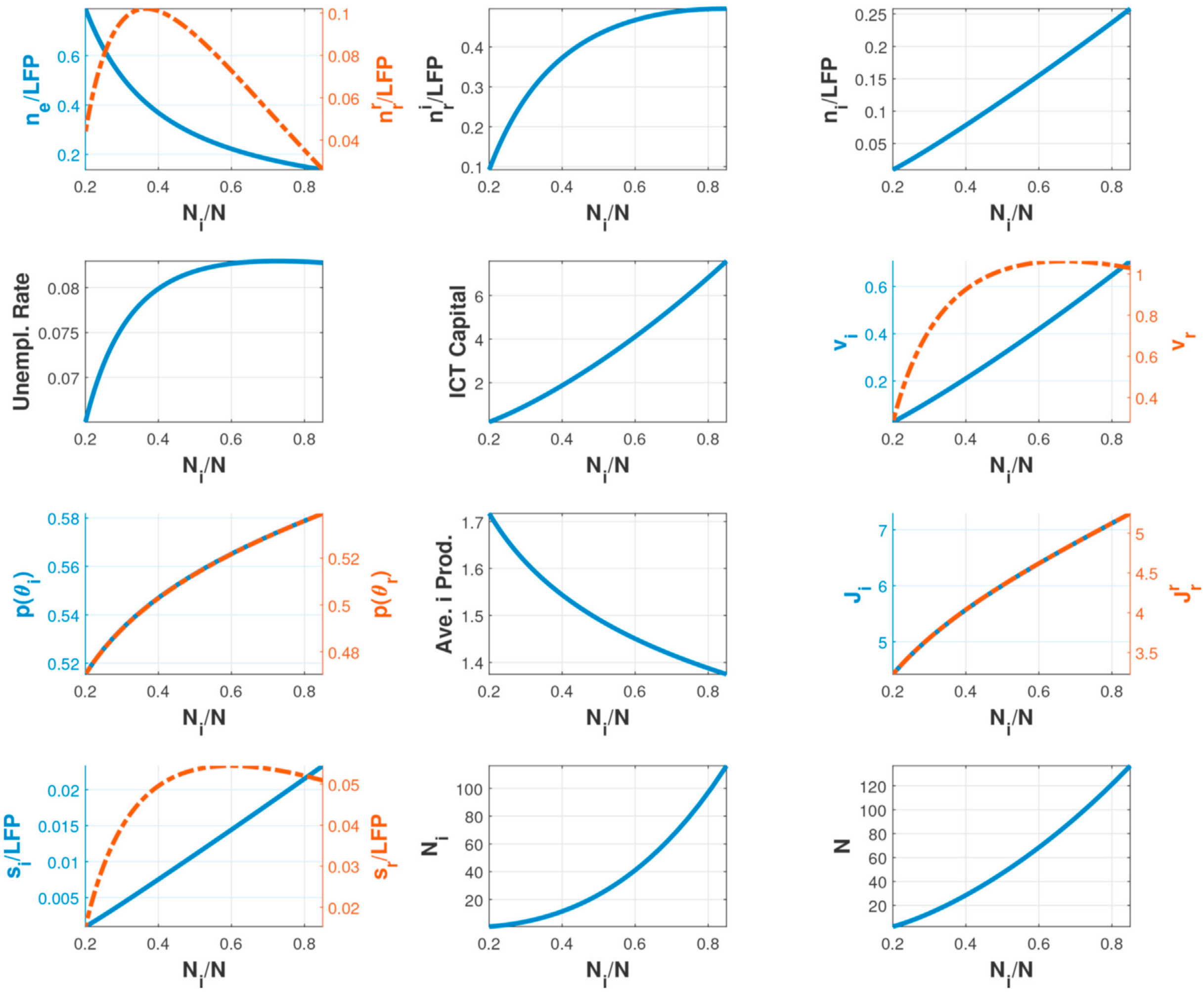

Fig. 3. Firm digital adoption and steady-state equilibria: benchmark model.

