IDB WORKING PAPER SERIES Nº IDB-WP-1333

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The Role of Digital Adoption Policies

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Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library

Finkelstein Shapiro, Alan.
Labor market and macroeconomic dynamics in Latin America amid COVID: the role of digital adoption policies / Alan Finkelstein Shapiro, Victoria Nuguer.
p. cm. — (IDB Working Paper Series ; 1333)
Includes bibliographic references.
1. Labor market-Mexico-Econometric models. 2. Telecommuting-Economic aspects-Mexico-Econometric models. 3. Self-employed-Effect of technological innovations on-México-Econometric models. 4. Coronavirus infections-Economic aspects-Mexico-Econometric models. 5. Labor policy-Mexico. I. Nuguer, Victoria. II. Inter-American Development Bank. Department of Research and Chief Economist. III. Title. IV. Series.
IDB-WP-1333

http://www.iadb.org

Abstract[1]

We study how policies that facilitate firm digital adoption shape the labor market and economic recovery from COVID-19 in a search and matching framework with firm entry and exit where salaried firms can adopt digital technologies and the labor market and firm structure embodies key features of Latin American economies. Using Mexico as a case study, we first show that the model quantitatively replicates the dynamics of the labor market and output at the onset of the COVID recession and in its aftermath, including the sharp decline in labor force participation and informal employment that is unique to the COVID recession. We then show that a policy-induced permanent reduction in the barriers to adopting digital technologies introduced at the trough of the recession bolsters the recovery of GDP, total employment, and labor income, and leads to a larger expansion in the share of formal employment compared to the no-policy scenario. In the long run, the economy exhibits a long-run reduction in total employment and labor force participation, but higher levels of GDP and labor income, greater average firm productivity, a larger formal employment share, and a marginally lower unemployment rate.

JEL classifications: E24, J23, J24, J64, O14
Keywords: COVID, Business cycles and labor search frictions, Self-employment and informality, Unemployment, Labor force participation, Endogenous firm entry, Information and communications technologies (ICT), Latin America

[1] We thank Andy Powell, Eduardo Cavallo, Arturo Galindo, Laura Ripani, Oliver Azuara Herrera, and David Kaplan for useful comments and feedback. Santiago Novoa provided outstanding research assistance. This paper was written to support the analysis of the state of labor markets in Latin America and the Caribbean and the role of labor market policies amid COVID-19 in Chapter 5 of the Inter-American Development Bank Macroeconomic Report 2022, "From Recovery to Renaissance: Turning Crisis into Opportunity."The section "Digital Adoption, Automation, and Labor Market Recovery: New Firm Entry and Job Creation" of Chapter 5 of the Macro Report presents a summary of the paper's main findings. The views in this paper are solely the responsibility of the authors and should not be interpreted as representing the views of the Inter-American Development Bank, its Executive Board, or its Management. Any errors are our own.
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1 Introduction

In 2020, the COVID pandemic triggered an unprecedented recession around the world, with the Latin America and the Caribbean (LAC) region experiencing the most dramatic contraction in employment and economic activity. Since the onset of COVID, several studies have documented how the 2020 recession had a unique impact on Latin American labor markets compared to past recessions: the COVID shock led not only to a dramatic reduction in labor force participation but also to a decline in informal employment, which stands in stark contrast to the typical and well-known role of informality as a countercyclical employment and income buffer in LAC labor markets (ECLAC, 2021; Leyva and Urrutia, 2022). In addition, survey-based evidence suggests that firms in the region experienced a record collapse in sales, which not only led to firms exiting but also put a sharp dent in new firm creation. Critically, micro and small firms, which account for 50 percent of total employment and tend to be in high-contact sectors, were the most affected (ECLAC, 2020a).

Prior to COVID, digital adoption rates by firms and households in the region had been expanding at a steady pace, with the latest available data showing that around 70 percent of the population in the region uses the internet. Moreover, alongside greater internet use, the share of the population making and receiving digital payments had been steadily growing as well. Recent evidence suggests that digital adoption rates by firms increased sharply at the onset of COVID. Importantly, several governments in the region actively adopted and promoted policies aimed specifically at supporting and facilitating greater firm digital adoption (ECLAC, 2020b; Díaz de Astraloa et al., 2021).[2] A key objective of these policies is to leverage the use of digital technologies to reduce barriers to firm entry, the rationale being that lower barriers will support greater firm and employment creation, limit the adverse effects from the contraction in economic activity, and bolster a faster recovery from the COVID downturn by improving firm productivity via technology adoption.[3] More broadly,

[2]Examples of these policies include: free or cheaper access to online marketplaces; technical assistance aimed at improving firms' digital presence, payments, and sales; and partnerships between banks and businesses supported by the government to improve access and expand online interactions and transactions.

[3]As recently shown in Finkelstein Shapiro and Mandelman (2021), there is a negative relationship between barriers to firm entry and firm digital adoption. Examples of how digital adoption is associated with lower barriers to entry include: the expansion of potential markets via online sales and promotion (see Díaz de Astraloa et al., 2021, for evidence from Mercado Libre), the reduction in effective registration and admin-

policies that facilitate firm digital adoption have the potential to improve the productivity profile of firms and, in doing so, encourage greater firm and employment formality—a long-standing goal in the LAC region. While recent evidence suggests that digital technologies can improve firm-level outcomes, whether bolstering greater firm digital adoption has broader labor-market and macroeconomic consequences—both in the context of economic recoveries and in the long term—remains a key policy question.

In this paper, we adapt the framework in Finkelstein Shapiro and Mandelman (2021) to analyze the labor market and macroeconomic implications of digital adoption policies in LAC in the context of the COVID recession and recovery. The model features firm entry and exit, involuntary unemployment, and labor force participation, and explicitly captures key defining characteristics of the firm and employment structure of LAC economies. Importantly, the model includes a margin whereby salaried firms can choose between adopting a regular technology that relies solely on salaried labor, or a technology that combines salaried labor with information and communication technologies (ICT), thereby giving rise to endogenous digital adoption by firms. On the labor market front, the model features self-employment and two categories of salaried workers—high-wage (or formal) workers and low-wage (or informal) workers. Salaried firms that use the regular technology only hire low-wage workers. In contrast, salaried firms that adopt ICT hire both high-wage and low-wage workers, where high-wage workers complement ICT and low-wage workers are imperfectly substitutable with the ICT-high-wage worker complement.

Focusing on Mexico as a case study, we enrich this framework by introducing a set of shocks that allows us to quantitatively replicate the increase in unemployment and the contraction in employment, labor force participation, and output at the onset of the COVID-19 recession, as well as the subsequent (and ongoing) recovery. We then analyze how a policy-induced permanent reduction in the barriers to adopting digital technologies at the trough of the recession shapes labor market and aggregate dynamics along the recovery path relative to a no-policy scenario. We find that fostering greater digital adoption in the aftermath of the recession bolsters the recovery of GDP, total employment, and labor income, and leads

istrative costs associated with firm creation by using online filing systems, and the reduction in the effective costs of finding input suppliers and customers via digital platforms and markets.

to a larger expansion in the share of formal employment compared to a scenario without policy. In the long term, the policy induces a reduction in total employment and labor force participation that nonetheless result in higher levels of GDP and labor income, a larger formal employment share, and a marginally lower unemployment rate. This outcome stems from the change in the technological composition of firms and the associated improvement in average firm productivity induced by the policy.

Our work contributes to the literature on the effects of the COVID-19 pandemic in developing and emerging economies. Alon, Kim, Lagakos, and vanVuren (2020) analyze the effects of lockdowns, policies based on the age of the population, and school closures in a macro model with epidemics and incomplete markets that allows for differences in the economy's fiscal and healthcare capacity, the population's age structure, and the degree of informality. Their analysis highlights the relative effectiveness of age-based policies and school closures relative to lockdowns in a developing country context. Using a similar framework, Alon, Kim, Lagakos, and vanVuren (2021) show that the sharper decline in economic activity in emerging economies relative to lower-income and advanced economies can be explained by differences in public transfers and the share of employment in high-contact occupations. Closer to our focus on LAC, Alfaro, Becerra, and Eslava (2021) show that microentrepreneurship, informality, and limited telework job opportunities play an important role in explaining the collapse in employment in LAC in 2020 by comparing Colombia to a labor market structure that mimics the U.S. labor market. Finally, Leyva and Urrutia (2022) provide a comprehensive overview of labor market and output dynamics in Brazil, Chile, Colombia, Mexico, and Peru amid COVID, highlighting the unique behavior of informal employment and labor force participation during COVID relative to previous recessions in the region. They then use a macro model with self-employment and search frictions in formal employment to show that shocks to informal employment and labor supply are essential to explaining the dynamics of the labor market at the onset of COVID and its aftermath, and analyze the role of labor market policies in bolstering the recovery process. We complement these studies by analyzing how policies that expand firm digital adoption shape not only the labor market and economic recovery in the aftermath of COVID, but also long-term employment and macro outcomes in an environment that captures the distinct employment and firm structure of

LAC economies.

The rest of the paper is structured as follows. Section 2 provides a brief overview of labor market and macroeconomic dynamics in Mexico at the onset of the COVID recession and in its aftermath. Section 3 summarizes the key features of the model we use. Section 4 presents the results from our quantitative experiments and discusses the main economic mechanisms. Section 5 concludes.

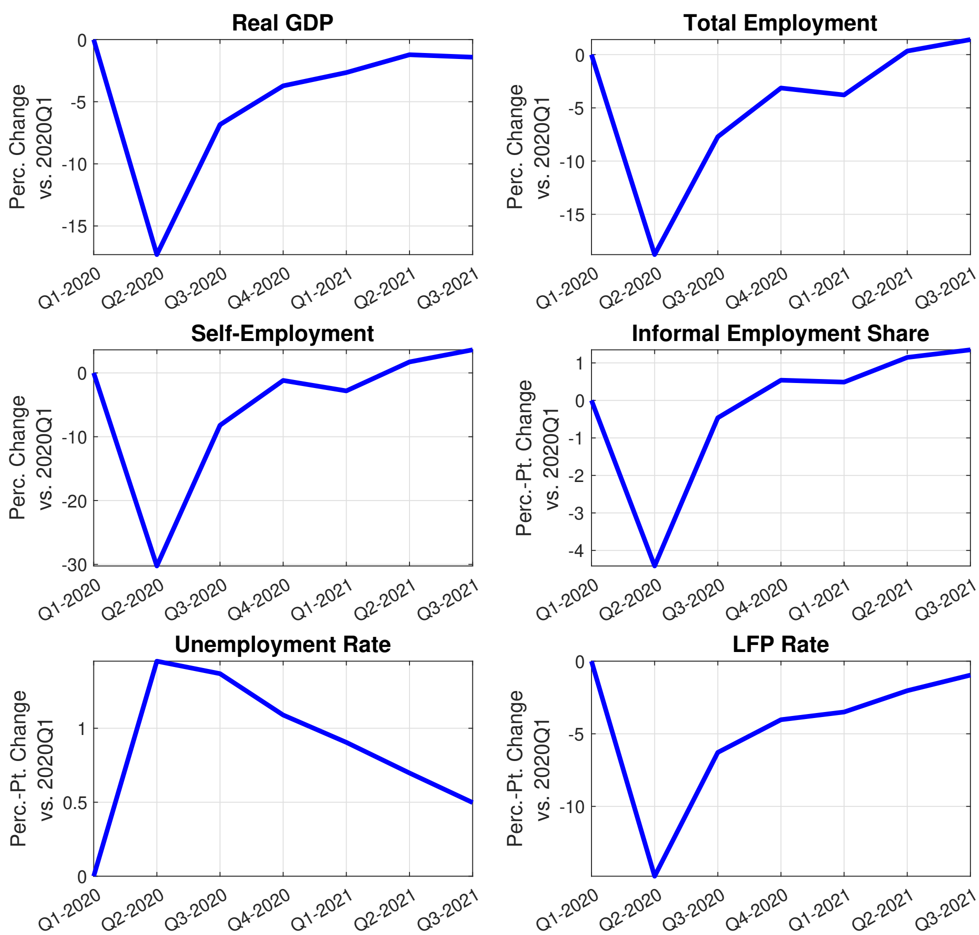
2 Overview: Labor Market and Macroeconomic Dynamics in Mexico Amid COVID

As noted in Section 1, Leyva and Urrutia (2022) document the dynamics of labor markets in five major LAC economies since the onset of COVID. For completeness, we present similar facts to those in their work with a focus on Mexico, which we choose as our LAC case study. We do so because, out of all the major LAC economies, Mexico implemented the fewest and most limited set of policies to counteract the adverse effects of COVID on economic activity, thereby making our analysis of digital adoption policies in the context of the COVID economic recovery more transparent.