number of salaried firms (N) in the economy expands, and a greater share of those firms use i intermediate goods (that is, N_i increases at a faster pace than N; see the last two bottom sub-panels of Fig. 3). Greater salaried-firm creation and the expansion in the share of i firms bolster the demand for ICT capital and raise salaried firms' value of having salaried workers (denoted by $\mathbf{J}_i$ for i firms and J_r^r for r firms in the figure). This leads to an increase in vacancy postings in both salaried-firm categories (v_i and v_r), which in turn attracts more salaried searchers (s_i and s_r). The household's response is reflected in an increase in the share of individuals that search for salaried jobs in the total labor force, and in a change in the composition of the unemployment rate away from self-employment searchers and towards salaried searchers.

Quantitatively, the expansion in job vacancies is greater than the increase in salaried searchers, which leads to a steady increase in salaried job-finding probabilities across categories. This contributes to an increase in the shares of i and r salaried employment in the labor force, with the expansion in r employment in i firms being a dominant force (see middle upper sub-panel of Fig. 3). In turn, the reallocation of searchers towards salaried employment amid greater salaried-firm entry generates significant downward pressure on self-employment, resulting in a large and monotonic reduction in the self-employment rate (n_e/LFP). Finally, under our baseline calibration, the increase in job vacancies is large and steady enough to offset the fall in self-employment, leading to a negligible expansion in the unemployment rate over the digital adoption range.

Two outcomes in Fig. 3 are worth highlighting. First, the bulk of the increase in total salaried employment as digital adoption increases—which is critical for understanding the relatively small changes in the unemployment rate—arises as salaried employment is reallocated to i firms. Second, despite the fact that r workers in i firms (n_r^i) and the ICT capital-i labor composite are imperfectly substitutable, both r and i employment in i firms (n_r^i and n_i^i) increase. This implies that the small and empirically-consistent increase in unemployment (from roughly 6.6 percent to 8.3 percent over the firm digital adoption range) is limited by both the rise in r salaried employment and the rise in i salaried employment as self-employment falls monotonically. More importantly, this outcome suggests that capital-skill complementarity—a mechanism we revisit briefly below in an additional experiment—does not seem to be the primary driving force behind the reduction in self-employment, the increase in salaried employment, and the muted behavior of unemployment.

4.3.1. Changes in self-employment: driving forces

The Importance of Firm-Creation Costs and Salaried Firm Creation Delving deeper into the model mechanisms underlying Fig. 2, consider a modified version of the model where, in contrast to our benchmark assumption, the fixed cost of technology adoption f_i and the sunk entry cost f_e are no longer linked. Given this separation in costs, we then reduce f_i to generate the range of firm digital adoption whilef_e remains unchanged at its baseline value. Fig. 4 shows results for

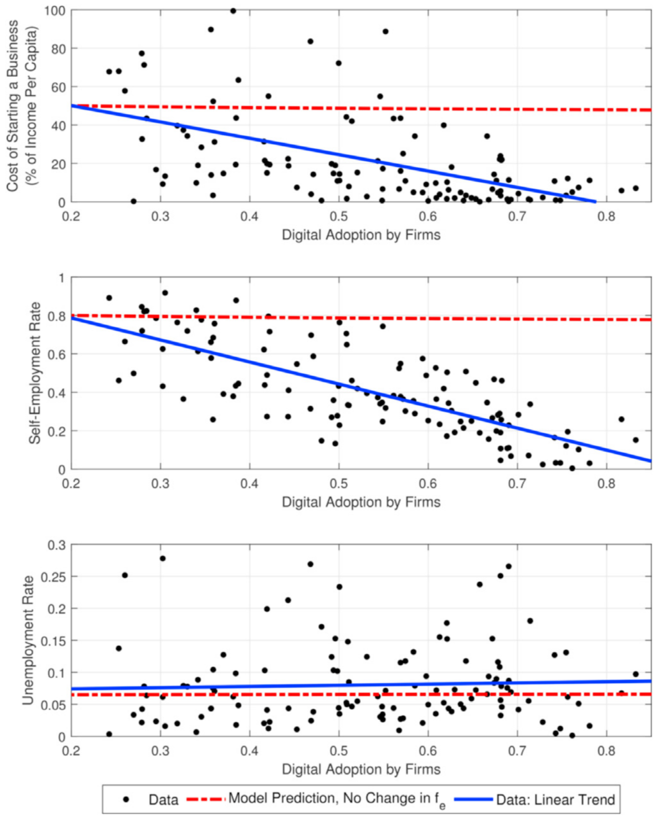

Fig. 4. Firm digital adoption and labor market outcomes: data vs. model, no change in f_e.