Figure 1 plots the dynamics of real GDP, total employment, self-employment, the share of informal employment in total employment, the unemployment rate, and the labor force participation rate for the period 2020Q1 through 2021Q3 (the latest quarter of available data for these variables). As the figure suggests, real GDP, total employment, and labor force participation all experienced a dramatic contraction in 2020Q2—which marked the onset of COVID—and 2020Q3, with GDP and total employment falling by almost 18 percent relative to 2020Q1, and with labor force participation falling by almost 15 percentage points relative to 2020Q1. As noted in Leyva and Urrutia (2022), in stark contrast to the typical countercyclicality of informal employment in Mexico and in LAC more generally, both self-employment and the share of informal employment (comprised of self-employment and informal salaried employment) experienced contractions, with self-employment falling by 30 percent relative to 2020Q1. At the same time, the unemployment rate rose by more than

1.5 percentage points relative to 2020Q1. While this may seem low compared to the increase in unemployment rates in other countries amid COVID, a 1.5 percentage-point increase is substantial compared to the expansion in unemployment in pre-COVID recessions in Mexico.

Figure 1: Labor Market and Macroeconomic Dynamics in Mexico, 2020-2021



Sources: St. Louis Federal Reserve Economic Database (FRED) and INEGI. Notes: LFP denotes Labor Force Participation. Perc.-Pt. Change denotes Percentage-Point Change.

While real GDP and labor force participation continue to remain below their pre-COVID levels by 2021Q3, total employment went back to its pre-COVID level in 2021Q2, roughly a year after its initial contraction. Importantly, the recovery in total employment has been driven primarily by the recovery of informal employment. As a result, the recovery from the original collapse in economic activity in 2020Q2 has been characterized by a change in the composition of total employment towards greater informality. In particular, as is evident from Figure 1, the share of informal employment in total employment surpassed its pre-COVID level in the second half of 2020 and has continued to grow. Given the well-known negative link between informality and productivity, this change in the composition of employment towards greater informality has relevant implications for the medium and long-term productivity profile of the economy if the share of informal employment remains above its pre-COVID level.

With this background in mind, Section 3 describes a framework that can shed light on how a policy that permanently reduces the barriers to digital adoption by firms affects the process of recovery from the COVID recession and shapes long-term labor market and macroeconomic outcomes.

3 Model Summary

Finkelstein Shapiro and Mandelman (2021) build a macroeconomic framework that features involuntary unemployment via search and matching frictions, endogenous labor force participation, and salaried firm entry and exit. In the model, households not only send household members to search for jobs at salaried firms but can also send their members to work in self-employment. Based on their idiosyncratic productivity level upon entry, salaried firms can use a regular technology that uses salaried labor subject to search and matching frictions or, after paying a fixed cost, choose to adopt a production technology that combines information and communication technologies (ICT) with salaried labor.

The production process of firms using ICT is such that ICT complements a sub-segment of salaried workers, thereby creating an ICT-salaried labor composite that is imperfectly substitutable with a different sub-segment of salaried employment within the firm. The category of salaried employment that complements ICT can be interpreted as high-skilled formal salaried employment, while the category that is substitutable with the ICT-salaried labor composite can be interpreted as low-skilled formal salaried employment. Finally, the category of workers employed by firms that do not use ICT can be interpreted as low-skilled informal employment. As such, the framework features both self-employment as well as different categories of salaried employment that are meant to capture formal and informal salaried work in a tractable way.

We adopt this model to conduct a quantitative analysis of digital adoption policies in a LAC labor market context in the context of COVID. In what follows, we provide a brief summary of the production structure, the labor market, and the household structure, pointing out the main modifications and additions we make to the model—mainly, changes to the timing of the labor market matching process and the inclusion of four shocks that allow the model to replicate the response of key labor market and macroeconomic variables to the pandemic—and refer the reader to Section 3 of Finkelstein Shapiro and Mandelman (2021) for details on the economic environment.

Total Output Total output $Y_t = \left[Y_{s,t}^{\frac{\phi_y - 1}{\phi_y}} + Y_{e,t}^{\frac{\phi_y - 1}{\phi_y}} \right]^{\frac{\phi_y}{\phi_y - 1}}$ is comprised of total output from salaried firms $Y_{s,t}$ and total output from self-employed individuals $Y_{e,t}$,where total salaried and self-employment output are imperfectly substitutable, with parameter $\phi_y > 1$ dictating the degree of substitutability. The relative prices of $Y_{s,t}$ and $Y_{e,t}$ are given by $p_{s,t}$ and $p_{e,t}$, respectively.

Salaried Firms: Production Technologies Firms operate in a monopolistically-competitive environment. Firm entry into the salaried sector is endogenous and subject to a sunk entry cost $f_e > 0$. Upon entry, firms draw their idiosyncratic productivity level a from a common distribution $G(a)$, and firms decide which production technology they adopt. Each firm's realized level of a remains unchanged until the firm exits the market with exogenous probability $0 < \delta < 1$.

Firms with productivity a below an endogenous threshold $a_{i,t}$ rely on a regular (r) production technology that uses salaried workers, denoted by $n^r_{r,t}(a)$, making them r firms. In turn, firms with productivity a above $a_{i,t}$ rely on a production technology that combines information-and-communication-technologies (ICT) capital $k_{i,t}(a)$ with two categories of salaried workers, one that complements ICT capital, denoted by $n^i_{i,t}(a)$, and one that is imperfectly substitutable with the ICT-salaried labor composite, denoted by $n^i_{r,t}(a)$. To adopt the ICT-based technology, each firm that decides to do so must incur a fixed cost

$f_i > 0$—the cost of digital adoption—making them i firms.

Given the complementarity between $n^i_{i,t}(a)$ and ICT capital, $n^i_{i,t}(a)$ can be interpreted as skilled labor while $n^i_{r,t}(a)$ can be interpreted as unskilled labor. $n^r_{r,t}(a)$ can be interpreted as unskilled labor as well. We assume that $n^i_{r,t}(a)$ and $n^r_{r,t}(a)$ are perfectly substitutable, the only difference being whether they work at i or r firms.

Salaried Firms: Individual-Firm Profits, Optimal Pricing, and Technology Choice Each salaried firm maximizes profits by choosing inputs and its real output price optimally subject to a standard downward-sloping demand function for its output, where the effective real marginal cost of inputs for a given firm depends on the production technology the firm uses. Denoting the real price of firm $j \in \{i, r\}$ by $\rho_{j,t}(a)$ and its effective real marginal cost by $mc_{j,t}/a$, optimal pricing yields a standard expression where the real price is a markup over marginal cost: $\rho_{j,t}(a) = (\varepsilon / (\varepsilon - 1))(mc_{j,t}/a)$ where $\varepsilon > 1$ is the elasticity of substitution between individual salaried-output categories. Finally, denoting individual profits for firm $j \in \{i, r\}$ by $d_{j,t}(a)$, a salaried firm is indifferent between technologies when $d_{i,t}(a_{i,t}) = d_{r,t}(a_{i,t})$,where we note that f_i is a component of $d_{i,t}(a)$ so that changes in the fixed cost f_i affect firms' choices on digital adoption.

Evolution of Salaried Firms, Salaried Firm Categories, and Average Profits Let $N_{e,t}$ be the number of new salaried entrants and N_t be the number of salaried firms that are active in period t. Recalling that salaried firms exit the market with probability $0 < \delta < 1$, the number of active salaried firms is given by $N_t = (1 - \delta)[N_{t-1} + N_{e,t-1}]$. In turn, given the optimal choice over production technologies, we can define the number of firms using the r and i technologies as $N_{r,t} = G(a_{i,t})N_t$ and $N_{i,t} = [1 - G(a_{i,t})]N_t$, respectively. We follow the literature and assume a Pareto distribution for $G(a) = \left[1 - (a_{\min}/a)^{k_p}\right]$, where the shape parameter $k_p > \varepsilon - 1$. Finally, average profits for a given salaried firm are given by $\widetilde{d}_t \equiv (N_{r,t}/N_t)\,\widetilde{d}_{r,t} + (N_{i,t}/N_t)\,\widetilde{d}_{i,t}$ where $\widetilde{d}_{r,t}$ and $\widetilde{d}_{i,t}$ are evaluated at their respective average idiosyncratic productivity levels.

Matching Processes for Salaried Employment The salaried labor market is subject to search and matching frictions. The matching functions for r and i salaried employment follow den Haan, Ramey, and Watson (2000). They are constant-returns-to-scale and are given by $m(s_{r,t}, v_{r,t}) = z_{m,t}\left(s_{r,t}v_{r,t}\right) / \left[s_{r,t}^{\xi} + v_{r,t}^{\xi}\right]^{1/\xi}$ and $m(s_{i,t}, v_{i,t}) = \left(s_{i,t}v_{i,t}\right) / \left[s_{i,t}^{\xi} + v_{i,t}^{\xi}\right]^{1/\xi}$, where $\xi > 0$ and $z_{m,t}$ is a matching efficiency shock associated with r employment. For each salaried category $j \in \{r, i\}$ $s_{j,t}$ denotes the measure of salaried searchers and $v_{j,t}$ denotes the aggregate number of vacancies in employment category j. Defining market tightness as $\theta_{j,t} = v_{j,t}/s_{j,t}$, the job-filling and job-finding probabilities for salaried category j are given by $q(\theta_{j,t}) = m(s_{j,t}, v_{j,t})/v_{j,t}$ and $f(\theta_{j,t}) = m(s_{j,t}, v_{j,t})/s_{j,t}$, respectively.

ICT Capital Accumulation, Salaried Job Creation, and Salaried Production Processes ICT capital follows a standard accumulation process whereby the existing stock of ICT capital $k_{i,t}$ depreciates at an exogenous rate $0 < \delta_i < 1$ and real resources are spent on ICT capital investment inv_t in order to bolster the future stock of ICT capital $k_{i,t+1}$. The profit maximization problem of i firms is subject to the evolution of ICT capital, and delivers a standard Euler equation for ICT capital.

Turning to salaried job creation, in the presence of search and matching frictions, finding salaried workers requires spending $\psi > 0$ per posted vacancy in each category of salaried employment.

From an aggregate standpoint, the evolution of salaried employment from the perspective of firms is given by

$$n_{r,t} = (1 - z_{\rho,t}\rho_s)n_{r,t-1} + v_{r,t}q(\theta_{r,t}),$$

and

$$n_{i,t}^{i} = (1 - z_{\rho,t}\rho_s)n_{i,t-1}^{i} + v_{i,t}q(\theta_{i,t}),$$

where $n_{r,t}^{i} = \omega_t n_{r,t}$ is the total measure of r workers working in i firms, $n_{r,t}^{r} = (1 - \omega_t)\, n_{r,t}$ is the total measure of r workers working in r firms, and $v_{r,t}$ and $v_{i,t}$ denote aggregate vacancies for salaried employment category $j \in \{i, r\}$. Here, ω_t represents the endogenous share of r employment that is employed by i firms. $q(\theta_{j,t})$ is the job-filling probability in salaried employment category $j \in \{i, r\}$, and $0 < \rho_s < 1$ is the exogenous job separation probability, and $z_{\rho,t}$ is a job destruction shock. The profit maximization problems of r and i firms are subject to the relevant perceived laws of motion for salaried employment, and deliver standard job creation conditions for each category of salaried employment. The aggregate production function of r firms is linear in labor $n^r_{r,t}$ and can be expressed as $H(n^r_{r,t}) = z_t n^r_{r,t}$ while the aggregate production function of i firms can be written as $F(n^i_{i,t}, n^i_{r,t}, k_{i,t}) = z_t z_i \left[(1 - z_{\phi,t}\phi_i) \left(n^i_{r,t}\right)^{\lambda_i} + z_{\phi,t}\phi_i \left(\alpha_k k^{\lambda_k}_{i,t} + (1-\alpha_k)(n^i_{i,t})^{\lambda_k}\right)^{\frac{\lambda_i}{\lambda_k}} \right]^{\frac{1}{\lambda_i}}$ where $0 < \phi_i, \alpha_k < 1$, $\lambda_i, \lambda_k < 1$. z_t represents aggregate productivity and $z_i > 0$ represents the exogenous sectoral productivity of i firms. Finally, $z_{\phi,t}$ represents a shock to the relative productivity of the ICT-salaried labor composite, where a positive shock makes the use of ICT (and the salaried workers that complement ICT) more attractive in relative terms.

With the above information in mind, firms' choices on job creation, the allocation of r workers across firm categories, and ICT capital can be expressed as

$$\begin{aligned}\frac{\psi}{q(\theta_{r,t})} &= (1-\omega_t)\left[mc_{r,t} H_{n^r_r,t} - w^r_{r,t}\right] \\ &\quad + \omega_t \left[mc_{i,t} F_{n^i_r,t} - w^i_{r,t}\right] + \mathbb{E}_t \Xi_{t+1|t}(1 - z_{\rho,t+1}\rho_s)\left[\frac{\psi}{q(\theta_{r,t+1})}\right],\end{aligned}$$

$$\frac{\psi}{q(\theta_{i,t})} = mc_{i,t} F_{n^i_i,t} - w^i_{i,t} + \mathbb{E}_t \Xi_{t+1|t}(1 - z_{\rho,t+1}\rho_s)\left[\frac{\psi}{q(\theta_{i,t+1})}\right],$$

$$mc_{i,t} F_{n^i_r,t} - w^i_{r,t} = mc_{r,t} z_t H_{n^r_r,t} - w^r_{r,t},$$

and

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

where $\Xi_{t+1|t}$ denotes the household's stochastic discount factor.

Households and Self-Employment Households are the ultimate owners of all firms. They consume and send their members to search for employment opportunities, which introduces a labor force participation margin. They also make decisions on the creation of new salaried firms subject to the evolution of salaried firms, taking individual salaried-firm profits as given. To capture an important component of the labor market structure in LAC, in addition to sending members to search for salaried positions in categories r and i, the household can also send its members to work in self-employment. A measure $n_{e,t}$ of self-employed individuals use their own labor to operate owner-only firms. Thus, households receive income from salaried firm profits $\widetilde{d}_t N_t$, wage income from employed salaried workers in the two categories $w_{i,t}n^i_{i,t}$, $w^i_{r,t}n^i_{r,t}$, and $w^r_{r,t}n^r_{r,t}$, and income from production by self-employed individuals $p_{e,t}z_t z_e n_{e,t}$, where z_e denotes exogenous self-employment productivity. These resources are used to finance consumption expenditures c_t and the cost of salaried firm creation $f_e N_{e,t}$.

The perceived evolution of, respectively, i salaried employment, r salaried employment, and self-employment that households are subject to are given by

$$n_{r,t} = (1 - z_{\rho,t}\rho_s)n_{r,t-1} + s_{r,t}f(\theta_{r,t}),$$

$$n_{i,t} = (1 - z_{\rho,t}\rho_s)n_{i,t-1} + s_{i,t}f(\theta_{i,t}),$$

and

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

where $s_{j,t}$ denotes the measure of searchers in category $j \in \{i, r, e\}$, $0 < \phi_e \leq 1$ is the exogenous probability that a household member searching for a self-employment opportunity finds one. Thus, we can define sectoral labor force participation as $lfp_{e,t} = n_{e,t} + (1-\phi_e)s_{e,t}$, $lfp_{i,t} = n_{i,t} + (1-f(\theta_{i,t}))s_{i,t}$, and $lfp_{r,t} = n_{r,t} + (1-f(\theta_{r,t}))s_{r,t}$. The labor force participation rate in the economy is therefore given by $lfp_t = lfp_{e,t} + lfp_{i,t} + lfp_{r,t}$ and the unemployment rate can be defined as $ur_t \equiv ((1-\phi_e)s_{e,t} + (1-f(\theta_{i,t})s_{i,t} + (1-f(\theta_{r,t})s_{r,t})/lfp_t$.

The household maximizes $\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{c_t^{1-\sigma_c}}{1-\sigma_c} - \sum\limits_{j\in\{i,r,e\}} \frac{z_{\kappa,t}\kappa_j (lfp_{j,t})^{1+\frac{1}{\chi}}}{1+\frac{1}{\chi}} \right]$ subject to its budget constraint, the evolution of salaried firms defined earlier, and the perceived evolution of each category of employment, where σ_c,$\kappa_j, \chi > 0$ and $z_{\kappa,t}$ is a shock to the disutility of labor force participation. The solution to the household's problem delivers a labor force participation condition for each of the three categories of employment (e, i, and r)

$$\begin{aligned}\frac{z_{\kappa,t}\kappa_r (lfp_{r,t})^{\frac{1}{\chi}}}{c_t^{-\sigma_c}} \frac{1}{f(\theta_{r,t})} &= w^r_{r,t}(1-\omega_t) + w^i_{r,t}\omega_t \\ &+ \mathbb{E}_t \Xi_{t+1|t}(1 - z_{\rho,t+1}\rho_s) \left[\left(\frac{1}{f(\theta_{r,t+1})} - 1 \right) \frac{z_{\kappa,t+1}\kappa_r (lfp_{r,t+1})^{\frac{1}{\chi}}}{c_{t+1}^{-\sigma_c}} \right],\end{aligned}$$

$$\frac{z_{\kappa,t}\kappa_i(lfp_{i,t})^{\frac{1}{\chi}}}{c_t^{-\sigma_c}}\frac{1}{f(\theta_{i,t})} = w_{i,t}^i + \mathbb{E}_t\Xi_{t+1|t}(1-z_{\rho,t+1}\rho_s)\left[\left(\frac{1}{f(\theta_{i,t+1})}-1\right)\frac{z_{\kappa,t+1}\kappa_i(lfp_{i,t+1})^{\frac{1}{\chi}}}{c_{t+1}^{-\sigma_c}}\right],$$

and

$$\frac{z_{\kappa,t}\kappa_e(lfp_{e,t})^{\frac{1}{\chi}}}{c_t^{-\sigma_c}}\frac{1}{\phi_e} = p_{e,t}z_t z_e + \mathbb{E}_t\Xi_{t+1|t}(1-z_{\rho,t+1}\rho_e)\left[\left(\frac{1}{\phi_e}-1\right)\frac{z_{\kappa,t+1}\kappa_e(lfp_{e,t+1})^{\frac{1}{\chi}}}{c_{t+1}^{-\sigma_c}}\right],$$

as well as a firm creation condition:

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

where $\Xi_{t+1|t} = \beta c_{t+1}^{-\sigma_c}/c_t^{-\sigma_c}$ and average salaried-firm profits $\widetilde{d}_t$ were defined earlier.

Wage Determination, Symmetric Equilibrium, and Market Clearing Real wages are determined via bilateral Nash bargaining between firms and salaried workers, where $0 < \nu < 1$ is the bargaining power of workers (see Appendix A.3 for the value equations associated with salaried firms and the household).[4] Following the literature, we assume a symmetric equilibrium, which allows us to focus on average firm-level outcomes. Finally, in the presence of labor search frictions, endogenous firm entry, and costly technology adoption, the economy's resource constraint is given by

$$Y_t = c_t + (k_{i,t+1} - (1-\delta_i)k_{i,t}) + \psi\left(v_{r,t} + v_{i,t}\right) + f_e N_{e,t} + f_i N_{i,t}.$$

Appendix A.3 presents the list of equilibrium conditions.

Barriers to Firm Entry, Digital Adoption Costs, and Digital Adoption Following the empirical evidence and discussion in Finkelstein Shapiro and Mandelman (2021), we impose a positive link between the sunk cost of salaried firm creation and the cost of digital adoption. Specifically, we assume that $f_e = \lambda_f f_i$ with $\lambda_f > 1$. This assumption implies that any changes in digital adoption costs, which directly affect the number of firms adopting ICT in the model, will also change firm entry costs and vice versa. More broadly, this assumption

4

allows the model to be consistent with the negative link between barriers to firm entry and firm digital adoption in LAC (see Figure A1 in Appendix A.1).

Mapping of Employment and Firm Categories in Model to the Data For the purposes of mapping the categories of employment and salaried firms in the model to the data, we assume that salaried workers in r firms represent informal salaried workers while salaried workers in i firms (regardless of whether they complement ICT or are imperfectly substitutable with the ICT composite) are formal salaried workers. Then, total informal employment is given by the sum of informal salaried workers and self-employed workers. In turn, the informal employment share is defined as total informal employment divided by total (formal and informal) employment. Thus, r firms represent informal salaried firms while i firms represent formal salaried firms.

4 Quantitative Analysis

Models with endogenous firm entry exhibit a love-for-variety component that is not present in empirical measurements of the CPI (Bilbiie, Ghironi, and Melitz, 2012). Amid salaried firm creation, this implies that model-based quantity variables that are compared to their empirical counterparts need to be adjusted to purge the variety effect. With this in mind, denote by $o_{m,t}$ a quantity variable in the model that is inclusive of the variety effect. Then, given the aggregation of salaried and self-employment output categories, the model-based quantity variable $o_{d,t} = \Theta_t o_{m,t}$, where $\Theta_t = \left(N_t^{\frac{1-\phi_y}{1-\varepsilon}} + 1 \right)^{\frac{1}{1-\phi_y}}$ is readily comparable to its empirical counterpart.[5] In our quantitative analysis, all model-based quantity variables are expressed such that they are comparable to their counterparts in the data.

[5] See Cacciatore, Duval, Fiori, and Ghironi (2016) for a similar adjustment to model-based quantity variables in the context of a small open economy with firm entry, and Appendix A.4 for more details. Note that in the absence of salaried firm entry and exit, Θ_t collapses to a constant which, without loss of generality, can be normalized to 1 so that $o_{d,t} = o_{m,t}$.

4.1 Calibration

We calibrate the model to Mexico. As such, we borrow several parameter values from the emerging economy macro literature and related studies that also consider Mexico as their case study. The calibration of the model is based on a scenario without policy interventions. Having matched the dynamics of the COVID recession and ongoing recovery, we then consider how a policy that increases firm digital adoption by permanently reducing the barriers to adoption and that is implemented at the trough of the recession shapes the recovery path of the economy.

Parameters from Literature A period in the model represents a quarter. We set the subjective discount factor $\beta = 0.985$, the depreciation rate of ICT capital $\delta_i = 0.025$, and the risk aversion parameter $\sigma_c = 2$. We also set the exogenous salaried firm exit rate $\delta = 0.025$ based on available data on average firm exit rates and we normalize the minimum level of idiosyncratic productivity $a_{min} = 1$. We set $\varepsilon = 4$ and $k_p = 4.2$, which satisfies $\varepsilon - 1 < k_p$ and is consistent with average markups in the literature. We normalize the exogenous productivity of the self-employed $z_e = 1$. Turning to the labor market, we set the bargaining power of salaried workers $\nu = 0.5$, which is a common value in the search and matching literature. We set the separation probabilities $\rho_e = 0.03$ and $\rho_s = 0.05$, and $\phi_e = 0.20$, which is consistent with the probability of transitioning to self-employment in Mexico (Bosch and Maloney, 2008). Similar to Finkelstein Shapiro and Mandelman (2021), we choose a baseline elasticity of labor supply on the extensive margin of $\chi = 0.26$, set $\phi_y = 5$ as a baseline and, rooted in Eden and Gaggl (2017), choose $\lambda_i = 0.9$, $\phi_i = 0.47$, and $\lambda_k = 0.3$, implying imperfect substitutability between the ICT-labor composite and r employment.