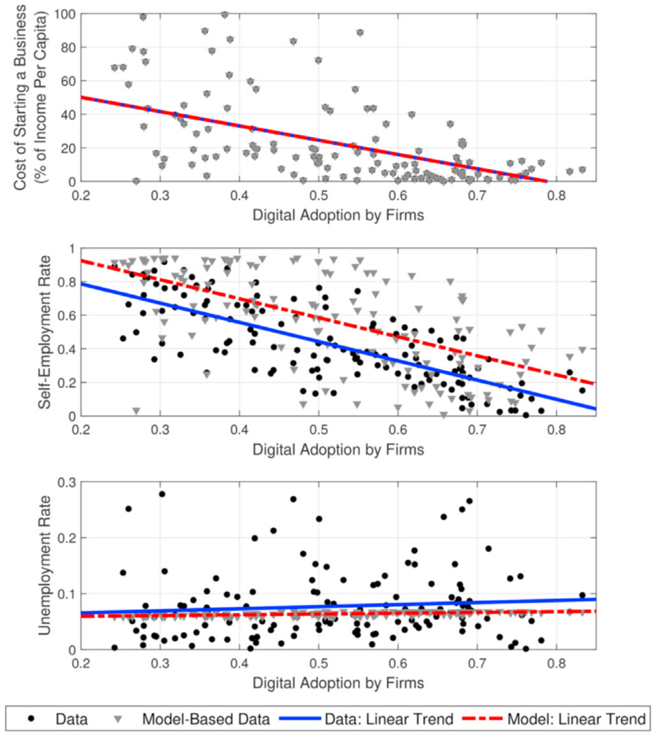

Fig. 5. Firm digital adoption and labor market outcomes: model-based cross-sectional observations vs. data.

this experiment.[7]

A reduction in f_i holding f_e constant increases N_i/N but is not powerful enough to generate a large labor reallocation of salaried employment towards self-employment. Thus, self-employment remains virtually unchanged. The reason for this is simple: absent a concomitant decrease in f_e the base that ultimately supports salaried employment in the economy—the number of salaried firms N—remains largely unchanged amid greater digital adoption (see Fig. A11 in the Appendix). That is, the reduction in f_i leads to a change in N_i/N that is driven by N_i and not N. In turn, the negligible quantitative change in N implies that there is little incentive for firms to drastically increase vacancy postings in response to a lower f_i only. Hence the small quantitative changes in self-employment and unemployment.[8]

With these results in mind, we highlight the importance of firm-creation costs for understanding changes in self-employment with a complementary exercise: starting from our baseline calibration, we consider pairs of f_i and f_e that replicate the exact cross-sectional observations of firm digital adoption and firm-creation costs in the data. In turn, this exercise generates cross-sectional observations for the self-employment and unemployment rates as outcomes.

Fig. 5 compares the resulting model-based scatter plots of firm digital adoption, self-employment, and unemployment to their empirical counterparts. The middle panel of the figure shows that conditional on matching the cross-sectional data on firm digital adoption and firm-creation costs in our country sample, the model generates a scatter plot for self-employment that is broadly consistent with the data (with a slight upward bias). Most importantly for our message, the trend line of the model-generated data has virtually the same slope as the data-based trend line, implying that the model can generate average reductions in self-employment as firm digital adoption increases that are quantitatively consistent with the data (even if it overestimates the intercept in the data). For completeness, the lower panel of Fig. 5 shows that the model-based scatter plot for the unemployment rate implies no link between firm digital adoption and unemployment, which is consistent with the results in Fig. 2 and the data. More broadly, the results for unemployment in Figs. 2, 4 and 5 suggest that other forces unrelated to digital adoption and barriers to firm entry may be behind cross-country differences in unemployment.