Calibrated Parameters We choose the values of the remaining parameters—λ_f, α_k, ξ, κ_e, κ_i, κ_r, ψ, f_i, and z_i—to match select first-moment targets using Mexican data. For targets associated with the labor market, we use data for 2020Q1—that is, the quarter prior to the onset of the pandemic recession. For variables at lower frequencies, we use the latest available data prior to 2020. In particular, we match a cost of creating a business of

18 percent of GDP per capita (per World Bank Enterprise Survey data), a cost of posting vacancies equivalent to roughly 3.5 percent of the average wage (in line with the average cost of hiring; see Levy, 2007), a share of self-employment in total employment of 22.7 percent, a share of employment with tertiary education (represented by n_i^i) in total employment of 16 percent, a labor force participation rate of 61.3 percent, an unemployment rate of 4 percent (per ENOE data), a share of salaried firms that use digital technologies of 41.5 percent (per business digital adoption data from the World Bank), a share of total expenditures on ICT (capital and adoption) of 1.4 percent of GDP, and a share of expenditures on ICT adoption costs in the total cost of using ICT of 10 percent (per the ITU-D ICT Database). The calibrated parameter values are as follows: $\lambda_f = 0.000619, \alpha_k = 0.0456, \xi = 0.5174, \kappa_e = 549.1948, \kappa_i = 6655.6, \kappa_r = 37.4081, \psi = 0.1181, f_i = 0.00028$, and $z_i = 1.9686$.

Calibration of Shocks: Onset of COVID Recession and Recovery Path To capture the contraction at the onset of the COVID recession and the subsequent recovery path, we introduce four shocks: a shock to aggregate productivity (reflected in a change in z_t), a shock to the disutility of labor force participation (reflected in a change in $z_{\kappa,t}$), a shock to the the matching efficiency of r employment (reflected in a change in $z_{m,t}$), and a shock to the relative productivity of the ICT-salaried labor composite (reflected in a change in $z_{\phi,t}$). Specifically, we assume that

$$z_t = (1 - \varrho_z)z + \varrho_z z_{t-1} - \epsilon_t^z,$$

$$z_{\kappa,t} = (1 - \varrho_\kappa)z_\kappa + \varrho_\kappa z_{\kappa,t-1} + \epsilon_t^\kappa,$$

$$z_{m,t} = (1 - \varrho_m)z_m + \varrho_m z_{m,t-1} - \epsilon_t^m,$$

and

$$z_{\phi,t} = (1 - \varrho_\phi)z_\phi + \varrho_\phi z_{\phi,t-1} - \epsilon_t^\phi,$$

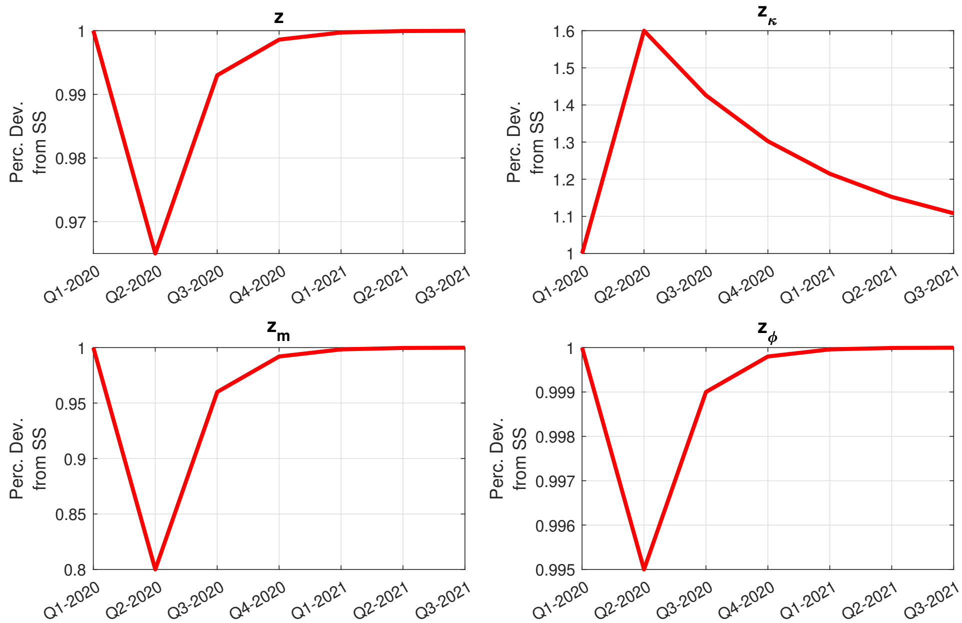
where $z = z_\kappa = z_m = z_\phi = 1$, $0 < \varrho_z, \varrho_\kappa, \varrho_m, \varrho_\phi < 1$ and $\epsilon_t^j \sim N(0, \sigma_j)$ for $j \in \{z, \kappa, m, \phi\}$. Given the unprecedented size of the COVID shock, the highly non-linear nature of the COVID recession, and the richness of our framework, we consider a perfect-foresight solution that allows us to solve the full non-linear version of the model.[6]

For the purposes of transparency, we consider a scenario where these shocks materialize only once so that the model jointly replicates the contraction in GDP, total employment, total salaried employment, and labor force participation, respectively, at the onset of the COVID recession in 2020Q2. In turn, we set the persistence of $z_t, z_{\kappa,t}, z_{m,t}$, and $z_{\phi,t}$ so that the model replicates the recovery path of GDP, total employment, total salaried employment, and labor force participation through 2021Q3 (the latest available quarter of data). The resulting values for the persistence parameters are $\varrho_z = \varrho_m = \varrho_\phi = 0.20$, and $\varrho_\kappa = 0.71$. In turn, letting period 0 in the model represent 2020Q2, we set the values for the shocks as follows: $\epsilon_0^z = 0.035$, $\epsilon_0^\kappa = 0.60$, $\epsilon_0^m = 0.20$, and $\epsilon_0^\phi = 0.005$, and $\epsilon_t^z = \epsilon_t^\kappa = \epsilon_t^m = \epsilon_t^\phi = 0$ for $t > 0$.

Figure 2 shows the path of z_t, $z_{\kappa,t}$,$z_{m,t}$, and $z_{\phi,t}$ after the shocks materialize. As the figure suggests, the COVID recession in the model stems from simultaneous reductions in aggregate productivity z, the efficiency of the matching process associated with r employment z_m, and the disutility of labor force participation z_κ, and an increase in the relative productivity of the ICT-labor composite z_ϕ. In turn, Figure 3 shows the responses of GDP, total employment, salaried employment, and labor force participation when these shocks materialize in the benchmark model and compares these variables against their empirical counterparts.

[6]Specifically, we consider the perfect foresight solution using the historical algorithm as described in Juillard (1996).

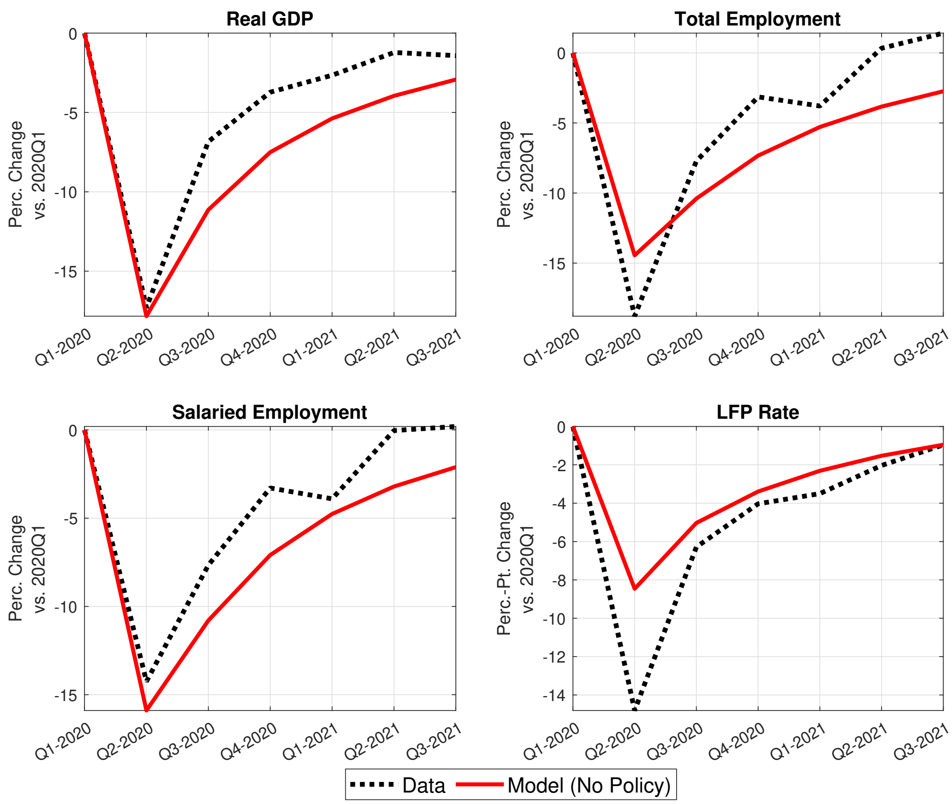
Figure 2: Model Shocks



The model can quantitatively match the contraction in GDP and salaried employment in 2020Q2, as well as a significant fraction of the contraction in total employment and labor force participation in that same period.[7] At the same time, given that the shocks take place in a single period and are zero afterwards, the model faces limitations in quantitatively replicating the rebound immediately after the contraction in 2020Q2. This limitation notwithstanding, from a comprehensive standpoint, the model does well in matching the pace of the recovery of these variables.

[7]The model cannot match the contraction in labor force participation without generating a contraction in GDP that is significantly greater than what is observed in the data. One potential explanation behind this limitation is the absence of household heterogeneity. See Figure A2 for an expanded version of Figure 3 that includes the informal employment share and the unemployment rate.

Figure 3: Onset and Aftermath of COVID Recession in Data vs. Benchmark Model, Select Variables



4.2 Digital Adoption Policies

We consider a policy that increases the share of i firms in the economy, N_i/N, by 1 percentage point in the steady state. This increase in N_i/N is engineered via a permanent reduction in the cost of digital adoption f_i. Recalling the link between f_i and f_e—that is, $f_e = \lambda_f f_i$ with $\lambda_f > 1$—the reduction in f_i also reduces the barriers to entry for salaried firms. The policy has a fiscal cost of roughly 1 percent of GDP.[8]

[8]Specifically, the total cost of the policy is $\left(f_e^{policy} N_E^{policy} + f_i^{policy} N_i^{policy} - \left(f_e^{base} N_E^{base} + f_i^{base} N_i^{base}\right)\right)$, where the superscript *base* denotes variables and parameters associated with the baseline (no-policy) economy. We assume that the reduction in costs is financed with revenue from lump-sum taxes.

4.2.1 Steady State Effects

Summary of Results Table 1 shows the steady-state changes of select variables in response to the policy. First, note that both the number of firms that use ICT, N_i, and the total number of salaried firms, N, increase. Therefore, the 1-percentage-point increase in N_i/N stems from a larger increase in N_i relative to N. This change in the composition of salaried firms towards those that use ICT is reflected in an increase, albeit moderate, in average firm productivity. Second, in response to the policy, output and consumption increase by 0.60 and 0.40 percent, respectively. The policy also leads to greater real wages across worker categories, which increase by roughly 3 percent on average and ultimately contribute to greater total household labor income, even as self-employment, and the household income associated with work in self-employment, fall. Interestingly, the policy generates a decline in labor force participation of roughly 1 percentage point, but by increasing the number of firms using ICT and the total number of salaried firms, the policy also changes the composition of employment towards greater labor formality. On net, given the change in labor force participation and the reallocation of workers across employment categories, the unemployment rate exhibits a reduction (albeit small). As we discuss in more detail below, the response of labor market variables to the policy hinge critically on how the equilibrium change in consumption affects participation decisions, and therefore on the degree of household risk aversion.

Table 1: Steady State Changes in Response to Greater Firm Digital Adoption

Variable	**Percent Change** Relative to No-Policy Baseline
Salaried Firms (N)	32.50
Firms using ICT (N_i)	35.74
Economy-Wide Ave. Firm Productivity	0.13
Total Output	0.58
Consumption	0.39
i Worker Real Wage	3.29
r Worker Real Wage	2.48
Total Labor Income	0.23
Self-Employment (n_e)	-3.15
	Percentage-Pt. Change Relative to No-Policy Baseline
Self-Employment Rate	-0.32
Informal Employment Share	-0.66
Unemployment Rate	-0.10
LFP Rate	-1.04
Share of Firms using ICT (N_i/N)	1.01
Policy Expend./Output	1.00

Notes: Values in blue denote beneficial changes (relative to the baseline, no-policy scenario) of select variables of interest. Values in red denote adverse changes (relative to the baseline, no-policy scenario) of select variables of interest. Total labor income is defined as the sum of informal salaried labor income, formal salaried labor income and total self-employment income.

Economic Mechanisms To better understand the results in Table 1, especially those associated with the labor market, note that the policy-induced reduction in f_i (and therefore in f_e as well) reduces the marginal cost of creating new salaried firms, as well as the marginal cost of adopting the ICT production technology. As a result, more salaried firms enter, bolstering the demand for r and i labor, improving labor market conditions for salaried workers and, in doing so, real wages (via greater labor market tightness, which is a component of the real wage in both salaried firm categories). At the same time, the reduction in barriers to entry and ICT adoption makes self-employment less attractive, leading to a reduction in self-employment. The latter contributes to the reduction in the informal employment share.

Despite the increase in real wages, which all else equal encourages more search for salaried jobs, the equilibrium measure of individuals searching for salaried jobs actually declines with the policy. This result traces back to the strength of the income effect, where the latter stems from the positive impact of the policy on salaried wages and on consumption. As such, its quantitative impact is therefore influenced the household's degree of relative risk aversion. To see this more clearly, without loss of generality, consider the optimal participation decision for i workers in steady state, which can be written as

$$\frac{\kappa_i(lfp_i)^{\frac{1}{\chi}}}{c^{-\sigma_c}}\left[\frac{(1-\beta(1-\rho_s))}{f(\theta_i)}+\beta(1-\rho_s)\right]=w_i^i.$$

Given the value of σ_c we adopt in our baseline calibration, which is consistent with those in the emerging economy business cycle literature, the quantitative change in the equilibrium job-finding probability and in consumption—which embodies the income effect—are such that sectoral salaried search and labor force participation decline.[9] The equilibrium response of searchers and participation across salaried employment categories, coupled with the decline in participation by the self-employed, ultimately leads to in an equilibrium reduction in the total labor force participation rate. The reduction in the measure of searchers across employment categories, and the increase in job-finding probabilities stemming from greater vacancy postings by salaried firms leads to a reduction, albeit small, in the unemployment rate.

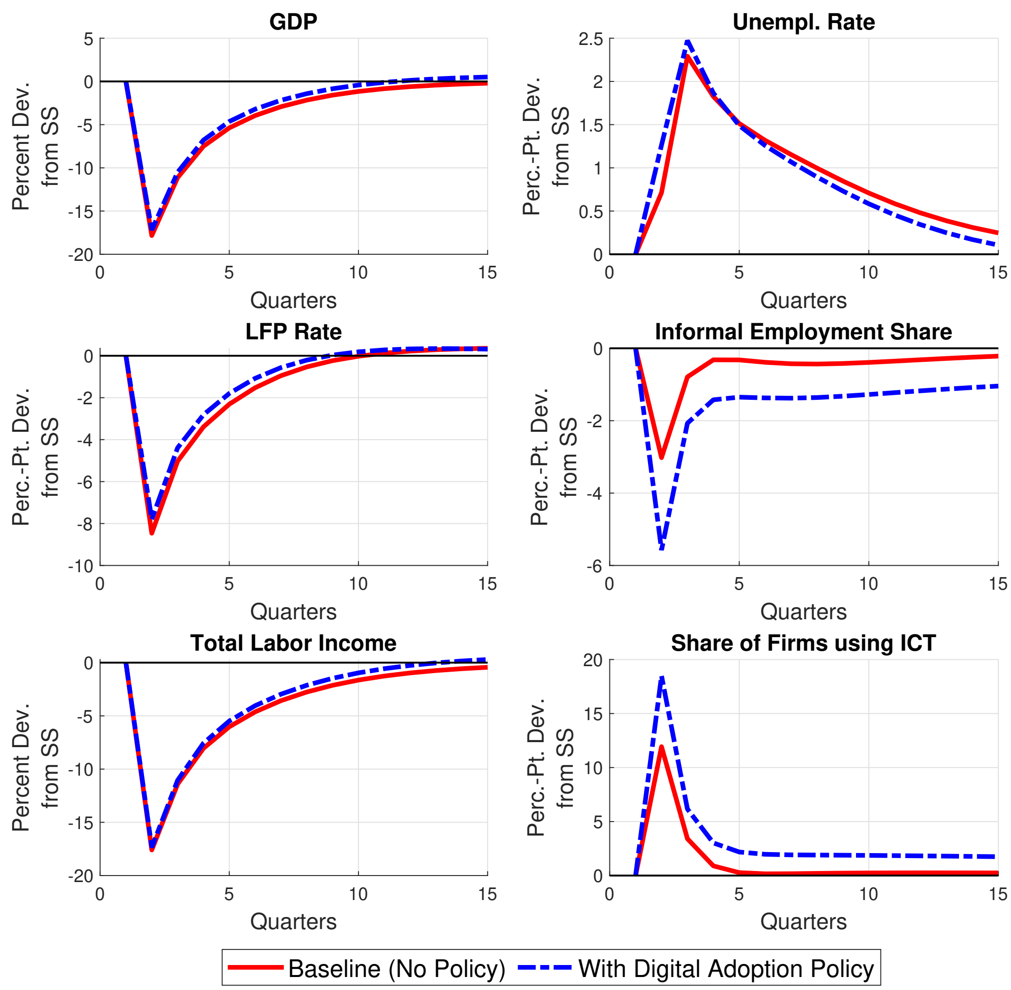
Under the baseline calibration, the average productivity of i firms is endogenously greater relative to the productivity of r firms. The increase in the number of firms that adopt the ICT technology narrows this average productivity differential, but by increasing the share of i firms in the economy and therefore changing the composition of salaried firms towards those that are endogenously more productive, it increases average firm productivity at the economy-wide level. The resulting change in the composition of salaried firms offsets the reduction in self-employment production and is strong enough to ultimately bolster total output.

[9] This result is also present when considering the labor force participation decision associated with jobs in r firms. A simple counterfactual experiment where we assume household risk neutrality confirms the quantitative relevance of the income effect on labor force participation across salaried employment categories.

4.2.2 Model Response to Shocks and Recovery Process Under Policy

Summary of Results Figure 4 shows the response of GDP, the unemployment rate, the labor force participation rate, the informal employment share, total labor income, and the share of firms using the ICT technology to the set of shocks that replicate the dynamics of the Mexican economy under COVID. The red solid line shows the benchmark (no-policy) scenario while the blue dash-dotted line shows the response under the digital adoption policy.

Figure 4: Labor Market and Macroeconomic Dynamics amid COVID: Benchmark vs. Policy Scenario

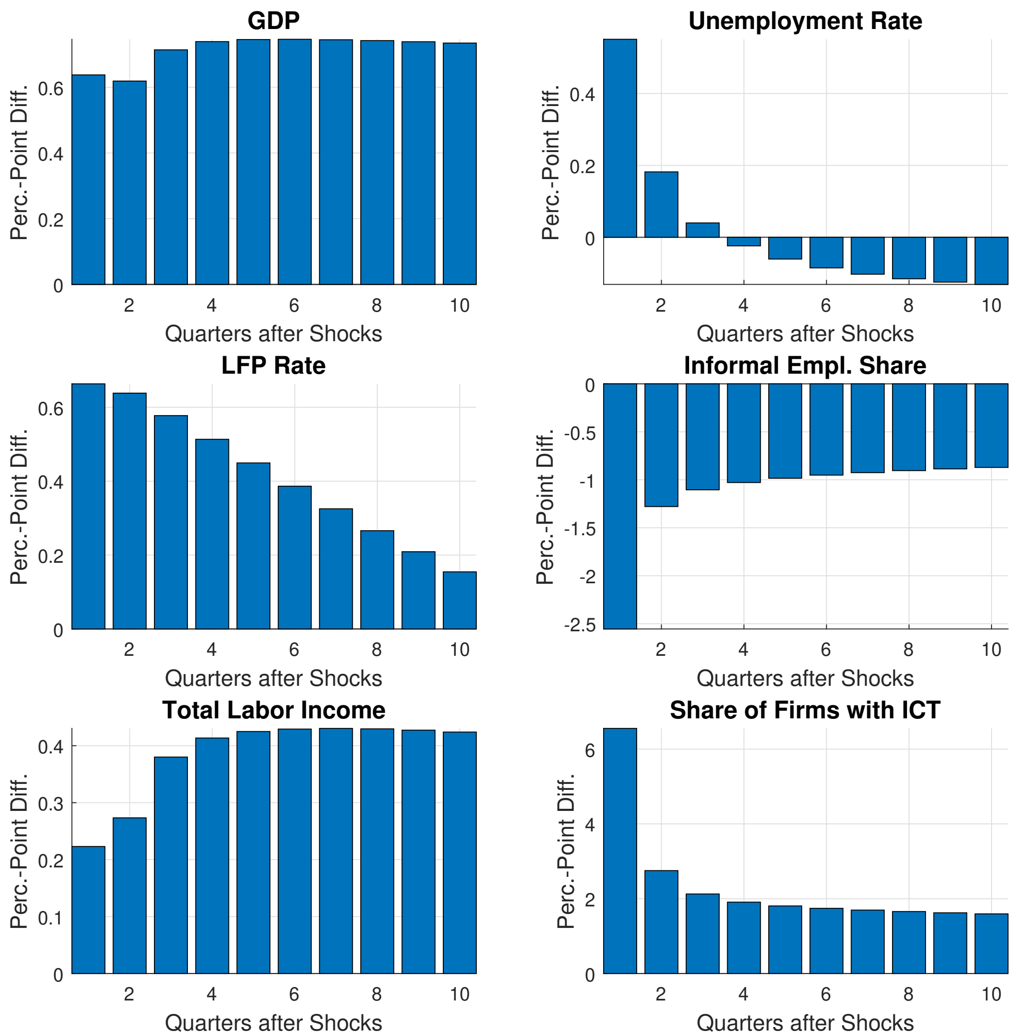


Notes: Informal salaried labor income is defined as $w_r^r n_r^r$. Formal salaried labor income is defined as $w_r^i n_r^i + w_i^i n_i^i$. Total labor income is the sum of informal salaried labor income, formal salaried labor income and total self-employment income.

As the figure suggests, the policy limits the contraction in output, labor force participation, and total labor income, and fosters their earlier recovery as the shocks subside. At the same time, the policy leads to a larger and persistent decline in the share of informal employment. The larger reduction in the informal employment share is accompanied by an initially larger increase in the unemployment rate, but a faster subsequent fall from its peak, implying a faster recovery in the employment rate. Recall per Table 1 that in the long term, the unemployment rate under the policy ends up being marginally lower compared to its pre-COVID level. Finally, the policy leads to a sharper increase in the share of firms using ICT that overshoots its long-term level in the first year after the shocks.