Alternative Linkages Between Digital Adoption and Salaried Job Creation To further emphasize the central role of the relationship between firm digital adoption and barriers to salaried-firm creation, we consider three alternative environments. The first one is a version of our model where reductions in f_i are associated with lower vacancy-posting costs. The second one is a version of the model where reductions in f_i are associated with higher (exogenous) sectoral productivity z_i among i firms. The third one, is a version of the model where reductions in f_i are associated with an increase in the weight of the ICT capital-i labor composite in the production of intermediate goods for i firms (that is,

[7] For comparability with our baseline results, this experiment adopts the same calibrated parameter values as those in our benchmark model—implying that the baseline-economy steady states of the two models are the same—instead of recalibrating the model under a scenario where f_i and f_e are independent of each other (recalibrating this last model and changing f_i so as to generate the range of digital adoption in the data does not change our findings). We also note that another alternative experiment would be to change f_e so as to generate the empirical range for firm digital adoption while holding f_i at its baseline level. Importantly, generating the digital adoption range by only changing f_e requires increasing f_e (otherwise, a reduction in f_e alone would reduce N_i/N by increasing N more than N_i). Given the empirical evidence on the link between firm-creation costs and digital adoption in Fig. 1, the outcome from this alternative experiment is inconsistent with the data.

[8] Fig. A11 in the Appendix shows the counterpart of Fig. 3 when f_e and f_i are independent of each other. While the steady-state changes are qualitatively similar to those in our benchmark model, the quantitative changes in all variables—including N_i and N—are negligible, especially given the non-trivial quantitative change in firm digital adoption over its empirical range.