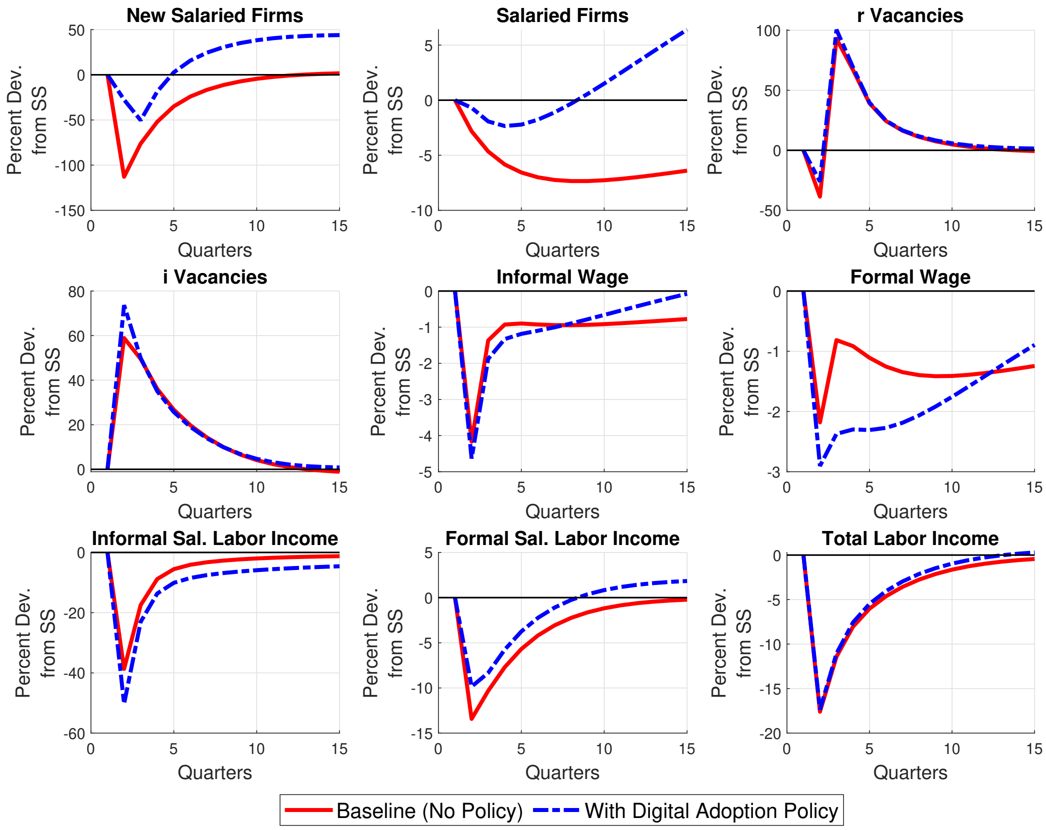
Given the magnitude of the response of the economy to the shocks, Figure 4 does not fully illustrate the extent of the policy's impact. To show the effects of the policy more clearly, Figure 5 plots the difference between response of the economy under the policy and the benchmark (no-policy) economy for the first 10 quarters after the shocks for each of the variables presented in Figure 4.

Figure 5: Labor Market and Macroeconomic Dynamics amid COVID: Benchmark vs. Policy Scenario



Economic Mechanisms To better understand the driving mechanisms behind the results in Figures 4 and 5, we delve deeper into how salaried firms respond to the shocks that generate the COVID recession, and how the policy shapes firms' responses.

Figure 6: Labor Market and Macroeconomic Dynamics amid COVID: Firm, Labor Market, and Labor Income Dynamics



Notes: Informal salaried labor income is defined as $w_r^r n_r^r$. Formal salaried labor income is defined as $w_r^i n_r^i + w_i^i n_i^i$. Total labor income is the sum of informal salaried labor income, formal salaried labor income and total self-employment income.

Figure 6 shows that in the benchmark economy, the shocks lead to a sharp initial decline in the number of new salaried firms, which translates into a persistent contraction in the number of salaried firms. Given the simultaneous reduction in aggregate productivity z and the relative improvement in the productivity of the ICT-labor composite z_ϕ (recall Figure 2), salaried firms initially reduce the number of job vacancies posted associated with r employment and increase the number of vacancies posted associated with i employment. The increase in i vacancy postings reflects the relative improvement in the return to labor that complements ICT capital.

As the effects from the shocks begin to subside, and new firm creation recovers gradually, salaried firms start posting r vacancies, leading to a sharp rebound in these vacancies above their pre-shock level. The behavior of vacancies has direct implications for salaried labor market conditions, which in turn shape the response of wages to the shocks: a sharp contraction followed a subsequent rebound. In turn, the response of sectoral employment (not shown) and wages shapes the dynamics of formal, informal, and total labor income.

By reducing barriers to salaried-firm entry and digital adoption at the through of the recession, the policy limits the sharp contraction in new salaried firm creation that otherwise takes place, leading not only to a more subdued reduction in the number of salaried firms, but also to a faster recovery. The more subdued response of salaried firms under the policy not only implies that salaried firms post more i vacancies, but also that the contraction in r vacancies is smaller and their subsequent rebound is greater. In turn, the change in the response of vacancies feeds into wages, leading to faster recovery in the latter. Since the policy changes the composition of total employment towards greater formality (recall Table 1 and Figures 4 and 5), informal salaried labor income—and total informal labor income more generally—remains more subdued compared to the benchmark economy. However, by limiting the contraction in formal employment, the policy not only limits the contraction in total formal salaried income, but by fostering greater ICT adoption and improving the productivity profile of firms, bolsters the recovery of formal income as well. On net, the response of total formal salaried income as the economy recovers more than offsets the contraction in informal income, thereby explaining the earlier recovery in total labor income.

4.2.3 Firm Digital Adoption and Salaried-Firm Hiring Costs

Based on evidence on the negative link between firm digital adoption and barriers to firm entry and for reasons outlined earlier and in Finkelstein Shapiro and Mandelman (2021), our analysis assumes that reductions in the cost of firm digital adoption are also reflected in lower salaried-firm sunk entry costs. Another plausible scenario is that greater firm digital adoption is also associated with lower costs of searching and hiring salaried workers (that is, lower vacancy posting costs).[10]

[10] For example, digital adoption can allow salaried firms to access online hiring platforms and virtual job intermediation services, as well as streamline the job application, review, and interview processes. Also, while not studied in our framework, the impact of digital adoption policies on labor market outcomes can also be influenced by the degree of wage rigidities, and by institutional factors associated with the formal

Figure 7: Labor Market and Macroeconomic Dynamics amid COVID: Benchmark vs. Policy Scenario, Digital Adoption Reduces Hiring Costs

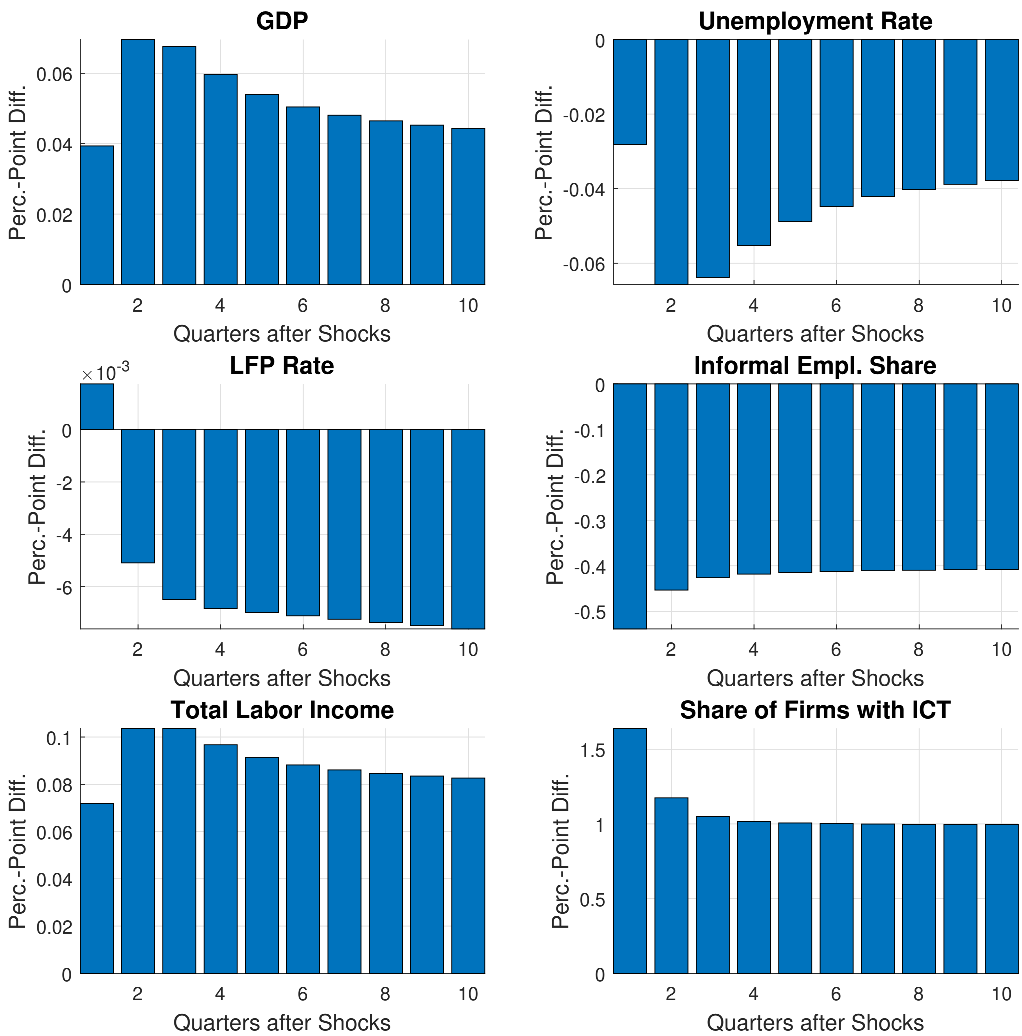


Figure 7 shows an analogous figure to Figure 5, which focuses on the short-term response to the shocks, when we consider an alternative policy whereby digital adoption also reduces firms' hiring costs (similar to the experiments above, we consider a policy that is implemented at the trough of the recession and that permanently increases the share of firms that use ICT by 1 percentage point; Figure A3 in Appendix A.5 shows the counterpart of Figure 4 under this alternative policy scenario). Qualitatively, the results for GDP, the informal employ-

labor market, such as firing costs and payroll taxes (see, for example, Lama and Medina, 2019, and Lama et al., 2022, respectively).

ment share, and total labor income are similar to those that emerge under our benchmark digital adoption policy. However, the alternative policy reduces the unemployment rate and increases labor force participation in the short term. However, for the same increase in the share of firms using ICT, the alternative policy has smaller quantitative effects across variables compared to the benchmark digital adoption policy. These smaller quantitative effects trace back to the fact that the alternative policy has negligible effects on overall salaried firm creation, which plays an important role in bolstering GDP and labor income under the benchmark digital adoption policy. More broadly, these findings highlight the importance of the interconnection between digital adoption policies and economic dynamism—embodied in firm entry—for a faster economic recovery in the context of COVID.

5 Conclusion

In 2020 and as a result of the COVID pandemic, the Latin America and the Caribbean (LAC) region experienced the most dramatic contraction in employment and economic activity relative to other regions around the world. The adoption and use of digital technologies by firms was an important adjustment margin in response to the adverse economic effects of the COVID shock.

Using a search and matching framework with firm entry and exit where salaried firms can choose to adopt digital technologies and the labor market and firm structure is consistent with the LAC context, we analyze how policies that bolster firm digital adoption shape the labor market and economic recovery from COVID-19. Using Mexico as a case study in the region, we show that the model can quantitatively capture the dynamics of the labor market and output during COVID, including the behavior of labor force participation and informal employment.

Using the model, we show that a permanent reduction in the barriers to adopting digital technologies introduced at the trough of the recession contributes to an earlier recovery in GDP, total employment, and labor income, and to a larger expansion in the share of formal employment compared to a scenario without policy. Even though this policy induces a reduction in total employment and labor force participation in the long term, it also improves the average productivity profile of firms, and leads to greater levels of GDP and labor income, a larger share of formal employment, and marginally lower unemployment. Therefore, fostering greater firm digital adoption can not only support earlier labor market and economic recoveries, but also lead to improved long-term macroeconomic outcomes.