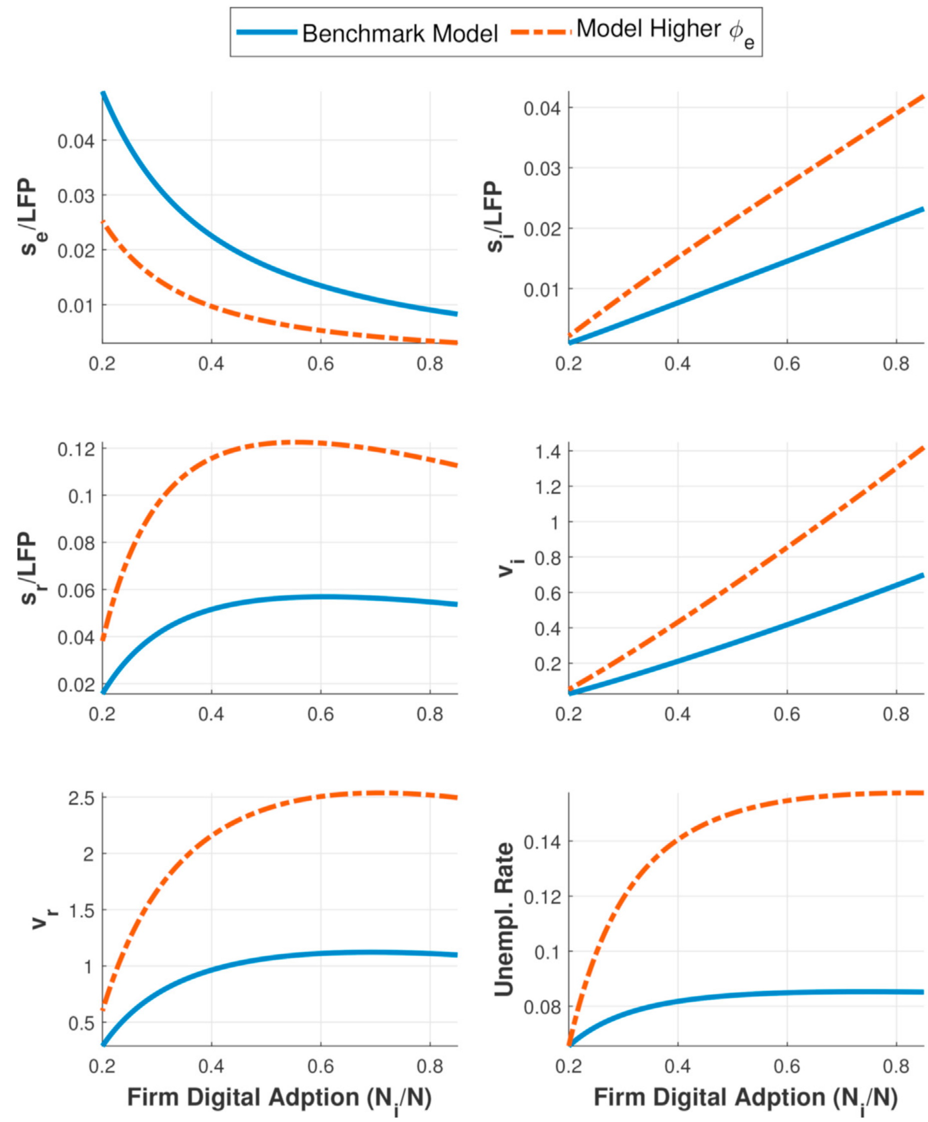

Fig. 6. Sectoral search and unemployment: benchmark model and model with higher ϕ_e.

reductions in f_i are associated with greater importance of capital-skill complementarity in the production process). In all three scenarios, we hold f_e constant at its baseline value.

The results from these experiments—presented, respectively, in Figs. A13–A15 of the Appendix—further highlight the importance of reductions in barriers to firm entry: even if greater firm digital adoption is reflected in lower vacancy-posting costs, greater sectoral productivity, or greater ICT capital-skill complementarity, absent concomitant reductions in barriers to salaried-firm creation, greater firm digital adoption is associated with negligible reductions in self-employment.

4.3.2. Changes in unemployment: driving forces

Our analysis so far has shown that the link between firm digital adoption and barriers to salaried-firm entry is crucial for understanding the strong negative relationship between digital adoption and self-employment. However, a comparison of the model prediction for unemployment in Figs. 2 and 4 suggests that other factors are behind the weak link between digital adoption and unemployment in the data.

A fundamental factor that shapes households' search for salaried employment is the extent to which self-employment is an accessible outside option and employment state. In our model, the accessibility of self-employment is embodied in the (exogenous) probability of finding self-employment opportunities and entering self-employment, ϕ_e.[9] Intuitively, the higher is ϕ_e, the easier it is for individuals to become self-employed and, importantly, the more households are willing to send individuals to search for salaried employment amid an increase in salaried labor demand due to greater digital adoption. In other words, the responsiveness of search for salaried employment to greater firm digital adoption is increasing in the baseline value of ϕ_e.

To see this more clearly, Fig. 6 compares the response of select labor market variables in the benchmark model to those of a version where the baseline exogenous probability of self-employment entry ϕ_e is higher (specifically, we calibrate ϕ_e so that the effective (marginal) cost of participating in self-employment is roughly half of the cost in our benchmark calibration; the resulting value of ϕ_e is 0.954 vs. 0.50 in the baseline calibration). Focusing on the change in labor market variables as greater digital adoption takes hold, with a higher baseline ϕ_e, households react to the rise in vacancy postings by increasing the shares of individuals searching for salaried employment (s_r/LFP and s_i/LFP) more forcefully as firm digital adoption expands, especially at

[9] See Finkelstein Shapiro (2014, 2018) for a possible way to endogenize this probability.

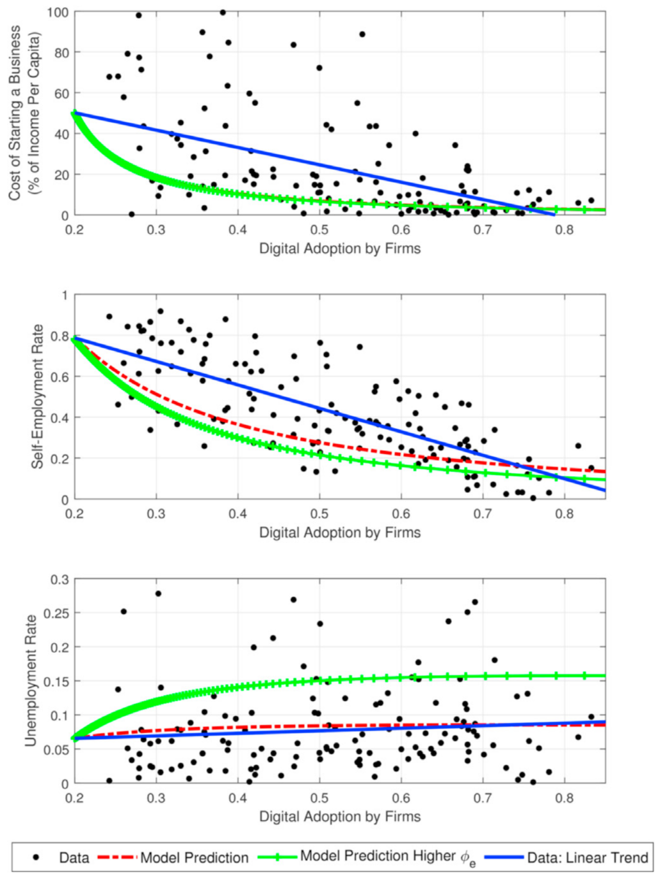

Fig. 7. Firm digital adoption and labor market outcomes: data vs. benchmark model and model with higher ϕ_e.

Table 3
Digital adoption costs and firm-entry costs, and self-employment rates in developing countries.

Dep. Var.: BDAI	(1)	(2)
Cost of Fixed Broadband	−0.442***	−0.171*
	(-4.69)	(-1.67)
Cost of Firm Creation		−0.316***
		(-5.41)
Constant	0.604***	0.632***
	(27.72)	(33.87)
Adjusted R^2	0.14	0.37
Observations	112	112
Dep. Var.: Self-Empl. Rate	**(1)**	**(2)**
Cost of Fixed Broadband	0.594***	0.250
	(3.53)	(1.23)
Cost of Firm Creation		0.401***
		(3.81)
Constant	0.314***	0.277***
	(9.12)	(7.54)
Adjusted R^2	0.11	0.27
Observations	112	112

Sources: World Bank World Development Indicators, World Telecommunication/ICT Indicators Database, and Doing Business Report. Notes: BDAI is the Business Digital Adoption Index (our measure of firm digital adoption). The self-employment rate refers to the share of self-employed individuals in the labor force in 2016 and takes values between 0 and 0.90. The cost of fixed broadband refers to the real US dollar cost (in PPP terms) of fixed-broadband basket based on monthly data usage of a minimum of 1 GB in 2016 (see https://www.itu.int/en/ITU-D/Statistics/Pages/ICTprices/default.aspx for more details). In turn, the cost of firm creation (also in 2016) is expressed as a share of income per capita. *t* statistics in parentheses. Standard errors are heteroskedasticity-robust. *** and * denote significance at the 1 and 10 percent levels, respectively.

lower levels of firm digital adoption.[10] In particular, the larger and steeper increase in these shares exerts significant upward pressure on the unemployment rate and more than offsets the fall in the share of individuals searching for self-employment. This yields a much larger increase in unemployment compared to the change in the model under the baseline calibration of ϕ_e. Fig. 7 shows how assuming that entry into self-employment is significantly more accessible (via a substantially higher baseline ϕ_e) implies a worse fit with the data compared to the fit under the benchmark calibration.

More broadly, while we abstract from explicitly modeling the underlying structure that generates barriers to self-employment entry and let ϕ_e reflect the extent of those barriers in a reduced-form way, our findings suggest that the ease of entry into self-employment is an important factor that shapes the link between firm digital adoption and unemployment rates in developing countries.