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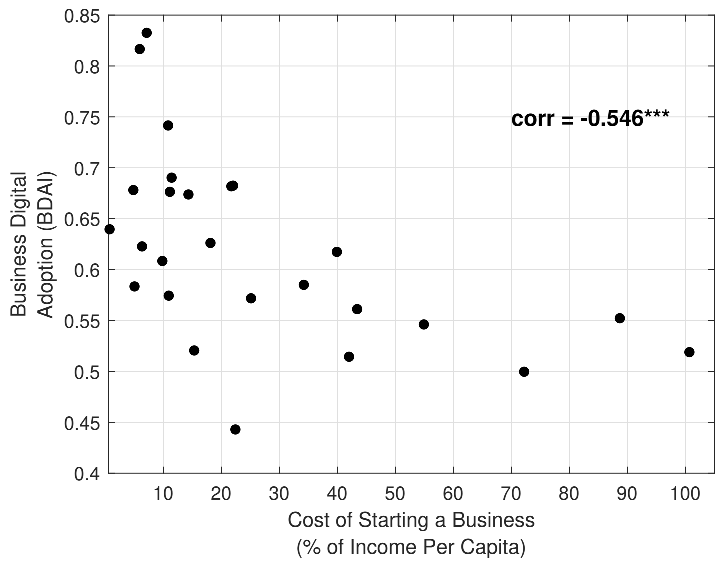
A Online Appendix

A.1 Barriers to Firm Entry and Firm Digital Adoption in LAC

Figure A1: Barriers to Firm Entry and Firm Digital Adoption in LAC



Sources: World Bank Enterprise Survey (WBES 2016 data) and World Bank World Development Report 2016. Notes: the country sample is comprised of Argentina, the Bahamas, Barbados, Belize, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Guyana, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, St. Lucia, Suriname, Trinidad and Tobago, Uruguay, and Venezuela. *** denotes significance at the 1 percent level.

A.2 Real Wage Determination

Real wages are determined via bilateral Nash bargaining between salaried workers and salaried firms. Given the timing of the labor market, the net values to the household of having an r worker employed at an r firm, an r worker employed at an i firm, and an i worker employed at an i firm are given by

$$\mathbf{W}^{r}_{r,t} = w^{r}_{r,t} + \mathbb{E}_t \Xi_{t+1|t} (1 - z_{\rho,t+1}\rho_s) \left(1 - f\left(\theta_{r,t+1}\right)\right) \mathbf{W}^{r}_{r,t+1}, \tag{1}$$

$$\mathbf{W}^{i}_{r,t} = w^{i}_{r,t} + \mathbb{E}_t \Xi_{t+1|t} (1 - z_{\rho,t+1}\rho_s) \left(1 - f\left(\theta_{r,t+1}\right)\right) \mathbf{W}^{i}_{r,t+1}, \tag{2}$$

and

$$\mathbf{W}^i_{i,t} = w^i_{i,t} + \mathbb{E}_t \Xi_{t+1|t}(1 - z_{\rho,t+1}\rho_s)\left(1 - f\left(\theta_{i,t+1}\right)\right)\mathbf{W}^i_{i,t+1}, \tag{3}$$

respectively. Turning to salaried firms, the values of each of these workers are given by

$$\mathbf{J}^r_{r,t} = mc_{r,t}F_{n^r_{r,t}} - w^r_{r,t} + (1 - z_{\rho,t}\rho_s)\mathbb{E}_t\Xi_{t+1|t}\mathbf{J}^r_{r,t+1}, \tag{4}$$

$$\mathbf{J}^i_{r,t} = mc_{i,t}F_{n^i_{r,t}} - w^i_{r,t} + (1 - z_{\rho,t}\rho_s)\mathbb{E}_t\Xi_{t+1|t}\mathbf{J}^i_{r,t+1}, \tag{5}$$

and

$$\mathbf{J}^i_{i,t} = mc_{i,t}F_{n^i_{i,t}} - w^i_{i,t} + (1 - z_{\rho,t}\rho_s)\mathbb{E}_t\Xi_{t+1|t}\mathbf{J}_{i,t+1}, \tag{6}$$

Let $0 < \nu < 1$ be the bargaining power of salaried workers. Then, it is easy to show that the Nash wages are implicitly given by $(1-\nu)\,\mathbf{W}^r_{r,t} = \nu\mathbf{J}^r_{r,t}$, $(1-\nu)\,\mathbf{W}^i_{r,t} = \nu\mathbf{J}^i_{r,t}$, and $(1-\nu)\,\mathbf{W}^i_{i,t} = \nu\mathbf{J}^i_{i,t}$ for each of the three categories of salaried workers.

A.3 Equilibrium Conditions: Benchmark Model

Taking the exogenous processes $\{z_t, z_{\rho,t}, z_{\kappa,t}, z_{\phi,t}\}$ as given, the endogenous variables $\{Y_t, p_{s,t}\}$, $\left\{c_t, Y_{e,t}, \widetilde{y}_{r,t}, \widetilde{y}_{i,t}, p_{e,t}, N_t, N_{i,t}, \widetilde{d}_{r,t}, \widetilde{d}_{i,t}, \widetilde{d}_t, mc_{r,t}, mc_{i,t}, \widetilde{a}_{i,t}, \widetilde{\rho}_{r,t}, \widetilde{\rho}_{i,t}, Y_{s,t}, \widetilde{a}_{r,t}, a_{i,t}, n^r_{r,t}, n^i_{r,t}, n^i_{i,t}, \omega_t\right\}$ and $\left\{v_{i,t}, v_{r,t}, k_{i,t}, n_{r,t}, n_{e,t}, N_{e,t}, w^r_{r,t}, w^i_{r,t}, w^i_{i,t}, s_{r,t}, s_{i,t}, s_{e,t}, N_{r,t}, \mathbf{J}^r_{r,t}, \mathbf{J}^i_{r,t}, \mathbf{J}^i_{i,t}, \mathbf{W}^r_{r,t}, \mathbf{W}^i_{r,t}, \mathbf{W}^i_{i,t}\right\}$ satisfy:

$$Y_t = c_t + (k_{i,t+1} - (1-\delta_i)k_{i,t}) + \psi\left(v_{r,t} + v_{i,t}\right) + f_e N_{e,t} + f_i N_{i,t}, \tag{7}$$

$$Y_{e,t} = z_t z_e n_{e,t}, \tag{8}$$

$$H(n^r_{r,t}) = N_{r,t}\left(\frac{\widetilde{y}_{r,t}}{\widetilde{a}_{r,t}}\right), \tag{9}$$

$$F(n^i_{i,t}, n^i_{r,t}, k_{i,t}) = N_{i,t}\left(\frac{\widetilde{y}_{i,t}}{\widetilde{a}_{i,t}}\right), \tag{10}$$

$$Y_t = \left[Y_{s,t}^{\frac{\phi_y - 1}{\phi_y}} + Y_{e,t}^{\frac{\phi_y - 1}{\phi_y}}\right]^{\frac{\phi_y}{\phi_y - 1}}, \tag{11}$$

$$Y_{s,t} = \left(p_{s,t}\right)^{-\phi_y} Y_t, \tag{12}$$

$$Y_{e,t} = (p_{e,t})^{-\phi_y} Y_t, \tag{13}$$

$$N_t = (1-\delta)\left[N_{t-1} + N_{e,t-1}\right], \tag{14}$$

$$N_{i,t} = \left(\frac{a_{min}}{a_{i,t}}\right)^{k_p} N_t, \tag{15}$$

$$\widetilde{d}_{r,t} = \left[\widetilde{\rho}_{r,t} - \frac{mc_{r,t}}{\widetilde{a}_{r,t}}\right] \widetilde{y}_{r,t} \tag{16}$$

$$\widetilde{d}_{i,t} = \left[\widetilde{\rho}_{i,t} - \frac{mc_{i,t}}{\widetilde{a}_{i,t}}\right] \widetilde{y}_{i,t} - f_i, \tag{17}$$

$$\widetilde{d}_t = \frac{N_{r,t}}{N_t}\widetilde{d}_{r,t} + \frac{N_{i,t}}{N_t}\widetilde{d}_{i,t}, \tag{18}$$

$$\widetilde{\rho}_{r,t} = \frac{\varepsilon}{\varepsilon - 1}\frac{mc_{r,t}}{\widetilde{a}_{r,t}}, \tag{19}$$

$$\widetilde{\rho}_{i,t} = \frac{\varepsilon}{\varepsilon - 1}\frac{mc_{i,t}}{\widetilde{a}_{i,t}}, \tag{20}$$

$$d_{i,t}(a_{i,t}) = d_{r,t}(a_{i,t}), \tag{21}$$

$$\widetilde{y}_{r,t} = (\widetilde{\rho}_{r,t}/p_{s,t})^{-\varepsilon} Y_{s,t}, \tag{22}$$

$$\widetilde{y}_{i,t} = (\widetilde{\rho}_{i,t}/p_{s,t})^{-\varepsilon} Y_{s,t}, \tag{23}$$

$$p_{s,t} = \left[N_{r,t}\left(\widetilde{\rho}_{r,t}\right)^{1-\varepsilon} + N_{i,t}\left(\widetilde{\rho}_{i,t}\right)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}}, \tag{24}$$

$$\widetilde{a}_{r,t} = \widetilde{a}_{i,t}\left(\left[\frac{a_{i,t}^{k_p-(\varepsilon-1)} - a_{min}^{k_p-(\varepsilon-1)}}{a_{i,t}^{k_p} - a_{min}^{k_p}}\right]\right)^{\frac{1}{\varepsilon-1}} a_{min} \tag{25}$$

$$\widetilde{a}_{i,t} = \left(\frac{k_p}{k_p - (\varepsilon - 1)}\right)^{\frac{1}{\varepsilon-1}} a_{i,t}, \tag{26}$$

$$n_{r,t} = (1 - z_{\rho,t}\rho_s)n_{r,t-1} + v_{r,t}q(\theta_{r,t}), \tag{27}$$

$$n^i_{i,t} = (1 - z_{\rho,t}\rho_s)n^i_{i,t-1} + v^i_{i,t}q(\theta_{i,t}), \tag{28}$$

$$\begin{aligned}\frac{\psi}{q(\theta_{r,t})} &= (1-\omega_t)\left[mc_{r,t}H_{n^r_r,t} - w^r_{r,t}\right] \\ &\quad + \omega_t\left[mc_{i,t}F_{n^i_r,t} - w^i_{r,t}\right] + \mathbb{E}_t\Xi_{t+1|t}(1 - z_{\rho,t+1}\rho_s)\left[\frac{\psi}{q(\theta_{r,t+1})}\right],\end{aligned} \tag{29}$$

$$\frac{\psi}{q(\theta_{i,t})} = mc_{i,t}F_{n_i^i,t} - w_{i,t}^i + \mathbb{E}_t\Xi_{t+1|t}(1 - z_{\rho,t+1}\rho_s)\left[\frac{\psi}{q(\theta_{i,t+1})}\right], \tag{30}$$

$$mc_{i,t}F_{n_r^i,t} - w_{r,t}^i = mc_{r,t}z_tH_{n_r^r,t} - w_{r,t}^r, \tag{31}$$

$$1 = \mathbb{E}_t\Xi_{t+1|t}\left[mc_{i,t+1}F_{k_i,t+1} + (1 - \delta_i)\right], \tag{32}$$

$$n_{e,t} = (1 - z_{\rho,t}\rho_e)n_{e,t-1} + s_{e,t}\phi_e, \tag{33}$$

$$f_e = (1 - \delta)\mathbb{E}_t\Xi_{t+1|t}\left[\widetilde{d}_{t+1} + f_e\right], \tag{34}$$

$$n_{r,t}^r = (1 - \omega_t)n_{r,t}, \tag{35}$$

$$n_{r,t}^i = \omega_t n_{r,t}, \tag{36}$$

$$(1 - \nu)\,\mathbf{W}_{r,t}^r = \nu\mathbf{J}_{r,t}^r, \tag{37}$$

$$(1 - \nu)\,\mathbf{W}_{r,t}^i = \nu\mathbf{J}_{r,t}^i, \tag{38}$$

$$(1 - \nu)\,\mathbf{W}_{i,t}^i = \nu\mathbf{J}_{i,t}^i, \tag{39}$$

$$\mathbf{J}_{r,t}^r = mc_{r,t}H_{n_{r,t}^r} - w_{r,t}^r + \mathbb{E}_t\Xi_{t+1|t}(1 - z_{\rho,t+1}\rho_s)\mathbf{J}_{r,t+1}^r, \tag{40}$$

$$\mathbf{J}_{r,t}^i = mc_{i,t}F_{n_{r,t}^i} - w_{r,t}^i + \mathbb{E}_t\Xi_{t+1|t}(1 - z_{\rho,t+1}\rho_s)\mathbf{J}_{r,t+1}^i, \tag{41}$$