4.3.3. Testable implications: barriers to firm entry, digital adoption costs, and self-employment

Fig. 4 and our model analysis delivers the following implication: if greater digital adoption is not associated with lower firm-creation costs, there is no relationship between digital adoption costs—and hence firm digital adoption—and self-employment. Put differently, holding the cost of firm creation constant, reductions in the cost of digital adoption alone—which have a direct positive impact on firm digital adoption—have no tangible effects on self-employment rates.

To determine whether this model implication holds in the data—and therefore whether the model mechanisms are plausible—recall from Section 2 that our empirical measure of firm digital adoption, BDAI, combines information on the number of secure servers, the speed at which files are downloaded, 3G coverage, and the share of firms with websites. Then, a natural measure of the cost of digital adoption is the cost of fixed broadband.

Using available data on the real cost of fixed broadband for our sample of developing countries (expressed in PPP terms), column (1) in the upper section of Table 3 first shows a negative and significant association between the cost of fixed broadband and firm digital adoption. Moreover, as shown in column (2) in the upper section of the same table, this negative relationship continues to hold even if we control for the cost of firm creation, though the relationship becomes weaker. One way to interpret this second result is that the cost of digital adoption is itself partially reflecting some of the barriers to firm entry. More broadly, these results support the linkages between firm-entry costs, digital adoption costs, and firm digital adoption in the data, which are at the heart of our framework.

More importantly, turning to the connection between self-employment, digital adoption costs, and entry barriers, column (1) in the lower section of Table 3 shows a positive and significant relationship between the cost of fixed broadband and self-employment rates. Critically, though, once we control for the cost of firm creation, the link between the cost of broadband and self-employment vanishes. This is exactly what the model experiments in Fig. 4 suggest. All told, we interpret the results in Table 3 as providing suggestive evidence of some of the model mechanisms that rationalize the strong and negative relationship between firm digital adoption and self-employment in the data.

Robustness Analysis Figs. A5, A4, A7, and A8 in the Appendix show that our main findings are robust to a lower elasticity of substi-

[10] The discrepancy in the shares of searchers for self-employment and r employment between the two models at the baseline $N_i/N = 0.20$ stems from the difference in the baseline value of ϕ_e between the two models.

tution between self-employment and salaried output, to asymmetries in vacancy posting costs between employment categories, to expressing the costs of labor force participation as resource costs, and to the inclusion of generic (non-ICT) capital in salaried-firm production. Fig. A9 shows that a similar claim applies to a version of the benchmark model calibrated to have higher baseline firm-creation costs. Finally, Fig. A10 shows that a model with exogenous labor force participation fails to replicate the empirical relationship between firm digital adoption and self-employment rates, which highlights the relevance of accounting for household participation decisions.

5. Conclusion

We study the link between firm digital adoption and labor market outcomes in developing countries. Using a large sample of countries, we first document a strong, negative, and significant link between firm digital adoption and self-employment rates, and the absence of a link between digital adoption and unemployment. These facts hold under a host of other factors associated with differences in self-employment and unemployment across economies, including the level of development and the sectoral composition of employment. To shed light on the economic mechanisms behind these patterns, we build a labor search and matching model with self-employment, endogenous salaried-firm entry, and endogenous technology adoption. Our model can quantitatively generate the relationships between firm digital adoption, self-employment, and unemployment in the data.

Our analysis suggests that reductions in the cost of digital adoption alongside declines in barriers to salaried-firm entry, and not reductions in the cost of digital adoption alone, are crucial to quantitatively rationalize the negative link between digital adoption and self-employment. In turn, the extent to which self-employment is an accessible employment option plays a key role in shaping the link between firm digital adoption and unemployment rates. Our findings stress the role of barriers to salaried-firm creation and entry into self-employment for a better understanding of the link between firm digital adoption and labor market outcomes in developing countries. More broadly, our results may be relevant for understanding changes in the composition of employment as developing countries increasingly focus on reforms that facilitate firm creation via the adoption of digital technologies by firms, households, and governments, as well as the potential consequences of automation in these economies.

Declaration of competing interest

I declare that we have no relevant or material financial interests that relate to the research described in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jdeveco.2021.102656.

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