$$\mathbf{J}_{i,t}^i = mc_{i,t}F_{n_{i,t}^i} - w_{i,t}^i + \mathbb{E}_t\Xi_{t+1|t}(1 - z_{\rho,t+1}\rho_s)\mathbf{J}_{i,t+1}, \tag{42}$$

$$\mathbf{W}_{r,t}^r = w_{r,t}^r + \mathbb{E}_t\Xi_{t+1|t}(1 - z_{\rho,t+1}\rho_s)\left(1 - f\left(\theta_{r,t+1}\right)\right)\mathbf{W}_{r,t+1}^r, \tag{43}$$

$$\mathbf{W}_{r,t}^i = w_{r,t}^i + \mathbb{E}_t\Xi_{t+1|t}(1 - z_{\rho,t+1}\rho_s)\left(1 - f\left(\theta_{r,t+1}\right)\right)\mathbf{W}_{r,t+1}^i, \tag{44}$$

$$\mathbf{W}_{i,t}^i = w_{i,t}^i + \mathbb{E}_t\Xi_{t+1|t}(1 - z_{\rho,t+1}\rho_s)\left(1 - f\left(\theta_{i,t+1}\right)\right)\mathbf{W}_{i,t+1}^i, \tag{45}$$

$$\frac{\mathbf{h}_{lfp_{r,t}}}{\mathbf{u}'(c_t)}\frac{1}{f(\theta_{r,t})} = w_{r,t}^r(1-\omega_t) + w_{r,t}^i\omega_t + \mathbb{E}_t\Xi_{t+1|t}(1-z_{\rho,t+1}\rho_s)\left[\left(\frac{1}{f(\theta_{r,t+1})} - 1\right)\frac{\mathbf{h}_{lfp_{r,t+1}}}{\mathbf{u}'(c_{t+1})}\right], \tag{46}$$

$$\frac{\mathbf{h}_{lfp_{i,t}}}{\mathbf{u}'(c_t)}\frac{1}{f(\theta_{i,t})} = w_{i,t}^i + \mathbb{E}_t\Xi_{t+1|t}(1 - z_{\rho,t+1}\rho_s)\left[\left(\frac{1}{f(\theta_{i,t+1})} - 1\right)\frac{\mathbf{h}_{lfp_{i,t+1}}}{\mathbf{u}'(c_{t+1})}\right], \tag{47}$$

$$\frac{\mathbf{h}_{lfp_{e,t}}}{\mathbf{u}'(c_t)}\frac{1}{\phi_e} = p_{e,t}z_tz_e + \mathbb{E}_t\Xi_{t+1|t}(1 - z_{\rho,t+1}\rho_e)\left[\left(\frac{1}{\phi_e} - 1\right)\frac{\mathbf{h}_{lfp_{e,t+1}}}{\mathbf{u}'(c_{t+1})}\right], \tag{48}$$

$$N_{r,t} = N_t - N_{i,t}. \tag{49}$$

A.4 Data-Consistent Model Quantities

In a symmetric equilibrium, the nominal price of salaried output can be written as

$$P_{s,t} = \left[N_{r,t}\left(\widetilde{p}_{r,t}\right)^{1-\varepsilon} + N_{i,t}\left(\widetilde{p}_{i,t}\right)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}},$$

or

$$P_{s,t} = N_t^{\frac{1}{1-\varepsilon}}\left[G(a_{i,t})\left(\widetilde{p}_{r,t}\right)^{1-\varepsilon} + (1-G(a_{i,t}))\left(\widetilde{p}_{i,t}\right)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}},$$

where $\widetilde{p}_{r,t} \equiv p_{r,t}(\widetilde{a}_{r,t})$ and $\widetilde{p}_{i,t} \equiv p_{i,t}(\widetilde{a}_{i,t})$. Recalling that total output is given by $Y_t = \left[Y_{s,t}^{\frac{\phi_y-1}{\phi_y}} + Y_{e,t}^{\frac{\phi_y-1}{\phi_y}}\right]^{\frac{\phi_y}{\phi_y-1}}$, it is easy to show that the economy's aggregate price index is

$$P_t = \left[P_{s,t}^{1-\phi_y} + P_{e,t}^{1-\phi_y}\right]^{\frac{1}{1-\phi_y}}.$$

Thus, we can write this last expression as

$$P_t = \left[N_t^{\frac{1-\phi_y}{1-\varepsilon}}\left[G(a_{i,t})\left(\widetilde{p}_{r,t}\right)^{1-\varepsilon} + (1-G(a_{i,t}))\left(\widetilde{p}_{i,t}\right)^{1-\varepsilon}\right]^{\frac{1-\phi_y}{1-\varepsilon}} + P_{e,t}^{1-\phi_y}\right]^{\frac{1}{1-\phi_y}}.$$

where the love-for-variety component comes from the presence of N_t, which only applies to the salaried-firm component of prices. Hence the term $\Theta_t = \left(N_t^{\frac{1-\phi_y}{1-\varepsilon}} + 1\right)^{\frac{1}{1-\phi_y}}$ when converting model-based quantity variables that include this variety component to be comparable to their empirical counterparts (see Cacciatore, Duval, Fiori, and Ghironi, 2016, for an analogous adjustment in a small open economy context with endogenous firm entry).

A.5 Additional Quantitative Results

Figure A2: Onset and Aftermath of COVID in Data vs. Benchmark Model, Select Variables (Extended)

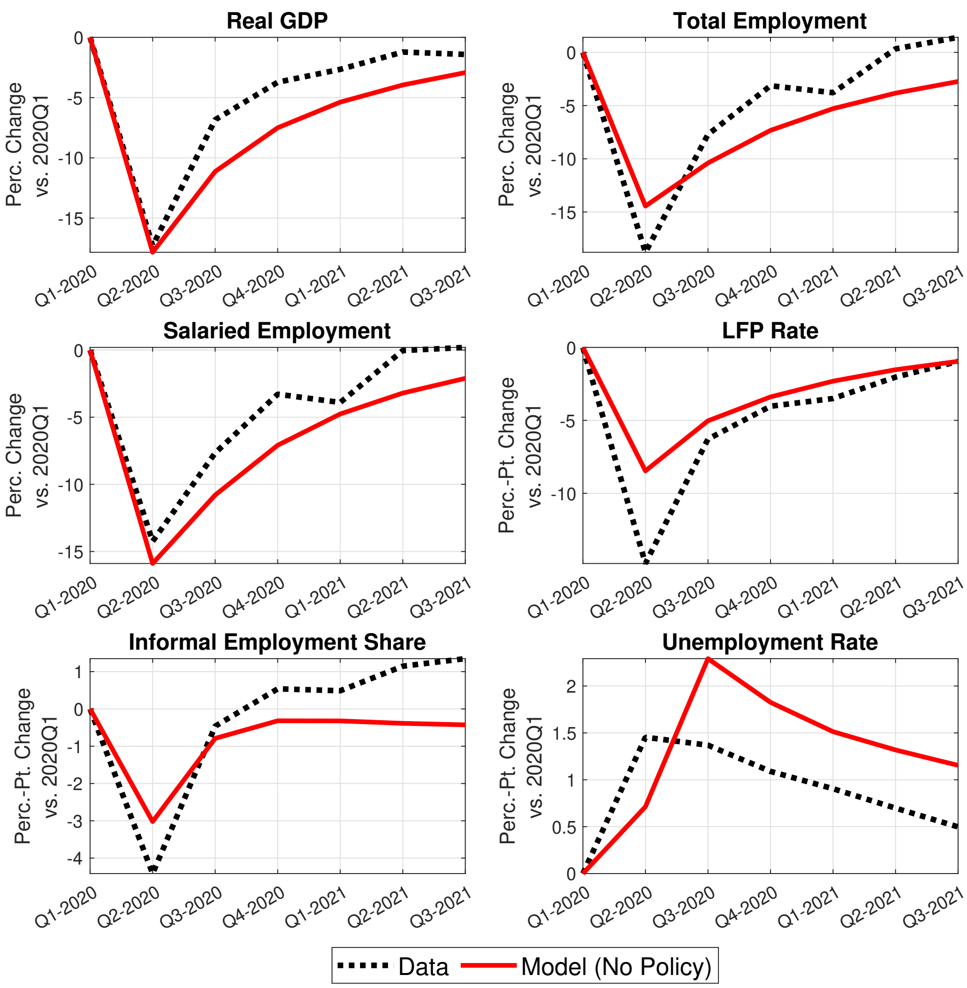
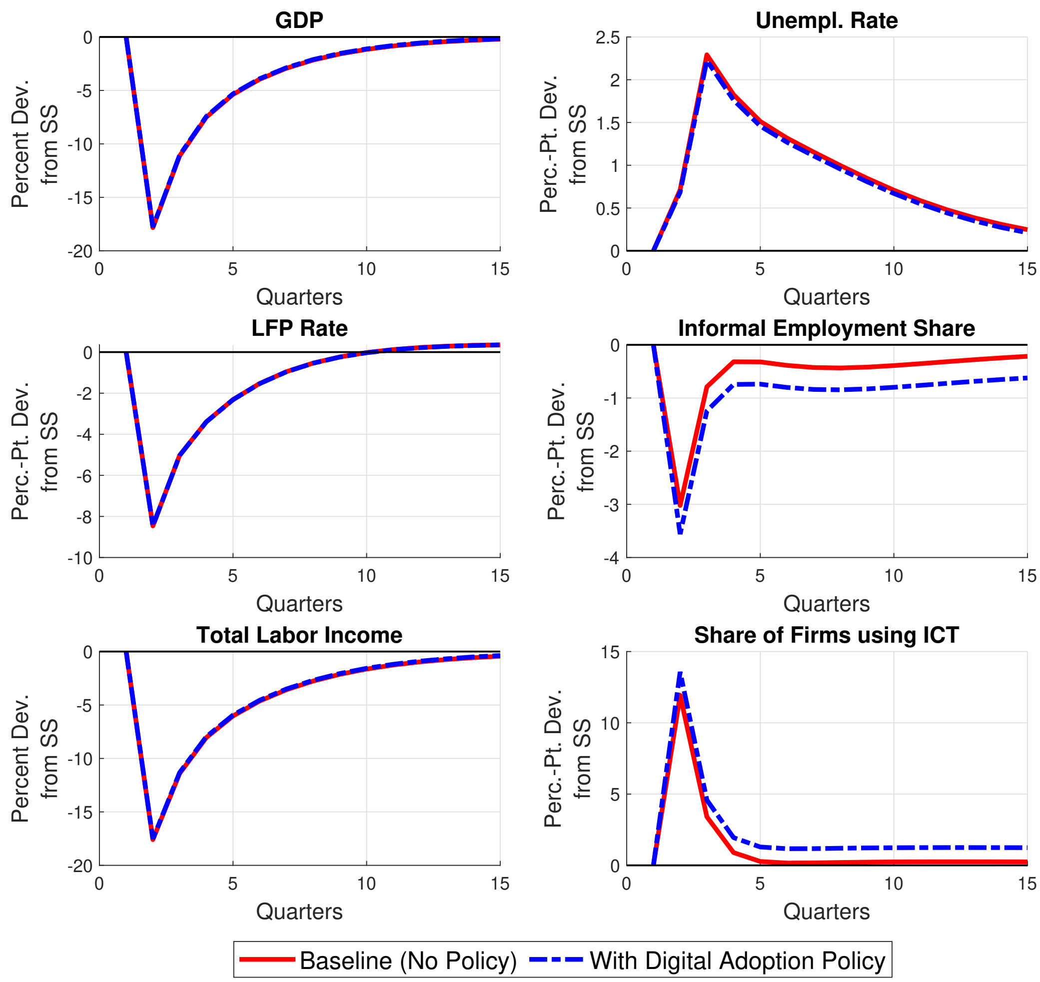


Figure A3: Labor Market and Macroeconomic Dynamics amid COVID: Benchmark vs. Policy Scenario, Digital Adoption Reduces Hiring Costs



Notes: Informal salaried labor income is defined as $w_r^r n_r^r$. Formal salaried labor income is defined as $w_r^i n_r^i + w_i^i n_i^i$. Total labor income is the sum of informal salaried labor income, formal salaried labor income and total self-employment income.